PROJECT 3.1: STATISTICALLY DOWNSCALED CLIMATE CHANGE PROJECTIONS FOR THE SOUTH-WEST

Principal Investigator

Steve Charles, CSIRO Land and Water, Private Bag No. 5, Wembley WA 6913
Phone: 08 9333 6795; Email: Steve.Charles@csiro.au

Research Question (9)

Can point-scale projections of daily rainfall and temperature series be produced for multiple locations across the South-West?

Key research findings and highlights

Milestones 3.1.1 and 3.1.2 are completed.

Milestone 3.1.1. *Report on the performance of IPCC AR4 GCMs for present-day climatic conditions in the South-West*

Global Climate Model (GCM) selection, or weighting, is an emerging discipline in the scientific literature with no universally acceptable methodology for GCM assessment. A score based method was developed and used to assess the performance of 25 IPCC AR4 GCMs in simulating South-West Western Australia (SWWA) monthly mean sea level pressure (MSLP) and, at 850, 700 and 500 hPa pressure levels, air temperature, specific humidity, geopotential height, and *u* and *v* wind speed (16 variables in total) compared to corresponding NCEP/NCAR Reanalysis (NNR) observations. These variables were selected because they are available as daily fields from IPCC AR4 GCMs and thus suitable for producing statistical downscaled projections. The performance criteria used assessed the reproduction of observed long-term mean and standard deviation, the seasonal (monthly) variation of the annual cycle, temporal trends, spatial distributions, and probability density functions (PDFs) of the 16 variables (see Appendix).

Combining the performance scores for all variables and criteria show that selecting better performing GCMs is not clear cut (Figure 1). However, some GCMs perform consistently better than others – e.g., CSIRO Mk 3.5, GFDL CM 2.1, MIROC 3.2 hires, MRI CGCM 2.3.2, and NCAR CCSM3. Identifying IPCC GCMs that provide credible simulations of predictors for present-day conditions will give more confidence in using these GCMs for generating statistically downscaled climate change projections for SWWA, in the next stage of this project.

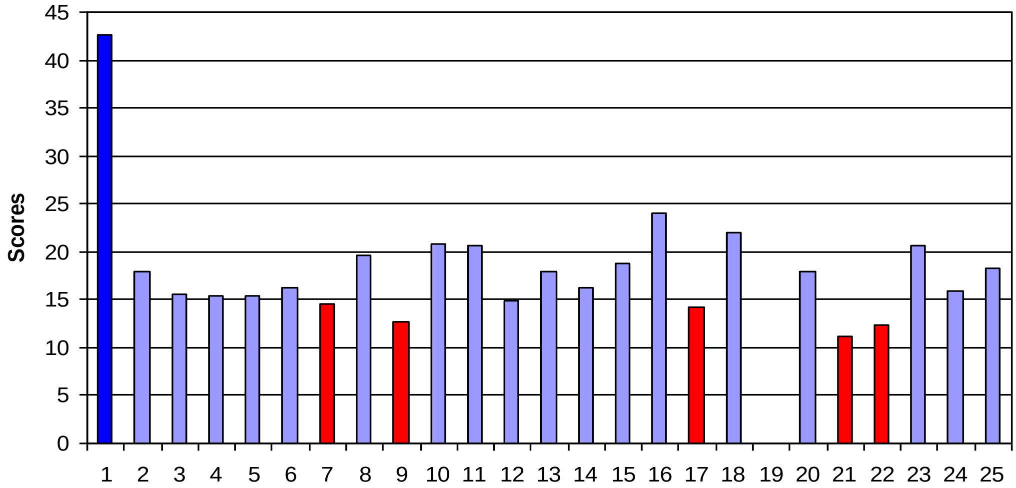
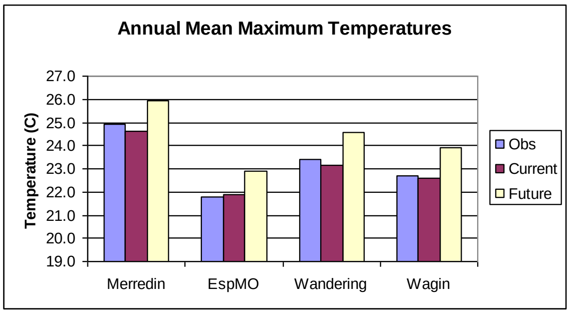


Figure 1 Combined IPCC AR4 GCM performance scores (See Appendix for key to GCMs; GCM 19 not included as insufficient data were available for assessment)

Milestone 3.1.2. *Interim report on development and testing of the extended downscaling model*

The NHMM rainfall downscaling model has been extended to simulate multi-site daily rainfall occurrences and amounts concurrently. This is an improvement on the previous version used in IOCI2 that simulated weather states based on occurrences only, with a subsequent regression model used to simulate amounts. It is advantageous to use both occurrence and amounts in weather state definition, given both potentially change due to projected climate change. Further NHMM rainfall downscaling model extension is on-going in collaboration with Dr Sergey Kirshner, Purdue University. This will further enhance the NHMM to incorporate within-state conditioning of amounts on atmospheric predictors related to rainfall intensity, to determine whether the same weather patterns will produce more intense daily rainfall under projected climate change.

Research extending the NHMM to incorporate daily temperature has implemented a stochastic weather generator model for statistically downscaling daily maximum and minimum temperature for individual sites conditional on both the (i) NHMM weather-state and (ii) wet/dry status of the day. For exploratory analysis results see the attached Appendix. For climate change projections, the changes to the mean annual cycle of maximum and minimum temperature projected by climate models are added to the observed annual cycle. An interim application of this technique has been developed that was used in a GRDC funded project that completed in 2009 (Foster *et al.*, 2009).



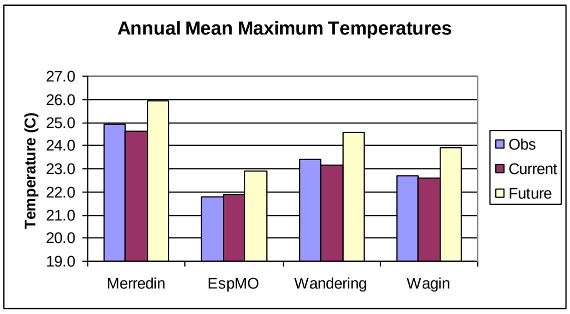


Figure 2 Mean annual daily maximum and minimum temperatures from stochastic downscaling of a CCAM A2 projection for four SWWA stations (current: 1976-2005; future: 2035-2064).

A literature review has determined a method to extend this temperature downscaling model for multiple sites (Khalili *et al.*, 2009) to maintain observed spatial correlations, and implementing this has commenced as part of the research being undertaken for Milestone 3.1.3. Although Milestone 3.1.3 is behind schedule, it is envisaged that it will be completed on time.

References

Foster I, Farre I and Charles S (2009). Climate change, wheat yield and cropping risks in Western Australia. GRDC Project Report DAW00088, 18pp.

Khalili, M., F. Brissette and R. Leconte (2009). Stochastic multi-site generation of daily weather data. *Stochastic Environmental Research and Risk Assessment* 23(6): 837-849.

Summary of new linkages to other IOCI 3 Projects

- None

Summary of any new research opportunities that have arisen

- A suite of 60km resolution atmospheric climate model (CSIRO CCAM) dynamically downscaled runs for 1961 to 2100 (following the IPCC SRES A2 scenario, forced by five IPCC AR4 GCMs) are now available over Australia, produced for the Tasmanian Climate Futures project. Statistically downscaled projections from these CCAM runs will be compared to those obtained from downscaling the host GCMs directly, to determine whether projections are more consistent when statistical and dynamical downscaling are used together.
- Collaboration with Dr Sergey Kirshner will investigate incorporating temperature, in addition to rainfall, into the NHMM code directly rather

than have temperature downscaling as a secondary process as in the methods applied so far.

List of publications accepted and submitted

Bates BC, Chandler RE, Charles SP, Campbell EP, 2010, Assessment of apparent non-stationarity in time series of annual inflow, daily precipitation and atmospheric circulation indices: A case study from southwest Western Australia, *Water Resources Research*, revised version submitted.

Fu GB, Charles SP, Yu JJ, 2009, A critical overview of pan evaporation trends over the last 50 years, *Climatic Change*, 97 , 193-214.

Fu GB, Viney NR, Charles SP, 2010, Evaluation of various root transformations of daily precipitation amounts fitted with a normal distribution for Australia, *Theoretical and Applied Climatology*, 99, 229–238.

Fu G, Viney NR, Charles SP, Liu JR, 2010, Long-term temporal variation of extreme rainfall events in Australia: 1910–2006, *Journal of Hydrometeorology*, In press, DOI: 10.1175/2010JHM1204.1

Liu Z, Fu G, Xu Z, Charles SP, Chen Y, 2010, A Score Based Method for Assessing the Performance of GCMs. Submitted to *Climatic Change.*

List of IOCI-related presentations at national international conferences, symposia and workshops

Nil

APPENDICES TO PROJECT 3.1 MILESTONE REPORT

Appendix to Milestone 3.1.1.

In order to have confidence in statistically downscaled projections, there is a need to assess whether Global Climate Models (GCMs) can adequately simulate the atmospheric predictors required by statistical downscaling models for present-day conditions. The performance of GCM historically forced 20th century runs (20C3M) were assessed against NCEP/NCAR Reanalysis (NNR) observations for 1961–2000. Identifying a subset of IPCC GCMs that provide credible simulations of predictors for present-day conditions will give more confidence in using these GCMs for generating statistically downscaled climate change projections for South-West Western Australia (SWWA).

A score based method was developed and used to assess the performance of 25 IPCC AR4 GCMs (Table 1) in simulating monthly mean sea level pressure (MSLP) and, at 850, 700 and 500 hPa pressure levels, air temperature, specific humidity, geopotential height, and *u* and *v* wind speed (16 variables in total) for 1961—2000 over SWWA compared to corresponding NNR data. These variables were selected because they are available as daily fields from IPCC AR4 GCMs and thus suitable for use in statistical downscaling. The performance criteria used assessed the reproduction of observed long-term mean and standard deviation, the seasonal (monthly) variation of the annual cycle, temporal trends, spatial distributions, and probability density functions (PDFs) of the 16 variables. Results show that:

1) GCMs usually provide better simulations of climate variables (such as MSLP) than precipitation. For example, 18 out of 25 GCMs simulate annual MSLP within ±0.2%, while they cannot simulate annual precipitation over SWWA within this range (Figure 3). This highlights the importance and necessity of statistical downscaling.

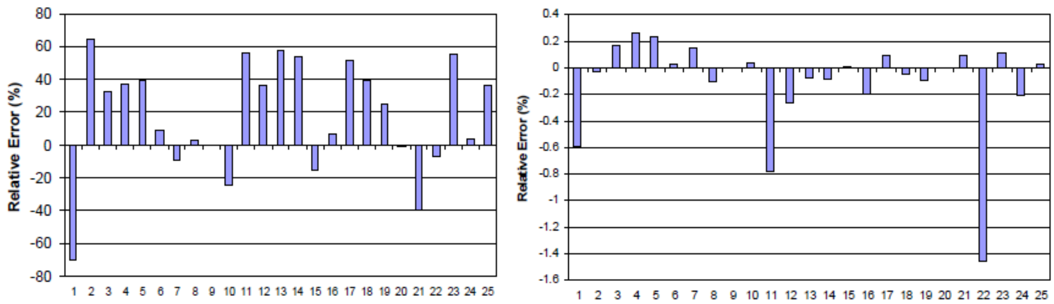


Figure 3 Relative errors (%, relative to NNR) of long-term (1961—2000) SWWA annual rainfall (left) and mean sea level pressure (right) simulated by the 25 IPCC AR4 GCMs (x-axis values are the GCM ID numbers in Table 1).

2) In addition to long-term mean values, other statistics are also critical for GCM assessment. For example, a GCM can simulate SWWA long-term annual rainfall within 10% relative error, but have poor spatial distribution (Figure 2). This justifies the use of multi-criteria rather than single criterion to assess GCMs.

3) The performance scores for all variables and criteria show that selecting better performing GCMs is not clear cut (Figure 5). However, some GCMs perform consistently better than others — e.g., CSIRO Mk 3.5, GFDL CM 2.1, MIROC 3.2 hires, MRI CGCM 2.3.2, and NCAR CCSM3. The BCC model performs poorly in almost all criteria for every variable and thus it is ranks much worse than the other GCMs (Figure 5, where a high score is poor relative performance).

Table 1 IPCC AR4 GCMs

GCMs	ID	Originating Group(s)	Country	Resolution
BCC:CM1	1	Beijing Climatic Center	China	1.9º×1.9º
BCCR:BCM20	2	Bjerknes Centre for Climatic Research	Norway	1.9º×1.9º
CGCM3.1_T47	3	Canadian Centre for Climatic Modelling & Analysis	Canada	2.8º×2.8º
CGCM3.1_T63	4			1.9º×1.9º
CNRM:CM3	5	Météo-France / Centre National de Recherches Météorologiques	France	1.9º×1.9º
CSIRO:MK30	6	Commonwealth Scientific and Industrial Research Organisation (CSIRO) Atmospheric Research	Australia	1.9º×1.9º
CSIRO:MK35	7			1.9º×1.9º
GFDL:CM20	8	US Department of Commerce / National Oceanic and Atmospheric Administration (NOAA) / Geophysical Fluid Dynamics Laboratory (GFDL)	USA	2.0º×2.5º
GFDL:CM21	9			2.0º×2.5º
GISS:AOM	10	National Aeronautics and Space Administration (NASA) / Goddard Institute for Space Studies (GISS)	USA	3º×4º
GISS:EH	11			4º×5º
GISS:ER	12			4º×5º
FGOALS:g10	13	National Key Laboratory of Numerical Modelling for Atmospheric Sciences and Geophysical Fluid Dynamics (LASG) / Institute of Atmospheric Physics	China	2.8º×2.8º
ECHAM4	14	Climatic Research Centre	Italy	2.8º×2.8º
INM:CM30	15	Institute for Numerical Mathematics	Russia	4º×5º
IPSL:CM4	16	Institut Pierre Simon Laplace	France	2.5º×3.75º
MIROC3.2_hires	17	Center for Climatic System Research (University of Tokyo), National Institute for Environmental Studies, and Frontier Research Center for Global Change (JAMSTEC)	Japan	1.1º×1.1º
MIROC3.2_medres	18			2.8º×2.8º
ECHO_G	19	Meteorological Institute of the University of Bonn, Meteorological Research Institute of KMA, and Model and Data group.	Germany / Korea	3.9º×3.9º
ECHAM5	20	Max Planck Institute for Meteorology	Germany	1.9º×1.9º
CGCM2.3.2	21	Meteorological Research Institute	Japan	2.8º×2.8º
CCSM3	22	National Center for Atmospheric	USA	1.4º×1.4º

PCM	23	Research	USA	2.8º×2.8º
HadCM3	24	Hadley Centre for Climatic Prediction and Research / Met Office	UK	2.5º×3.75º
HadGEM1	25			1.3º×1.9º

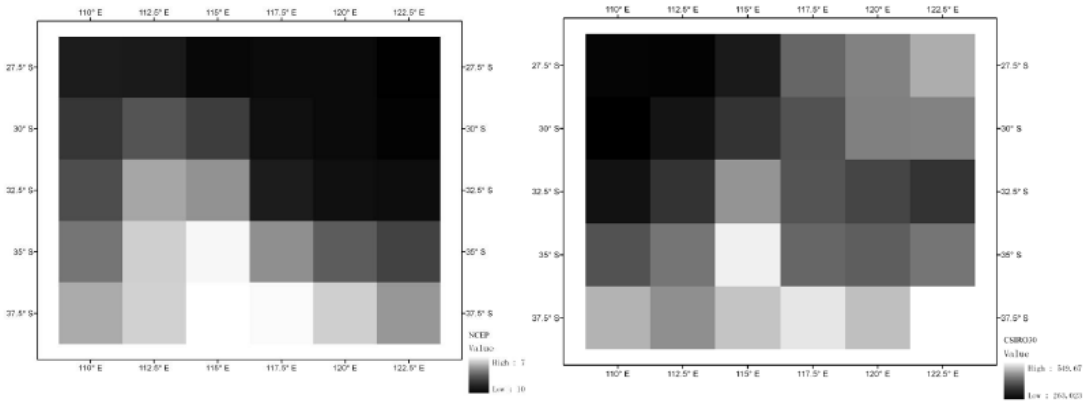


Figure 4 Spatial distribution of SWWA long-term (1961–2000) annual rainfall for NNR (left) and CSIRO Mk3.0 (right). CSIRO Mk3.0 produces a mean relative error of 8.9% in Figure 3. Dark shading is low rainfall, light shading is high rainfall.

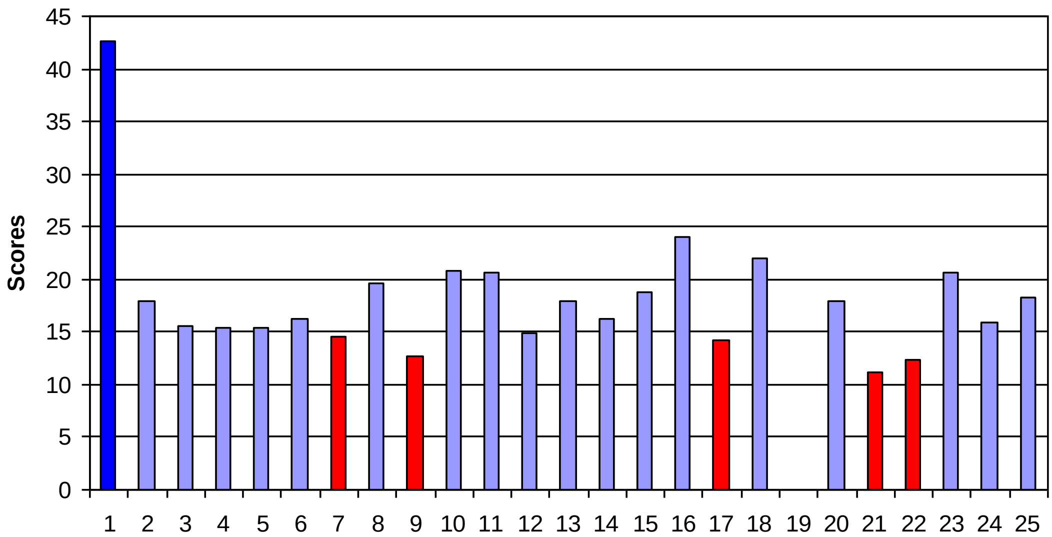


Figure 5 Combined IPCC AR4 GCM performance scores (GCM 19, ECHO_G, not included as insufficient data were available for assessment)

4) Correlations between the overall scores (Figure 5) and the scores for individual variables and individual criterion are shown in Figure 6 (upper and lower plots, respectively). Of the variables assessed, the scores obtained for geopotential heights and wind speeds have the highest correlation with the overall scores. Of the criteria used, scores obtained for the long-term means, root mean square errors, PDFs and seasonal distributions (CE(monthly)) correlate highest with the overall scores (Figure 6). This suggests, for example, that assessment of GCMs based on MSLP only would not provide a good indication of their performance for the other variables assessed whereas assessment based on geopotential heights would. It also suggests that ability to reproduce the mean is a good measure of overall performance whereas ability to reproduce spatial distribution (EOF), for example, is not. This emphasises that there are considerable inconsistencies

when assessing GCMs across a range of variables and criteria, and hence any score based ranking system is sensitive to the variables and criteria assessed.

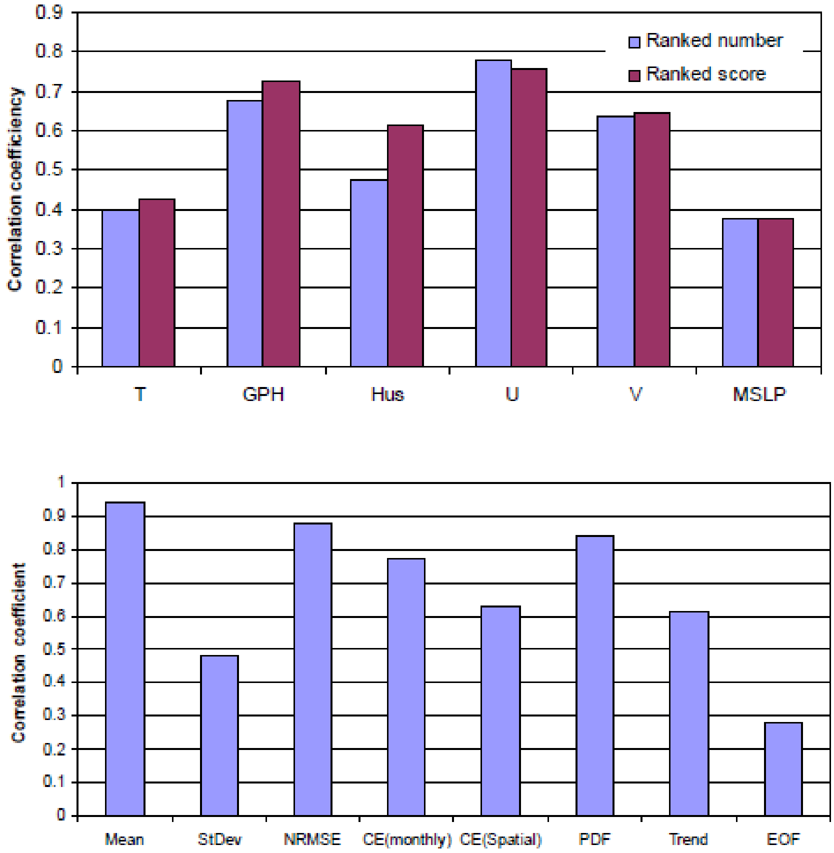


Figure 6. Correlation coefficients between the overall ranked scores (as shown in Figure 5) and (upper plot) those for each individual predictor (T is temperature, GPH is geopotential height, Hus is specific humidity, U is westerly wind, V is northerly wind) and (lower plot) each individual criterion.

Appendix to Milestone 3.1.2.

Research extending the NHMM to incorporate daily temperature has implemented a stochastic weather generator model for statistically downscaling daily maximum and minimum temperature for individual sites conditional on (i) NHMM weather-state and (ii) the wet/dry status of the day. Exploratory analysis shows how conditioning on both weather state and wet/dry status differentiates pertinent temperature characteristics. For example, Figure 7 shows how the distributions of daily maximum and minimum temperatures for the May-October season for Wongan Hills vary between 6 states and wet/dry status.

The median values (white bar in the centre of each box-plot) of daily maximum temperatures are lower for the wet-days of each weather state. This is as expected given wet-days occur more often in mid-winter and are associated with overcast conditions. The ranges vary considerably between states and wet/dry days, with contrasts such as between the small range of State 5 (wettest state; Wongan Hills is wet on 97% of days for this state) and the large range of State 6 (driest state; Wongan Hills is wet on 3% of days for this state).

The medians of daily minimum temperatures are higher for wet days for all states except State 5 (wettest state). Dry days for State 6 (driest state) have the largest range, as expected given dry days at the beginning or end of the season can be warm whereas dry clear nights in mid-winter produce the greatest radiative cooling and hence the coldest nights.

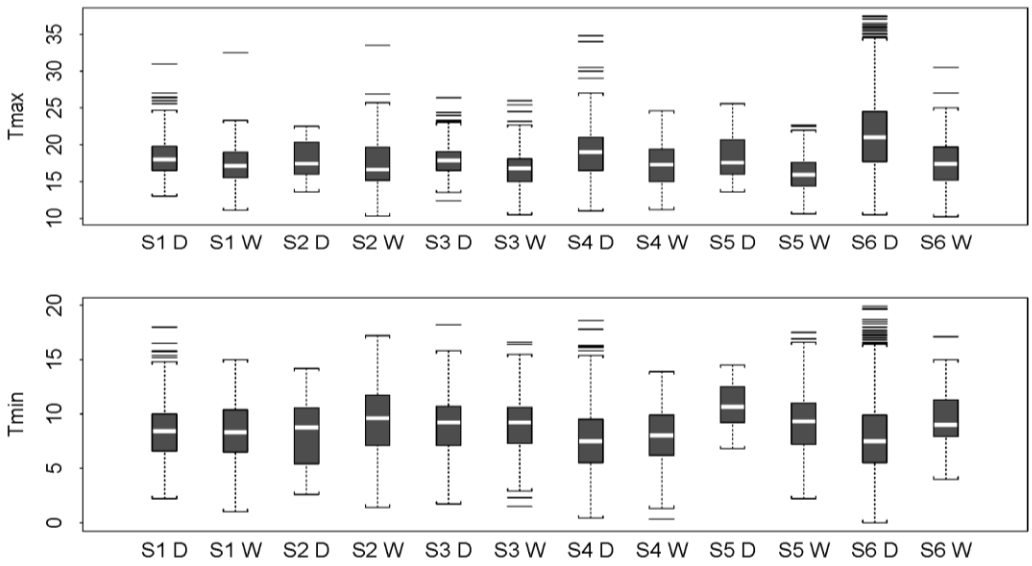


Figure 7 Daily maximum (upper plot) and minimum (lower plot) temperature distributions for the May-October season for Wongan Hills conditional on the 6 states of a NHMM (S1 to S6) and wet/dry status of days within each state ('D' dry; 'W' wet). The mean wet-day probabilities are 0.38, 0.84, 0.69, 0.10, 0.97 and 0.03 for the 6 states respectively.

The weather states of a NHMM are specified in terms of multi-site daily rainfall patterns. Although this means they are determined independently of temperature data, the states correspond to particular synoptic situations with corresponding wind direction, wind strength and cloudiness characteristics – all of which combine to uniquely influence maximum and minimum temperature distributions at individual stations. Thus station-specific characteristics are captured in stochastically downscaled series, whereas this level of detail would not be present in GCM grid-scale simulations.

Dynamically downscaled temperature projections produced by CSIRO CCAM with far-field atmospheric and SST forcing from 5 GCMs (GFDL 2.0 and 2.1, MIROC-medres, CSIRO Mk3.5, and MPI-ECHAM5 GCMs) will be compared and used to condition/change the annual cycle of maximum and minimum temperature means and variance. The resulting projected changes to the full probability distribution functions (PDFs) of daily temperature will be examined to infer changes to the statistics of temperature extremes. In addition, collaboration with Dr Sergey Kirshner will investigate incorporating temperature, in addition to rainfall, into the NHMM code directly rather than have temperature downscaling as a secondary process as in the methods applied so far.