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Assessing future droughts in Australia - a nesting model to correct for long-term persistence in general circulation model precipitation simulations

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Abstract: To produce meaningful predictions for water resources assessments, we need to be able to correctly model climate variability on a range of time scales. Inability to represent low-frequency variability in precipitation and streamflow leads to a poor simulation of droughts, and can result in biased estimates of the security of water resources systems. This is particularly important in regions, such as Australia, where climate teleconnections lead to variability at interannual and interdecadal scales. The impacts of climate change on this variability are important to consider.

The precipitation outputs of General Circulation Models (GCMs) are biased compared to observations at a range of time scales. At the daily scale, rainfall occurrence is poorly modelled with rainfall occurring too often, with too low intensities. At monthly and annual scales, the distributions of rainfall amounts can be biased, in some cases over-predicting rainfall amounts and in others, especially in coastal areas, under-predicting rainfall totals. Interannual variability is also poorly modelled. We demonstrate the extent of this bias by comparing the precipitation from the CSIRO Mk3.5 model to observed data over Australia.

We propose a framework to address and correct for these weaknesses in the GCM outputs. The model involves nesting the GCM simulations into monthly and annual time series of observed data, such that monthly and annual means, variances and lag correlations are appropriately simulated.

Daily precipitation outputs from the CSIRO Mk3.5 model are corrected using the above model. The nesting model (NBC) is also compared to a simple monthly correction (MBC), and is found to provide better performance in terms of prediction error at annual and interannual time scales. At monthly time scales, the MBC gives slightly better predictions. The root mean square errors of the predictions compared to the observed Bureau of Meteorology data are presented in Table 1 for a range of statistics at different time scales. This data is presented for the validation period of 1951 to 2000.

Table 1. Comparison of raw and bias corrected (MBC and NBC) prediction errors for key statistics.

Statistic	Raw GCM RMSE	MBC RMSE	NBC RMSE
Annual Mean	214.0	48.8	47.4
Annual Std. Dev.	84.6	53.9	39.2
Annual Lag 1 Cor.	0.20	0.20	0.20
Monthly Mean	26.5	11.3	11.8
Monthly Std. Dev.	16.7	16.8	18.2
2 Year Minimum Sum	0.33	0.25	0.16
5 Year Minimum Sum	0.52	0.44	0.37
5th Percentile 1 Year SPI	1.28	0.45	0.29
5th Percentile 2 Year SPI	1.63	1.01	0.60
5th Percentile 5 Year SPI	2.08	1.31	0.84

The results of the models are also used to assess the difference in drought predictions using the Standardised Precipitation Index (SPI). Predictions of the SPI are compared for the raw GCM precipitation and the bias corrected outputs. The final three rows of Table 1 present the results of this analysis for the period 1951 to 2000, showing the superior performance of the NBC methodology. For future climate projections, using the SRESA2 scenario for 2080, it is found that drought frequencies are overestimated when using the raw GCM precipitation outputs. Overall the study demonstrates that bias correction with nesting at multiple time scales can address some of the weaknesses of GCM precipitation fields.

Keywords: *Climate change, bias correction, precipitation, general circulation model (GCM)*

1. INTRODUCTION

The impacts of climate change on water resources systems are of concern to a range of stakeholders from governments to water utilities, agriculturalists to urban consumers. Impact assessments seek to answer questions regarding future risks to water resources systems, particularly at a regional or watershed scale. To produce meaningful predictions for these assessments, we need to be able to correctly model climate variability on a range of time scales. But there are problems with general circulation model (GCM) rainfall outputs on all temporal scales.

Firstly, although GCMs are expected to provide more reliable results at seasonal to annual time frames, there can still be significant biases in the annual and monthly statistics of precipitation when compared to observations. Figure 1(a) shows the observed annual mean rainfall and Figure 1(b) the bias in the annual means from the CSIRO Mk3.5 GCM for Australia for 1961 to 2000. We see that over the relatively dry, flat interior of Australia, the model overpredicts the annual rainfall by up to 200% in some locations. In coastal areas, annual average rainfall is underestimated. In Figure 1(c) we present a comparison of the ratio of the projected changes in annual average rainfall by 2080 to the bias in the annual average rainfall for the 20th century. Areas shown in light grey are those where the ratio of the change is larger than the bias, medium grey shows areas where the change and bias are of the same order of magnitude. Areas shown in black indicate where the bias is much larger than the projected changes for the SRESA2 scenario.

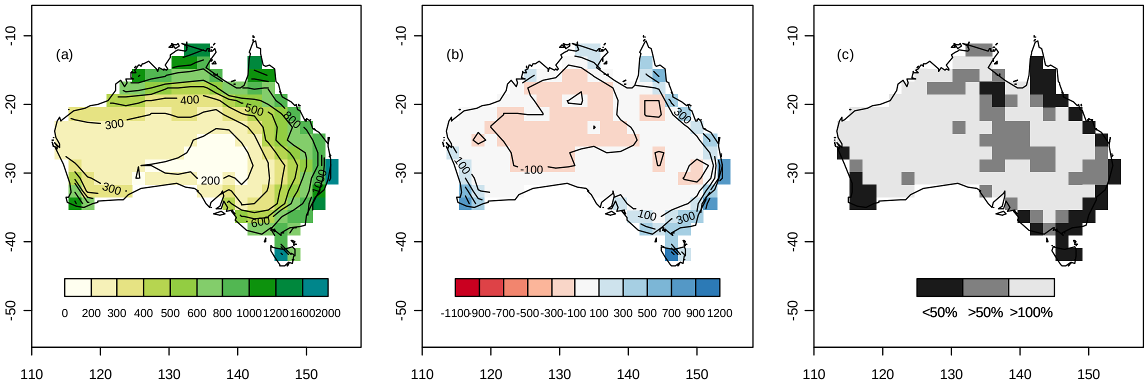

Figure 1. Biases in mean annual GCM rainfall outputs a) observed mean annual rainfall (mm/yr) for 1901 to 2000, b) mean annual bias (observed – modelled) in mean annual rainfall (mm/yr), c) ratio of changes projected for SRESA2 for 2061 to 2000 compared to bias for 1901 to 2000.

Secondly, at a finer time scale it is well known that there are problems in the modelling of daily rainfall both in rainfall occurrence and rainfall intensity. Sun et al. (2006) found that GCMs tend to overestimate the number of days with rainfall less than 10 mm, whilst underestimating more intense events, with the errors cancelling each other out to give seasonal totals that can be reasonably realistic, although this is very model dependent (Randall et al., 2007). Other problems related to the modelling of daily rainfalls include preserving observed dry and wet spell lengths (Ines and Hansen, 2006).

Thirdly, interannual variability of rainfall is dependent on regional and global climate teleconnections, and the nature and extent of this variability changes around the world. In Australia, major climate teleconnections that affect interannual rainfall variability include the El Nino Southern Oscillation (ENSO), the Interdecadal Pacific Oscillation (IPO), the Southern Annular Mode (SAM) and the Indian Ocean Dipole (IOD). Inability to represent low-frequency variability in precipitation and flow, results in a poor simulation of droughts and biased estimates of the security offered by existing water resources systems in a warmer climate. The modelling of ENSO in GCMs has been assessed in many studies. ArchutaRao and Sperber (2006) investigated how well ENSO was modelled in the GCMs submitted to the 3rd Coupled Model Intercomparison Project (CMIP3) for the IPCC Fourth Assessment Report. They attributed overall improvements since one of the earliest assessments of ENSO modelling (Neelin et al., 1992) to improved coupled model formulations. However, they note “the importance of reducing systematic model error” (AchutaRao and Sperber, 2006) to ensure the accuracy of precipitation climatologies.

Despite the problems with GCM rainfall outputs, impact assessment studies still require future projections of rainfall for a range of applications. Stochastic and dynamic downscaling have both been used in many studies in an attempt to provide better future rainfall projections. However both stochastic and dynamic downscaling studies tend to be highly specialized and hence are developed for a particular region or specific question. We are interested in whether simple methods, which can quickly and easily be applied over different regions, could be used to improve some of the shortcomings of GCM rainfall.

The remainder of this paper is organised as follows. In Section 2, we examine techniques that have been proposed in the literature to bias correct GCM rainfall. Section 3 describes our proposed bias correction technique. Section 4 presents the results of the model applied to 20th century GCM simulations over Australia and future drought projections, and Section 5 presents the conclusions.

2. BIAS CORRECTION FOR GCM OUTPUTS

Bias correction techniques have been developed to allow the use of GCM outputs directly, whilst accepting that there are problems in GCM modelling of rainfall. Combined with a spatial disaggregation step, they can provide inputs at a scale that is suitable for hydrologic modelling. Without spatial disaggregation, bias correction can be used to make regional assessments of water availability.

Wood et al. (2004) compared three simple statistical downscaling approaches, including linear interpolation, spatial disaggregation and a combined bias correction and spatial disaggregation model. The bias correction method used quantile mapping to correct the monthly model climatology to the observed climatology. The bias correction with spatial disaggregation was the only method to “produce hydrologically plausible results” (Wood et al., 2004). Areas suggested by Wood et al (2004) for future work included modelling of interannual variability and sub-grid spatial variability.

Maurer and Hidalgo (2008) compared the monthly quantile mapping of Wood et al (2004) to a constructed analogue downscaling approach. They commented that the advantage of the quantile mapping is that it “allows the mean and variability of a GCM to evolve in accordance with the GCM simulation, while matching all statistical moments between the GCM and observations for the base period” (Maurer and Hidalgo, 2008).

Ines and Hansen (2006) also applied the quantile mapping technique, this time to daily rainfalls instead of monthly totals. The model was more successful than multiplicative scaling of monthly data at predicting monthly means, and daily intensity and occurrence. However, they found that crop yields were generally under-predicted using the bias corrected rainfalls which they attributed to the modelled wet and dry spell lengths in the raw GCM outputs, which were not changed by the bias correction techniques.

3. NESTING METHODOLOGY

The bias correction methods described in the preceding section focused on monthly or daily statistics of rainfall. However, longer term variations in rainfall also need to be well modelled to enable accurate estimates of drought and water resources availability. In this study, we propose a method that addresses the missing interannual variability by using statistics from the observed rainfall at two time scales – monthly and annual, rather than just one time scale.

The issue of correctly modelling interannual variability in precipitation has been addressed by researchers looking at stochastic rainfall generation models. Srikanthan (2009) describes a nested two part model: daily, stochastically generated, rainfalls are modified by nesting in monthly and annual data to ensure that the daily, monthly and annual statistics of the observed rainfall are reproduced. A nesting procedure was also used by Wang and Nathan (2007), although in this case the nesting of the daily generated rainfall sequences was only carried out at the monthly level.

To adapt the nesting model to bias correction, we use the daily GCM outputs instead of generating daily rainfall. The daily GCM sequences are then modified by nesting in the observed monthly and annual time series. The process for the nesting is now described. We use the 0.25 degree gridded rainfall data product from the Australia Bureau of Meteorology (BOM), which has data from 1900 onwards. We split the observed data into two periods, a calibration period to derive the model parameters of 1901 to 1950, and a validation period of 1951 to 2000. The method is applied to daily precipitation from the CSIRO Mk3.5 model.

The observed and modeled rainfalls are aggregated to monthly data and parameters for the nesting model are calculated for each month of the year, using the all the years in the calibration period. For example, all January rainfalls from 1901 to 1950 are collated and the mean and standard deviation of these 50 values calculated. The time series of raw GCM monthly rainfalls ($\mathbf{y}$) is then standarized to create $\mathbf{y}'$ for each month in the time series by removing the model monthly mean and standard deviation for that month (i) as shown in (1).

$$y'_i = \frac{y_i - \mu_{mod,i}}{\sigma_{mod,i}} \qquad (1)$$

We then remove the monthly lag one autocorrelations ($\rho_{mod,i}$) that are present in the model results from the standardized time series and instead apply the observed monthly lag one autocorrelations ($\rho_{obs,i}$) to create **y"** as shown. Monthly lag one autocorrelations are defined as the correlation of the time series of the values from month i with the time series of month i-1. For example, the monthly autocorrelation for February is calculated as the correlation of the February values from 1901 to 1950, with the time series of January values from 1901 to 1950.

$$y''_i = \rho_{obs.i} \times y''_{i-1} + \sqrt{1-\rho_{obs.i}{}^2}\left(\frac{y'_i - \rho_{mod,i} y'_{i-1}}{\sqrt{1-\rho_{mod,i}{}^2}}\right) \qquad (2)$$

We now rescale the observed means and standard deviations to create the nested time series (**y‴**) at the monthly level.

$$y'''_i = y''_i \times \sigma_{obs,i} + \mu_{obs,i} \qquad (3)$$

The nested monthly values (**y‴**) are then aggregated to the annual scale (**z**). The monthly process is repeated for the annual time step, with the difference that there is no need to allow for seasonality, as is done in the monthly model by calculating the model parameters separately for each month.

Beginning with the annual time series (**z**), we modify by standardising with the mean and standard deviation of the annual rainfall, such that for year j, where j is between 1901 to 1950 for the calibration period:

$$z'_j = \frac{z_j - \mu_{mod}}{\sigma_{mod}} \qquad (4)$$

We then remove any modelled lag one autocorrelations and apply the observed lag one autocorrelations. Yearly lag one autocorrelations are calculated as the correlation between the rainfall in one year and the next. As the observed lag one autocorrelations are generally quite small, this step does not generally lead to large changes compared to the standardised annual series (**z′**).

$$z''_j = \rho_{obs} \times z''_{j-1} + \sqrt{1-\rho_{obs}{}^2}\left(\frac{z'_j - \rho_{mod} z'_{j-1}}{\sqrt{1-\rho_{mod}{}^2}}\right) \qquad (5)$$

The last step is to create the final annual time series by rescaling with the observed annual means and standard deviations.

$$z'''_j = z''_j \times \sigma_{obs} + \mu_{obs} \qquad (6)$$

We now have four time series that we will use to correct the daily GCM time series (x), the uncorrected monthly time series (y), the nested monthly time series (y‴), the aggregated yearly time series (z) and the nested annual time series (z‴). From Srikanthan (2009), the corrections at the monthly and annual level can be applied to the daily time series at the same time to create a one step correction as follows, where for day t which is in month *m* in year *n*, the weighting factor is the ratio of the monthly corrected rainfall to the raw GCM rainfall for month *m*, multiplied by the ratio of the yearly corrected rainfall to the aggregated GCM rainfall for year *n*.

$$\hat{x}_t = \left(\frac{y'''_m}{y_m}\right) \times \left(\frac{z'''_n}{z_n}\right) \times x_t \qquad (7)$$

For future periods, we use the observed and modelled statistics for the observation period to adjust the future model results, and thereby assuming that the biases in the model for observed period remain the same in the future. In more detail, the future bias correction steps with equations (1), (2), (4) and (5) use the monthly and annual statistics from the GCM for the current climate and equations (3) and (6) use the observed statistics as before. The form of equation (7) is unchanged for the future period. We use the SRESA2 scenario, with data from the period 2061 to 2100. Results are presented for the average of this period, nominally termed 2080.

4. RESULTS

4.1. Modelling of Seasonal and Annual Rainfall Statistics

We compare the results of the nesting bias correction to those from a bias correction method that corrects just the monthly means and standard deviations. In the following text, the monthly mean and standard deviation correction is term the Monthly Bias Correction (MBC), whilst the nested algorithm outlined in Section 3 is term the Nested Bias Correction (NBC). Figure 2 shows the bias corrected results for the MBC and NBC methods at the annual level for the validation period of 1951 to 2000. In Figures 2 to 4, each individual point on the graph represents the respective annual statistic for each grid cell (i.e. each location where the bias correction has been applied). Both methods give good improvements for the mean annual rainfall, whilst the NBC shows improvement in the annual standard deviations and lag one autocorrelations compared to both the raw GCM outputs and the MBC. This demonstrates that improving the modelling of mean rainfall is not enough to correct model rainfall variability. The lag one autocorrelations do not show as good improvement as the means and standard deviations. This is because the autocorrelations of the observed data are not as similar as the other statistics between the calibration and validation periods. Despite this, by bias correcting with the nested model, which includes correcting the lag one autocorrelations, we model interannual variability much better. This is demonstrated in the following section.

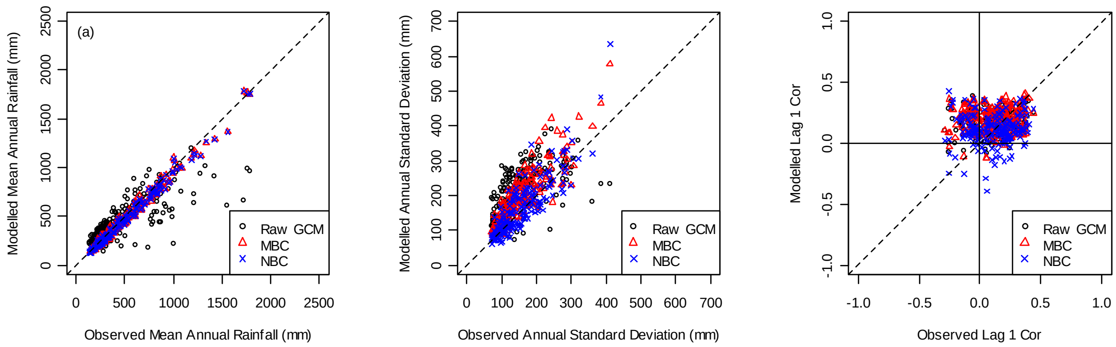

Figure 2: Modelled vs observed statistics of annual rainfall for raw GCM outputs and MBC and NBC bias corrected models for a) annual mean, b) annual standard deviation and c) annual lag one autocorrelation.

4.2. Modelling of Interannual Rainfall Variability

Looking at the statistics of interannual variability, we firstly consider the 2 and 5 year minimum rainfall totals. These statistics are standardised by the mean annual rainfall to allow comparisons of the statistics across Australia. Figure 3 presents plots of modelled vs observed for the validation period of 1961-2000. By correcting the GCM outputs at the annual level for the lag one autocorrelation, we improve the modelling of these minimum rainfall totals. This is important for ensuring that drought and flood periods are modelled correctly, particularly if the GCM outputs are being considered for analysis of dam capacities. The results from both Figure 2 and Figure 3 are summarised in Table 1, which presents the root mean square errors (RMSE) of the raw GCM outputs compared to observations and also the results from applying the MBC and NBC methods.

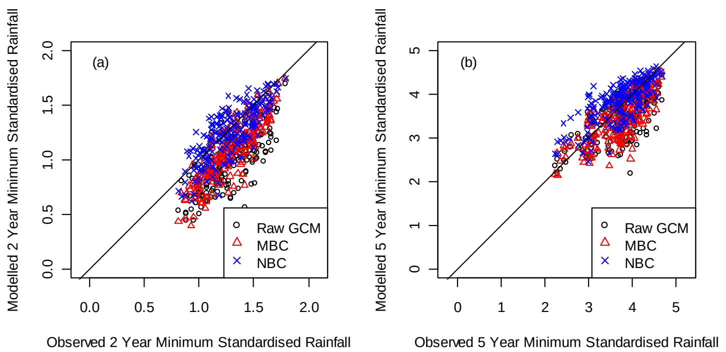

Figure 3. a) 2 year and b) 5 year minimum rainfall totals, standardised by mean annual rainfall

4.3. Modelling of Current and Future Drought Frequencies

We now also present the results from an application of the bias corrected outputs for drought analysis using the Standardised Precipitation Index (SPI). The SPI was developed to provide a simple calculation of drought (Guttman, 1999). A time series of precipitation is fitted to a standard normal distribution and the quantiles of the fitted distribution are used to assess the severity of the drought. Negative values of the index occur during dry periods, with positive values indicating wet conditions. The SPI can be calculated for varying intervals; intervals of 1, 2 and 5 years are assessed in this study.

We undertake two calculations using the SPI. The first compares the modelling of drought frequencies across Australia from the raw and bias corrected GCM outputs for the validation period of 1951 to 2000. Figure 4 shows scatter plots of the estimated 5th percentile of the SPI at each grid cell compared to the observed data for SPI values calculated for the three time periods. The 5th percentile has previously been defined as severe drought by Burke and Brown (2008).

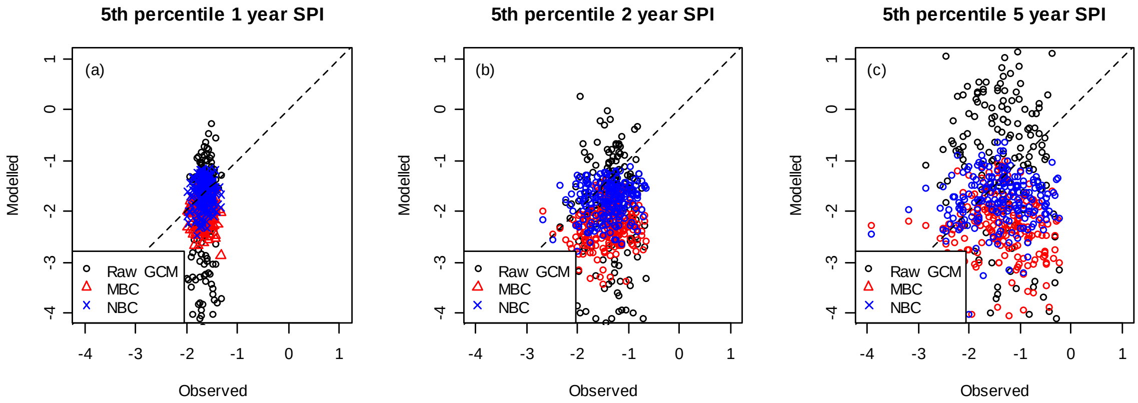

Figure 4. Modelled vs observed 5th percentile SPI values for a) 1 year SPI, b) 2 year SPI and c) 5 year SPI

Both bias correction methods improve the modelling of severe drought. The NBC is found to provide the best estimate of the magnitude of observed severe drought at each location. Table 1 presents the prediction error for each of the scenarios in Figure 4. For both bias correction methods, performance is best when we calculate the SPI at a one year interval and decreases for increasing SPI intervals. This is to be expected as our nesting model only corrects for lag one autocorrelations. We would require a measure of longer term persistence in our model to capture the variations of drought over longer periods. This is an area of ongoing research.

With confidence that the nested bias correction method can improve the modelling of droughts, we move to assessing the frequency of future severe droughts. To do this, we use the observed 5th percentile SPI value to define a severe drought threshold at each grid cell. We then use the future GCM projections (both raw and bias corrected) to see how frequently we expect severe droughts to occur in the future (Burke and Brown, 2008).

The results of this analysis highlight the impact of incorrectly modelling interannual variability in GCM outputs. Figure 5 shows the predictions of drought frequency for the future across Australia.

The mean frequency of severe droughts

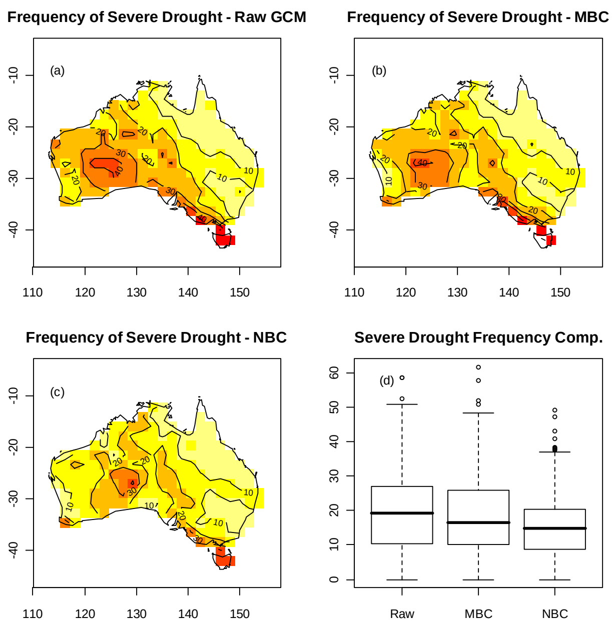

Figure 5. Maps of severe drought frequency in 2080 for a) raw GCM, b) monthly and c) nested bias correction. A comparison of the distribution of values for the three cases is shown in d).

occurring in the future using the raw GCM outputs is approximately 20% - meaning that in any one year, 20% of the country is likely to be suffering from a severe drought. If we only bias correct the GCM outputs using a monthly scaling, then the pattern of severe droughts is quite similar, and the mean occurrence frequency is approximately 18%. On the other hand, using the nesting bias correction technique, we find that severe droughts are less likely than it would seem from the raw GCM outputs. The mean occurrence frequency is 15% in this case, and we can see the difference in the spatial patterns of severe drought frequency, with decreases in occurrence frequency particularly in Western Australia. It is important to note that we are still seeing increases in the frequency of severe droughts over 90% of the country. Also, if we assessed drought using a combined precipitation and temperature based index (e.g. the Palmer Drought Severity Index), then with the combination of increasing temperatures we would expect droughts to occur even more frequently. Further research is being undertaken whether these findings are specific to the CSIRO GCM or they apply to other GCMs as well.

5. CONCLUSIONS

This paper has presented the details of a nesting bias correction methodology that can be applied to GCM rainfall outputs to address known weaknesses in the modelling of monthly, annual and interannual statistics of rainfall. The nested bias correction model performs better than simple monthly means corrections, which have often been used in climate change impact assessments. Future work will involve extensions to the model to account for longer term persistence. It is also proposed to apply the nesting model to multiple GCMs.

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REFERENCES

AchutaRao, K. and Sperber, K.R. (2006), ENSO simulation in coupled ocean-atmosphere models: are the current models better? *Climate Dynamics*, 27, 1-15.

Burke, E.J. and Brown, S.J. (2008), Evaluating uncertainties in the projection of future drought. *Journal of Hydrometeorology*, 9, 292-299.

Guttman, N.B. (1999), Accepting the standardized precipitation index: A calculation algorithm. *Journal of the American Water Resources Association*, 35, 311-322.

Ines, A. V. M. and Hansen, J.W. (2006), Bias correction of daily GCM rainfall for crop simulation studies. *Agricultural and Forest Meteorology*, 138, 44-53.

Maurer, E. P. and Hidalgo, H.G. (2008), Utility of daily vs. monthly large-scale climate data: an intercomparison of two statistical downscaling methods. *Hydrology and Earth System Sciences*, 12, 551.

Neelin, J.D., Latif, M., Allaart, M. A. F. , Cane, M. A., Cubasch, U., Gates, W. L., Gent, P. R., Ghil, M., Gordon, C., Lau, N. C., Mechoso, C. R., Meehl, G. A., Oberhuber, J. M., Philander, S. G. H., Schopf, P. S., Sperber, K. R., Sterl, K. R., Tokioka, T., Tribbia, J., and Zebiak, S. E. (1992), Tropical air-sea interaction in general circulation models. *Climate Dynamics*, 7, 73-104.

Randall, D.A., Wood, R. A., Bony, S., Colman, R., Fichefet, T., Fyfe, J., Kattsov, V., Pitman, A., Shukla, J., and Srinivasan, J. (2007), Climate Models and Their Evaluation. Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, S. Solomon, D. Qin, M. Manning, Z. Chen, M. Marquis, K. B. Averyt, M. Tignor, and H. L. Miller, Eds., Cambridge University Press,.

Srikanthan, R. (2009), A nested multisite daily rainfall stochastic generation model, *Journal of Hydrology*, doi: 10.1016/j.jhydrol.2009.03.025.

Sun, Y., S. Solomon, A. Dai, and R. W. Portmann (2006), How often does it rain? *Journal of Climate*, 19, 916-934.

Wang, Q. J. and Nathan, R.J. (2007), A method for coupling daily and monthly time scales in stochastic generation of rainfall series. *Journal of Hydrology*, 346, 122-130.

Wood, A. W., Leung, L.R., Sridhar, V., and Lettenmaier, D.P. (2004), Hydrologic implications of dynamical and statistical approaches to downscaling climate model outputs. *Climatic Change*, 62, 189-216.