# Assessment of rainfall simulations from global climate models and implications for climate change impact on runoff studies

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**Abstract:** Global warming can potentially lead to significant changes in future water resources availability. Rainfall is the key driver of water resources, where a change in mean annual rainfall in Australia is generally amplified as a two to three times bigger percentage change in mean annual runoff. The future catchment-scale climate series required to drive hydrological models in climate change impact studies is generally informed by the relative global climate model (GCM) simulations for the future and current climates.

This paper (i) presents the range of future rainfall projections from the 23 GCMs used in the IPCC Fourth Assessment Report for three large regions of Australia (south-east Australia, south-west Western Australia and northern Australia), (ii) assesses whether the GCMs can reproduce the observed characteristics of historical annual rainfall, and (iii) explores the implications of GCM selection, assessed against different criteria, on water resources impact studies.

The results indicate that most GCMs can reproduce the observed spatial mean annual rainfall pattern across Australia. However, the difference between the GCMs and observed mean annual rainfalls can be significant, with RMSEs of about one third of the mean annual rainfalls averaged over the regions. The future mean annual rainfall projections from the 23 GCMs per degree global warming range from -9 to +4 percent averaged across south-east Australia, -16 to 0 percent averaged across south-west Western Australia and -7 to +6 percent averaged across northern Australia.

The future runoff impact assessment will be more reliable if it is based on future climate projections from the better GCMs. However, it is difficult to objectively determine which GCMs are more likely to give reliable future climate projections. The results indicate that there is no clear difference in the future rainfall projections between the better and poorer GCMs, assessed based on their abilities to simulate the historical climate characteristics, across the three regions studied here. Therefore, using weights to favour the better GCMs give similar rainfall and runoff impact assessment results as the use of all the 23 GCMs. With the rapid progress in climate change science, global climate models will become more accurate and give more consistent projections and there will be better consensus in the research community on appropriate criteria to select GCMs for different applications. For now, the uncertainty and the range of future runoff in impact studies are probably best determined using future climate projections from a large range of archived GCM simulations.

Keywords: climate change impact, global climate models, rainfall, runoff, GCM assessment, GCM selection

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## 1. INTRODUCTION

Global warming can potentially lead to significant changes in future water resources availability. Rainfall is the key driver of water resources, where a change in mean annual rainfall in Australia is generally amplified as a two to three times bigger percentage change in mean annual runoff (Sankarasubramaniam et al., 2001; Chiew, 2006). The future catchment-scale climate series required to drive hydrological models in climate change impact studies is generally informed by the relative global climate model (GCM) simulations for the future and current climates.

This paper (i) presents the range of future rainfall projections from the 23 GCMs used in the IPCC Fourth Assessment Report (4AR) (IPCC, 2007) for three large regions of Australia (south-east Australia, south-west Western Australia and northern Australia), (ii) assesses whether the GCMs can reproduce the observed characteristics of historical annual rainfall, and (iii) explores the implications of GCM selection, assessed against different criteria, on water resources impact studies.

## 2. GCM SIMULATED RAINFALL VERSUS OBSERVED RAINFALL

Figure 1 shows the 1961–2000 observed mean annual rainfall and the 1961–2000 mean annual rainfall simulated by the 23 GCMs. The observed rainfall data come from the Australian Bureau of Meteorology 0.25° interpolated data (Jones and Beard, 1998). The GCM rainfall data are obtained from the Program for Climate Model Diagnosis and Intercomparison (PCMDI) website (http://www-pcmdi.llnl.gov).

Table 1 summarises, for the three regions (see Figure 1), the root mean square error (RMSE) between GCM mean annual rainfall and observed mean annual rainfall across the regions and the median value of the coefficient of variation (Cv) of GCM annual rainfall and observed annual rainfall. All the comparisons are carried out using data from 1961 to 2000 and at the GCM spatial resolution. For the coastal areas, the GCM grid cell is considered only if it has more than 40 percent land area. The median numbers of GCM grid cells are 32 ( $10^{th}$  to  $90^{th}$  percentile range of 14–83) in south-east Australia, 5 (2–15) in south-west Western Australia and 12 (26–63) in northern Australia.

The plots in Figure 1 show that the GCMs generally reproduce the observed spatial mean annual rainfall pattern. The spatial correlation between the GCM mean annual rainfall and observed rainfall is generally greater than 0.7 for comparisons across Australia and in each of the three regions. The numbers of GCMs that underestimate the observed inter-annual rainfall variability in south-east Australia and south-west Western Australia are similar to the numbers of GCMs that overestimate the observed inter-annual rainfall variability. Most of the GCMs underestimate the observed inter-annual rainfall variability in northern Australia.

Although the GCMs can generally reproduce the observed spatial mean annual rainfall pattern, there are considerable differences between the rainfall amounts simulated by the GCMs and the observed rainfall. The median RMSEs comparing the mean annual rainfall simulated by the 23 GCMs and the observed rainfall are 180 mm (10<sup>th</sup> to 90<sup>th</sup> percentile range of 130–320) in south-east Australia, 180 mm (110–280) in south-west Western Australia and 380 mm (270–650) in northern Australia. These values are about one third of the mean annual rainfalls averaged across each of the three regions. The GCMs can be ranked based on their abilities to reproduce the observed mean annual rainfall, but apart from several GCMs with very high RMSEs (for example, IPSL, BCCR, GISS-E-H and MRI), there is no clear threshold in the distribution of RMSE values to separate the better and poorer GCMs.

# 3. GCM PROJECTIONS OF FUTURE RAINFALL

Figure 2 and Table 1 show the future rainfall projections simulated by the 23 GCMs, expressed as a percentage change in mean annual rainfall per degree global warming. The change in each grid cell for each GCM is estimated using the pattern scaling method (Mitchell, 2003; Whetton et al., 2005), where the GCM simulated seasonal rainfall is plotted against the GCM simulated global average surface air temperature. A linear regression is then fitted through the data points and the slope of the linear regression gives the change in seasonal rainfall per degree global warming. The absolute change in seasonal rainfall is converted against the GCM 1975–2005 modelled baseline to express the change as a percentage change. The change in mean annual rainfall in Table 1 is the weighted average of the changes in the four seasons (weighted by the observed 1961–2000 mean seasonal rainfalls), averaged over each of the three regions.

All the simulations from 2001 to 2100 for the same GCM for different ensemble runs that are available in the archived data base are combined and used in the above analysis to estimate the percentage change in rainfall per degree global warming for the GCM. The entire data set can be used in the pattern scaling method to estimate the trend in future rainfall because the method decouples the GCM response from the particular

emission scenario used in the simulation. Whetton et al. (2005) and Suppiah et al. (2007) discuss some of the advantages of the pattern scaling method compared to considering the GCM simulations for a specific future time period. In general, the projections expressed in Table 1 reflect the percentage change in rainfall for a global warming of 1°C (median IPCC projected global average surface air temperature in 2030 relative to 1990).



Figure 1 Observed and GCM mean annual rainfalls, averaged over 1961 to 2000 (the plots are positioned from the driest GCM (smallest mean annual rainfall averaged across Australia) to the wettest GCM) (the boundaries show the three regions analysed in this study).

<b>Table 1</b> Summary statistics comparing observed mean annual rainfall and inter-annual rainfall variability
with those simulated by the 23 GCMs and projected changes in future rainfall in south-east Australia (SEA),
south-west Western Australia (SWWA) and Northern Australia (NA)

	RMSE of mean			Cv of annual rainfall			Suppiah	Smith	Percentage change		
	annual rainfall						et al.	et al.	in future mean		
						demerit	failure	annual rainfall			
							points	rates			
	SEA	SW	NA	SEA	SW	NA	•		SEA	SW	NA
		WA			WA					WA	
Observed				0.28	0.23	0.35					
BCCR	526	127	811	0.19	0.22	0.15	5	71	0	-8	-1
CCCMA T47	146	117	401	0.31	0.22	0.29	8	60	-2	-6	+6
CCCMA T63	145	101	382	0.27	0.21	0.27	10	50	+2	+1	+8
CNRM	205	165	416	0.37	0.31	0.23	4	63	-4	-7	-2
CSIRO Mk3.0	148	185	302	0.36	0.30	0.30	7	50	-18	-10	-14
CSIRO Mk3.5	150	298	284	0.45	0.44	0.43	-	-	-9	-7	-7
GFDL 2.0	190	199	255	0.37	0.32	0.48	4	10	-9	-16	-7
GFDL 2.1	129	182	320	0.48	0.38	0.38	2	10	-16	-18	-13
GISS-AOM	246	183	612	0.27	0.17	0.26	8	63	-9	-16	-2
GISS-E-H	477	124	954	0.09	0.12	0.08	14	100	+5	-7	+6
GISS-E-R	166	86	444	0.16	0.14	0.10	8	80	0	-9	+1
IAP	253	142	308	0.12	0.13	0.19	2	38	-3	-7	-4
INMCM	142	265	438	0.24	0.38	0.24	7	50	-7	+8	-1
IPSL	324	282	660	0.39	0.36	0.47	14	89	-5	-3	-1
MIROC-H	182	104	327	0.23	0.23	0.21	7	0	+2	-2	-1
MIROC-M	237	127	413	0.16	0.16	0.15	7	20	+5	-8	+4
MIUB	146	246	290	0.12	0.16	0.10	4	33	+6	-10	+3
MPI-ECHAM5	163	231	329	0.25	0.23	0.17	1	30	-6	-7	0
MRI	324	386	378	0.16	0.20	0.17	3	30	-8	-9	-6
NCAR-CCSM	230	155	263	0.13	0.22	0.15	2	38	+1	-7	+3
NCAR-PCM1	219	192	474	0.24	0.25	0.18	11	100	+1	+2	+3
HADCM3	131	241	296	0.26	0.32	0.28	6	0	-5	-15	-1
HADGEM1	130	138	201	0.28	0.30	0.29	2	30	-5	-6	-4

• RMSE is root mean square error comparing the difference between GCM and observed mean annual rainfalls in the GCM grid cells across each of the three regions.

• Cv is the coefficient of variation of annual rainfall (standard deviation divided by the mean). The median of the Cv values from the GCM grid cells in each of the three regions is tabulated.

- Suppiah et al. demerit points and Smith et al. failure rates are assessment of GCM performance against various criteria (see Section 4).
- The percentage change in future mean annual rainfall is change per degree global warming averaged across each of the three regions (see Section 3).
- Details about the GCMs can be found in IPCC (2007) and CSIRO and Bureau of Meteorology (2007).

The range in the future rainfall projections from the 23 GCMs is large (Figure 2 and Table 1). In south-east Australia, about two thirds of the GCMs simulate a decrease in future rainfall. Averaged across south-east Australia, the median projection is a 4 percent decrease in mean annual rainfall per degree global warming  $(10^{th} \text{ to } 90^{th} \text{ percentile range of } -9 \text{ to } +4 \text{ percent})$ . In south-west Western Australia, almost all the GCMs simulate a decrease in future rainfall. Averaged across south-east Western Australia, the median projection is a 7 percent decrease in mean annual rainfall per degree global warming  $(10^{th} \text{ to } 90^{th} \text{ percentile range of } -16 \text{ to } 0 \text{ percent})$ . In northern Australia, about 60 percent of the GCMs simulate a decrease in future rainfall. Averaged across northern Australia, the median projection is a 1 percent decrease in mean annual rainfall per degree global warming  $(10^{th} \text{ to } 90^{th} \text{ percentile range of } -16 \text{ to } 0 \text{ percent}$ ). In northern Australia, the median projection is a 1 percent decrease in future rainfall. Averaged across northern Australia, the median projection is a 1 percent decrease in mean annual rainfall per degree global warming  $(10^{th} \text{ to } 90^{th} \text{ percentile range of } -7 \text{ to } +6 \text{ percent}$ ). The difference in the rainfall projections from the different GCMs is significant, particularly as the change in rainfall will be amplified as a bigger percentage change in runoff.

# 4. FUTURE RAINFALL PROJECTIONS VERSUS GCM PERFORMANCE

To assess the implications of GCM selection on runoff impact assessment, Figure 3 shows the projected changes in the future mean annual rainfall from the 23 GCMs averaged across each of the three regions (see Table 1) plotted against the GCM performance assessed against three different methods. In the first column, the x-axis shows the RMSE of the GCM versus observed 1961–2000 mean annual rainfalls across each of the

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three regions (see Table 1). In the second column, the x-axis shows the demerit points from Suppiah et al.'s (2007) analysis of the GCMs abilities to reproduce the observed average 1961–1990 patterns of rainfall, temperature and mean sea level pressure across the whole of Australia (see Table 1). In the third column, the x-axis shows the failure rates from Smith et al.'s (2009) analysis combining the results from ten studies that assessed the GCM performance against different criteria (mainly GCM ability to reproduce the observed rainfall, temperature and mean sea level pressure across Australia, but also includes results from studies that consider a larger range of climate variables across the world and GCM ability to simulate El Nino/Southern Oscillation) (see Table 1). In all the plots in Figure 3, the better GCMs plot on the left hand side.



Figure 2 Percentage change in mean annual rainfall per degree global warming from the 23 GCMs (the positions of the GCMs in Figures 1 and 2 are the same).



**Figure 3** Percentage changes in mean annual rainfall per degree global warming from the 23 GCMs plotted against GCMs' abilities to simulate the observed historical climate characteristics assessed in this and two other studies.

The plots in Figure 3 indicate that there is no clear difference in the future rainfall projections between the better and poorer GCMs, assessed against the GCMs' abilities to simulate the observed historical climate characteristics. Some of the plots appear to suggest that the better GCMs simulate a drier future than the poorer GCMs, but the correlations are not statistically significant at  $\alpha = 0.05$  (all the linear correlations are less than 0.4). As there is no clear difference in the future rainfall projections between the better and poorer GCMs, using weights to favour the better GCMs [determined by the relative RMSEs, demerit points or failure rates; weights for a GCM calculated as (1 - RMSE of the GCM divided by the total RMSEs from all GCMs)] give similar rainfall and runoff impact assessment results as the use of all the 23 GCMs. Nevertheless, because of the (weak) correlations in Figure 3, using a limited number of the best GCMs (five or less) in some of the assessments leads to a drier future projection than using all the GCMs.

The rankings of the GCM performance in the three methods are also different. There is some similarity in the GCM rankings in Suppiah et al. and Smith et al., with a statistically significant correlation of 0.65. There is also some agreement between the Suppiah et al. and Smith et al. rankings and the RMSE analysis for northern Australia (R=0.7), but little to no agreement in south-east Australia (R=0.4) and south-west Western Australia (R=0). The GCMs that perform well in south-east Australia (as measured by the RMSE) are similar to the GCMs that perform well in northern Australia (R=0.85), but there is no correlation (R=0) between the GCM performance in south-east Australia with the GCM performance in south-west Western Australia. This could be due to the different processes driving rainfall in the different regions, although the GCMs are built to simulate the various interactions in the entire global climate system.

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### 5. SUMMARY AND CONCLUSIONS

The results indicate that most GCMs can reproduce the observed spatial mean annual rainfall pattern across Australia. However, the difference between the GCMs and observed mean annual rainfalls can be significant, with RMSEs of about one third of the mean annual rainfalls averaged over the regions. The future mean annual rainfall projections from the 23 GCMs per degree global warming range from -9 to +4 percent averaged across south-east Australia, -16 to 0 percent averaged across south-west Western Australia and -7 to +6 percent averaged across northern Australia. The difference between the rainfall projections from the different GCMs is significant, particularly as the change in mean annual rainfall will be amplified as a two to three times bigger percentage change in the mean annual runoff.

The future runoff impact assessment will be more reliable if it is based on future climate projections from the better GCMs. However, it is difficult to determine which GCMs are more likely to give reliable future climate projections, with some studies selecting the better GCMs based on their abilities to reproduce observed historical rainfall characteristics (Perkins et al., 2007; Suppiah et al., 2007; Watterson, 2008) and others considering the GCMs based on their abilities to reproduce the large scale atmospheric-oceanic drivers of rainfall (van Oldenborgh et al., 2005; Overland and Wang, 2007) or atmospheric predictors used to downscale to catchment-scale rainfall. It is also difficult to decide whether GCM performance should be assessed across the region of interest or across larger continental regions or the whole world.

The results in this study indicate that there is no clear difference in the future rainfall projections between the better and poorer GCMs across three large regions of Australia, therefore using weights to favour the better GCMs give similar rainfall and runoff impact assessment results as the use of all the 23 GCMs. With the rapid progress in climate change science and IPCC AR5, global climate models will become more accurate and give more consistent projections and there will be better consensus in the research community on appropriate criteria to select GCMs for different applications. For now, the uncertainty and the range of future runoff in impact studies are probably best determined using future climate projections from a large range of archived GCM simulations.

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