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Assessment of rainfall and potential evaporation from global climate models and its implications for Australian regional drought projection

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ABSTRACT: There is likely to be an increase in the area of the globe affected by drought under enhanced greenhouse gas conditions. Therefore water management and drought policy may need to be modified accordingly. Rainfall and potential evapotranspiration (PET) are the key factors defining meteorological drought, and the development of drought projections is facilitated by global climate model (GCM) simulations. This paper assesses how well a set of GCMs can reproduce observed characteristics of historical rainfall and PET on a regional basis and explores the implications for regional drought projections if the poorer performing GCMs are omitted. Fourteen of the GCMs used in the IPCC's 4th Assesment Report are considered and their results compared with 1951–2006 observed rainfall and PET over Australia. The results indicate that some GCMs can reproduce the observed spatial patterns of both the means and variability (represented as the coefficient of variation), but most GCMs fail to reproduce the linear long-term trends. There is less clear difference between the better and poorer GCMs at a national level, but there is a clearer distinction at the regional level. The omission of the poorer GCMs leads to a clearer sign of the likely change (either increase or decrease) in future drought intensity in some regions. It also results in a decreased range of model-to-model uncertainty in some regions. It is hoped such uncertainty reduction can be useful to end users, particularly for those dealing with water management. Copyright © 2010 Royal Meteorological Society

KEY WORDS global climate model evaluations; drought projection; Australia; reconnaissance drought index

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1. Introduction

The Intergovernmental Panel on Climate Change (IPCC, 2007) presented a substantial body of research which supports a picture of a warming world with significant changes in regional climate systems. For instance, an increase in the area of the globe affected by drought under enhanced greenhouse gas conditions is likely, despite much variation between regions and across climate change scenarios (Wang, 2005; IPCC, 2007; Sheffield and Wood, 2008). In Australia, the projected decreases in annual average rainfall are likely to lead to more exceptionally dry years in most regions being considered (Hennessy *et al*., 2008) and future drought policy may need to be modified accordingly.

The development of regional climate change projections in Australia is facilitated by the use of global climate model (GCM) simulations since, in the absence of regional climate modelling studies, GCMs represent the most credible tools for estimating the future response of regional climates to anthropogenic radiative forcings. As in any modelling exercise, there are uncertainties. These relate to the uncertainty in how much the global average surface temperature will increase at any point in the future and in how the climate of a region will respond to that increase in global average surface temperature. The former can be thought of as a combination of the uncertainties in the future evolution of greenhouse gas concentrations in the atmosphere as well as the sensitivity of the global average surface temperature to increases in atmospheric greenhouse gas concentrations. The uncertainty in the response of the climate of a region to a given global warming value can be sampled by considering the response characterized by multiple climate models. The consideration of multiple climate models is also necessary since there are inherent differences among the climate models themselves relating to, for example, the parameterization schemes and the model components representing the atmosphere, ocean, sea ice and land surface (e.g. Meehl *et al*., 2004).

In Australia, the range of projected changes in rainfall (one of the most important climate factors for water management), allowing for model-to-model differences, is relatively large (CSIRO and BoM, 2007). Scientists communicate this uncertainty, but when they do, the end users (policy, adaptation and mitigation groups) often conclude that no action is necessary because the uncertainties are so large (Jones, 2000). This leads to

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the model selection issue which poses questions such as: How does one select a model? Should one use all the available models for achieving a better representation of uncertainty? Should one assess and select models and, if so, on what criteria should the selection be based?

There are a number of studies with different views and approaches attempting to address this GCM evaluation/selection issue. Suppiah *et al.* (2007) and Watterson (2008) assessed GCMs based on their ability to simulate observed mean patterns of mean sea-level pressure (MSLP), temperature and rainfall over the whole Australian region. Other studies undertook assessment based on rainfall and/or MSLP for only a particular region, such as South-Eastern Australia (Maximo *et al.*, 2007; Chiew *et al.*, 2009a; Smith and Chandler, 2009), southwest of Western Australia (Charles *et al.*, 2007) and Northern Australia (Chiew *et al.*, 2009b). Perkins *et al.*, (2007) compare the observed and simulated distribution of the daily maximum temperature, minimum temperature and rainfall over 12 regions in Australia using probability density functions. Van Oldenborgh *et al.* (2005), Cai *et al.* (2009) and Frederiksen *et al.* (2009) have explored the performance of GCMs in simulating the El Nino-Southern Oscillation (ENSO) phenomenon, Australian rainfall teleconnections with Indo-Pacific climate drivers and Southern Hemisphere weather systems, respectively.

This paper assesses whether current GCMs can reproduce the observed characteristics of historical rainfall and potential evapotranspiration (PET) and explores the implications of omitting GCMs, based on specific criteria, on regional drought projections. Although GCM evaluations can be performed on many climate variables, we only consider selection criteria based on comparison rainfall and PET, as they are the two key factors in determining meteorological drought occurrence (Nicholls, 2004; Blekinsop and Fowler, 2007). The evaluation is conducted on an annual basis, as the required variables for drought projection in this study are annual rainfall and annual PET. However, the framework used in this paper is relatively general, and can therefore be easily extended to consider more climate variables and/or different time scales (e.g. seasonal).

GCM evaluation is conducted at both national and regional levels, but the drought projections are only for the 12 regions as mapped in Figure 1. In the following section, a short overview of the Australian drought policy is given to provide a context for the drought indices and the definitions used in Section 3. Section 4 describes the observed and simulated data used, while Section 5 discusses the assessment of model reliability. Drought projections which consider the model reliability are provided in Section 6. Section 7 summarizes key messages stemming from this study.

2. Australian drought policy

Australia's hydroclimatic variability is among the highest in the world (e.g. Peel *et al.*, 2001; McMahon *et al.*, 2007) and droughts are a normal component of the climate of Australia (McKernan, 2005). Drought affects Australia's environment, agricultural production, water resources and economy. The National Drought Policy (NDP), first agreed to by Commonwealth, State and Territory Ministers in 1992, recognizes climate variability and drought as normal features of the Australian environment in which agriculture must operate. As drought can have a dramatic effect on farm incomes, with significant flow-on effects throughout the economy and society, the NDP is focussed on providing relief from the immediate effect of drought on farm incomes while enhancing the longer term resilience of rural livelihoods (Nelson *et al.*, 2007). On the former measure, financial assistance can be provided when droughts are deemed to be exceptional. For the declaration of drought exceptional circumstances (DEC), six core criteria need to be satisfied. They relate to meteorological conditions, agronomic and stock conditions, water supplies, environmental impacts, farm income levels and the scale of the event (White *et al.*, 1998). Meteorological conditions need to constitute a 'rare and severe' event, likely to occur only once in 20–25 years and be of more than 12 months duration (DAFF, 2005). The Australian Government is currently conducting a comprehensive national review of its drought policy. The review includes three independent assessments. The first assesses the implications of future climate change for the current DEC standard of a 1 in 20–25 year event, while the others cover the economic and social aspects of DEC. It is hoped that the results from this paper can contribute to drought risk management in the future.

3. Drought indices and definition used in this study

In this study, we analyse drought events using two meteorological drought indices: annual rainfall time series and the annual reconnaissance drought index (RDI) (Tsakiris *et al.*, 2007). Rainfall time series are widely used because data are readily available. However, meteorological drought indices based on rainfall alone fail to include the important contribution of temperature change via evaporation (Nicholls, 2004). For this reason, the RDI, which considers both rainfall and potential PET, is also used. This index, recently introduced by Tsakiris and Vangelis (2005), is suitable in cases of a changing environment (Tsakiris *et al.*, 2007) and has been found to be appropriate for climate change scenarios and drought related studies (FAO/NDMC, 2008). A detailed presentation of the RDI can be found in Tsakiris and Vangelis (2005) and Tsakiris *et al.*, (2007) and a summary is provided in Appendix A.

The threshold used for defining a drought event is chosen by referring to the NDP and Hennessy *et al.* (2008). If drought events are defined as occurring (on average) once every 20 years, then the probability of an event occurring in any single year is 1 in 20, or 5%. Therefore, the critical threshold value used to define a drought event in this study is the 5th percentile. For each

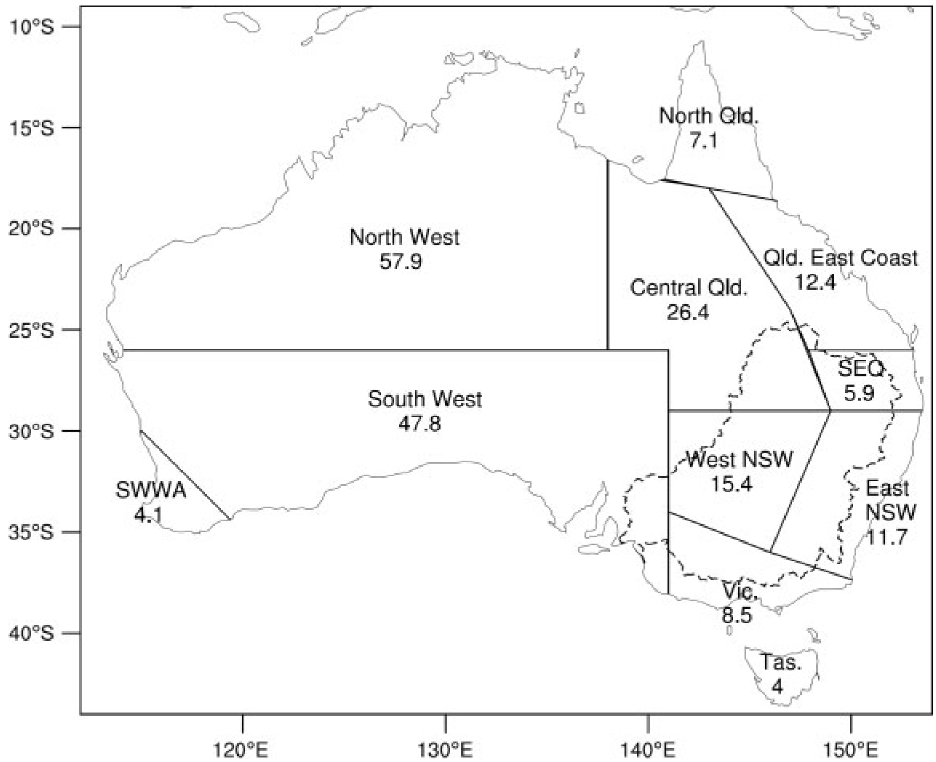

Figure 1. Study regions and the average number of the GCM's grid cell for each region. The region shown as dashed line is the Murray Darling Basin (MDB), and the average number of GCM's grid cell for this region is 31.7.

grid cell (pixel), the threshold for drought is calculated for the period 1900–2007. The projected change in drought for the next 100 years is then calculated relative to these thresholds.

4. Data

The Australian Bureau of Meteorology's interpolated high-quality monthly rainfall data on a $0.25^\circ \times 0.25^\circ$ grid (Jones and Beard, 1998) is used, along with monthly PET calculated from a number of gridded climate variables. The climate variables required for calculating the PET are obtained from the SILO gridded ($0.25^\circ \times 0.25^\circ$) database (Jeffrey *et al.*, 2001) for 1951–2006. This database is generated using observation data from the available Bureau of Meteorology stations and the data had been used extensively in many hydrological studies (e.g. Chiew *et al.*, 2009c). The PET is calculated using Morton's method (Morton, 1983) as this method was used to construct the Australian Bureau of Meteorology atlas for evaporation (BoM, 2001) and future projections for potential evaporation (CSIRO, 2001; CSIRO and BoM, 2007). The Morton model compares favourably with other methods for calculating potential evaporation for rainfall–runoff modelling (Chiew and McMahon, 1991) and has been widely used in drought related studies (e.g. Hennessy *et al.*, 2008; Mpelasoka *et al.*, 2008). The observed RDI time series are constructed on the basis of the annual rainfall and PET. This PET is the areal potential evapotranspiration and is defined as the evapotranspiration that would take place if there was an unlimited water supply from an area so large that the effects of any upwind boundary transitions are negligible and local variations are integrated to an areal average (Morton, 1983).

Future projection and 20th century reference fields for annual rainfall and PET from 14 GCMs were gathered from the Coupled Model Intercomparison Project 3 (CMIP3) database (http://www-pcmdi.llnl.gov). We use monthly data from 14 out of 23 GCMs which have the climate variables needed for the calculation of PET. The simulated PET values were calculated on the basis of the monthly time series of climate variables of these 14 GCMs using the Morton method. For 2001–2100, the data come from the simulations forced by the Special Report on Emissions Scenarios (SRES)-A1B (IPCC, 2000) emission scenario (11 GCMs) and by the SRES-A2 emission scenario (3 GCMs). The CO_2 concentration associated with the A1B and A2 scenarios reaches 720 and 850 ppm, respectively, by 2100. The use of multiple GCMs and different future emission scenarios results in scenarios that represent a range of probable outcomes of climate under enhanced greenhouse conditions. Since the raw GCMs data were used in this study, it must be noted that all the projected changes in the future are relative to the modelled present condition and not the observed present condition.

5. Assessment of model reliability

The assessment of model reliability is conducted at both national and regional levels. Annual simulated rainfall

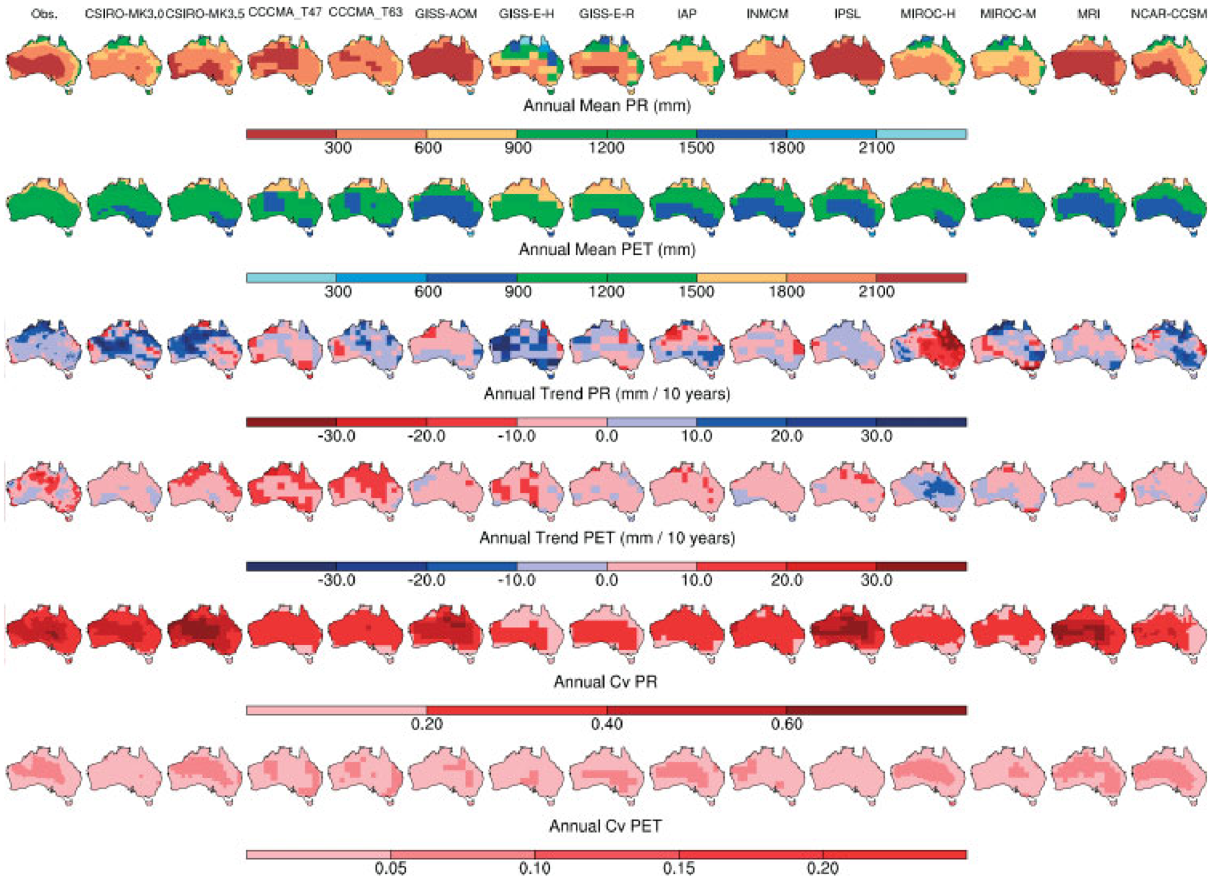

Figure 2. Observed and modelled statistics of annual rainfall and PET for the period of 1951–2006.

and PET are compared with the observed rainfall and PET over each of the regions using data from 1951 to 2006. Three statistics are used to test whether the models adequately reproduce the observed climatology of rainfall and PET: the mean climatology, the coefficient of variation (C_V, standard deviation divided by the mean) and the linear long-term trend. The first statistic can be used to measure the reliability of the model to reproduce the spatial pattern and model bias, while the last two statistics represent the model's ability to reproduce the observed inter-annual variability and long-term trends.

Figure 2 shows the simulated and observed values for each statistic for annual rainfall and PET. Some models can reproduce the spatial distribution of the annual mean rainfall, and most models tend to be much drier (i.e. GISS-AOM, IPSL and MRI) or wetter (i.e. GISS-EH, IAP and MIROC-M) than the observations (Figure 3). Most models are also capable of reproducing the spatial pattern of the annual C_V, although they tend to underestimate the observed values. The observed linear trends are not very well reproduced by most models. There are models that even show contrasting trends. For example, the GISS-AOM and IAP models each simulate a decrease in rainfall over the northern part of Australia where there is a clear evidence of an increasing trend (Smith, 2004).

With regard to potential evaporation, the models generally reproduce the spatial distribution of the annual mean, even though some models tend to underestimate the observed values. Some models (e.g. CSIRO-MK3.5, IAP, MIROC-H, MRI and NCAR-CCSM) are reasonably good at reproducing the observed C_V, while others underestimate the observed values. The calculated linear trends are not very well reproduced by most models.

To quantify such visual examinations, we use an approach similar to that of Murphy (1988) and Pierce *et al.* (2009). We calculate a model skill score (SS) defined as

$$\mathrm{SS} = r_{\mathrm{m,o}}^2 - [r_{\mathrm{m,o}} - (s_{\mathrm{m}}/s_{\mathrm{o}})]^2 - [(\overline{m} - \overline{o})/s_{\mathrm{o}}]^2 \quad (1)$$

where $r_{\mathrm{m,o}}$ is the product moment spatial correlation coefficient between the model and observations, s_{m} and s_{o} indicate the sample standard deviation of the model and observations and the overbars indicate the spatial mean of the model and observations, respectively.

The evaluation is carried out at each model's spatial resolution. The skill scores for each metric (mean, C_V and trend) are calculated for each of the 12 regions as well as for the country as a whole. The models can then be ordered with respect to their performance by considering each model's skill score. As in Pierce *et al.* (2009), the ordering is given by Δ_{ss}, the Euclidian distance from each model's score to a perfect score (1, 1, ..., 1). Lower values indicate better matches to the observations. The results for each region are presented in Tables I and II, where the GCMs are ordered from better to poorer skill.

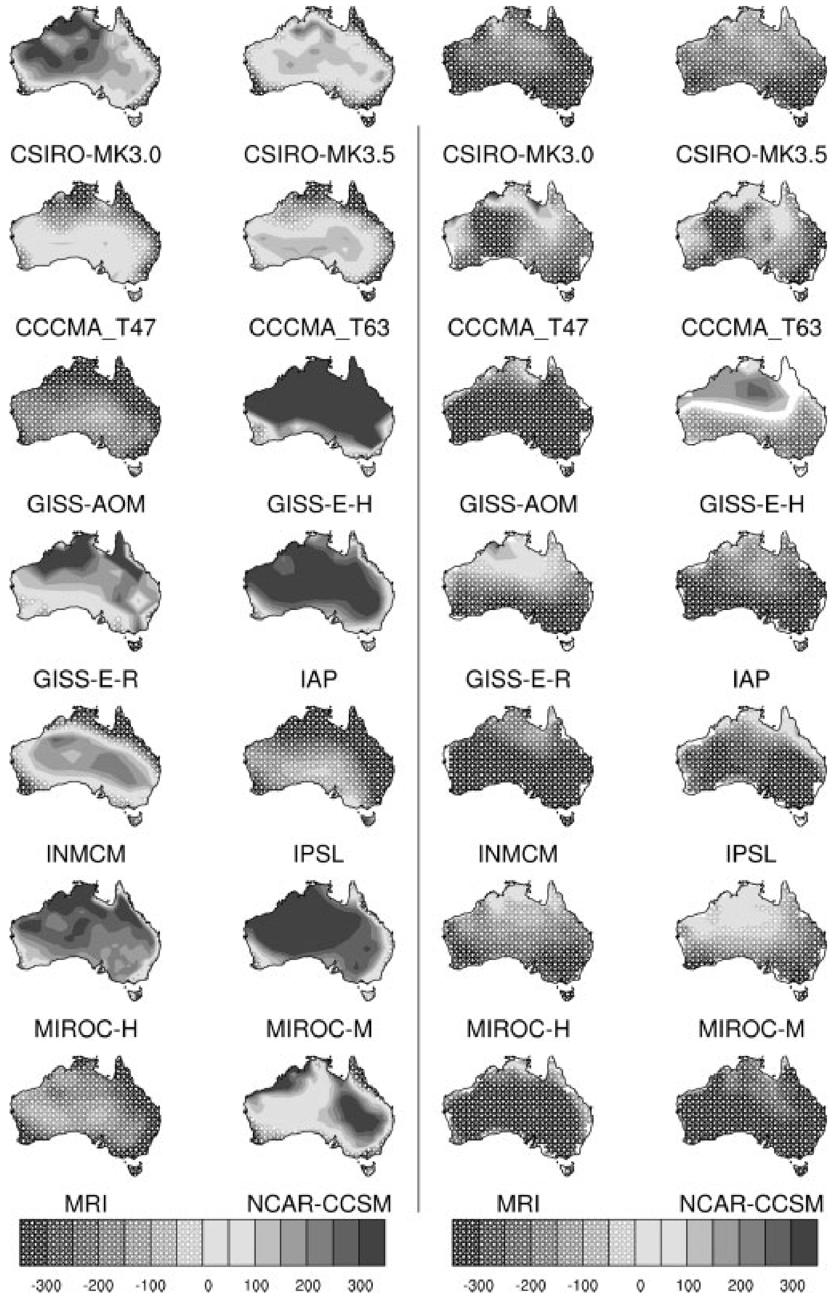

Figure 3. Difference between observed and modelled mean annual rainfall (the first two columns) and PET (the last two columns) for the period of 1951–2006. The unit is millimetres.

Table I shows each model's total Δ_{ss} when only the annual rainfall metrics are considered. At the national level, there is not much difference in Δ_{ss} between the better and poorer GCMs. Δ_{ss} only ranges from 2.1 (CSIRO-MK3.0, the best) to 7.8 (GISS-EH, the poorest). However, at the regional level, generally there is clearer distinction between the better and poorer GCMs, especially for small regions. For example, over the Victorian region, Δ_{ss} ranges from 4.4 (MIROC-M, the best) to 84.4 (CCCMA_T47, the poorest), and over North Queensland (Qld) region from 2.4 (MIROC-M, the best) to 33.7 (IPSL, the poorest). Over the Murray Darling Basin (MDB) region, which is relatively large in area, there is not much difference between the better and poorer performing GCMs (with Δ_{ss} ranging from 3.6 to 10.0) as previously observed by Chiew *et al*. (2009a). Such a small range is also found for other large regions such as South West, North West and Central Qld. A possible reason for this is that, for larger regions, more grid cells are considered in the skill score calculation and hence a greater range of good/poor grid cells may be reflected in the overall result. Conversely, in smaller regions, fewer grid cells are included in the calculation and the result is dominated by either good or by poor cells.

The order of the models in different regions of interest is not necessarily the same, and a model that is superior in a given region can be inferior in another region and vice versa. However, there are models that are consistently,

Table I. Order of model for each region based on total skill scores for each rainfall metric.

Order	National	South West	Tas.	MDB	Vic.	North West	SWWA	North Qld	SEQ	Qld. East Coast	Central Qld	West NSW	East NSW
1	CSIRO-MK3.0 2.09	GISS-E-R 2.76	IAP 3.50	INMCM 3.60	MIROC-M 4.44	CCCMA_T63 5.37	GISS-E-R 1.28	MIROC-M 2.39	MIROC-H 4.11	IAP 3.70	CCCMA_T47 2.63	GISS-E-R 3.53	INMCM 5.09
2	CCCMA T63 2.62	CCCMA T63 3.50	CCCMA T47 4.22	CCCMA T47 3.84	GISS-E-R 5.48	CSIRO-MK3.0 5.64	IAP 2.10	IAP 2.88	CCCMA T63 7.53	MIROC-M 4.55	CSIRO-MK3.0 2.88	CCCMA T47 3.65	CSIRO-MK3.0 6.59
3	CCCMA T47 2.76	IPSL 3.60	CSIRO-MK3.0 4.67	CSIRO-MK3.0 3.95	CSIRO-MK3.0 6.24	CSIRO-MK3.5 6.34	MIROC-M 2.29	CSIRO-MK3.0 4.40	CCCMA T47 7.86	CCCMA T47 5.29	CSIRO-MK3.5 3.40	CSIRO-MK3.5 3.91	MIROC-H 6.62
4	NCAR-CCSM 2.95	CSIRO-MK3.5 3.70	NCAR-CCSM 6.16	GISS-E-R 4.87	IAP 6.78	NCAR-CCSM 6.58	MIROC-H 3.74	MRI 5.59	INMCM 8.73	INMCM 5.37	CCCMA T63 3.76	INMCM 4.46	GISS-E-R 7.05
5	CSIRO-MK3.5 3.00	GISS-AOM 3.72	MIROC-M 7.01	GISS-AOM 5.02	MIROC-H 7.59	CCCMA T47 6.60	GISS-E-H 4.42	CCCMA T47 5.99	MIROC-M 9.56	MIROC-H 6.32	GISS-E-R 4.10	GISS-AOM 5.35	CCCMA T47 7.27
6	GISS-E-R 3.25	CCCMA T47 3.75	CSIRO-MK3.5 7.23	CCCMA T63 5.04	IPSL 8.63	INMCM 7.10	CCCMA T47 5.32	NCAR-CCSM 6.03	GISS-E-R 9.68	CCCMA T63 7.59	INMCM 4.23	CSIRO-MK3.0 8.54	CCCMA T63 7.50
7	GISS-AOM 3.61	CSIRO-MK3.0 3.86	CCCMA T63 7.88	MIROC-M 5.11	INMCM 9.11	MRI 7.24	CCCMA T63 5.45	CSIRO-MK3.5 6.20	IAP 10.09	MRI 10.54	MRI 4.48	IPSL 6.91	MIROC-M 7.73
8	IAP 3.64	NCAR-CCSM 4.36	MIROC-H 9.83	CSIRO-MK3.5 5.22	CCCMA T63 9.35	GISS-AOM 7.58	GISS-AOM 8.65	CCCMA T63 6.44	NCAR-CCSM 12.96	GISS-E-R 11.45	GISS-AOM 5.63	CCCMA T63 8.83	GISS-AOM 7.94
9	INMCM 3.69	INMCM 4.86	INMCM 10.03	MIROC-H 5.26	GISS-AOM 10.75	GISS-E-R 8.12	IPSL 12.77	MIROC-H 7.47	GISS-E-H 16.23	CSIRO-MK3.0 13.04	MIROC-M 6.49	MIROC-H 12.31	CSIRO-MK3.5 7.99
10	MRI 3.74	MRI 5.70	MRI 13.91	IAP 5.88	NCAR-CCSM 11.89	IPSL 8.94	NCAR-CCSM 24.08	GISS-E-R 8.30	CSIRO-MK3.0 18.78	NCAR-CCSM 15.64	IAP 6.55	GISS-E-H 15.32	IAP 8.05
11	MIROC-M 4.18	IAP 6.88	GISS-AOM 16.10	IPSL 7.36	MRI 15.67	IAP 9.53	CSIRO-MK3.02 7.64	GISS-AOM 11.01	CSIRO-MK3.5 28.97	CSIRO-MK3.5 18.13	NCAR-CCSM 8.08	MRI 15.59	NCAR-CCSM 10.81
12	MIROC-H 4.25	MIROC-H 7.21	GISS-E-R 26.10	MRI 7.69	CSIRO-MK3.5 15.79	MIROC-M 9.71	INMCM 41.60	INMCM 31.54	GISS-AOM 30.94	GISS-AOM 27.26	IPSL 8.91	MIROC-M 22.21	MRI 14.73
13	IPSL 4.69	GISS-E-H 7.45	IPSL 34.14	NCAR-CCSM 8.31	GISS-E-H 29.31	MIROC-H 10.36	MRI 90.77	GISS-E-H 31.69	MRI 31.62	GISS-E-H 33.44	MIROC-H 10.61	NCAR-CCSM 28.53	IPSL 15.23
14	GISS-E-H 7.77	MIROC-M 9.11	GISS-E-H 74.83	GISS-E-H 10.03	CCCMA_T47 84.43	GISS-E-H 13.92	CSIRO-MK3.5 136.94	IPSL 33.74	IPSL 49.80	IPSL 39.91	GISS-E-H 11.28	IAP 29.63	GISS-E-H 19.44

The models are ordered by Δ_{SS} (the Euclidian distance from perfect skill score). Each model is represented with different colour and Δ_{SS} is provided below the name of the model (lower values are better).

Table II. Order of model for each region based on total skill scores for each of rainfall and PET metric.

Order	National	South West	Tas.	MDB	Vic.	North West	SWWA	North Qld	SEQ	Qld. East Coast	Central Qld	West NSW	East NSW
1	CSIRO-MK3.5 6.70	CSIRO-MK3.5 16.01	CSIRO-MK3.55 0.48	MIROC-M 12.75	MIROC-H 61.23	CSIRO-MK3.5 10.21	MIROC-H 35.57	MIROC-M 6.91	GISS-E-R 39.06	MIROC-H 20.05	GISS-E-R 6.83	CCCMA T47 22.96	INMCM 31.79
2	CSIRO-MK3.0 6.93	CCCMA T63 16.94	IAP 51.05	GISS-E-R 15.35	CSIRO-MK3.5 71.99	CCCMA T63 10.58	CCCMA T63 39.08	IAP 11.38	GISS-E-H 42.83	MIROC-M 20.66	CSIRO-MK3.5 7.29	CCCMA T63 24.24	IAP 37.39
3	MIROC-M 7.20	GISS-E-H 17.74	CCCMA T63 60.14	IAP 16.70	MIROC-M 75.84	CSIRO-MK3.0 10.68	IAP 44.84	MIROC-H 13.12	MIROC-H 49.37	GISS-E-R 26.72	CSIRO-MK3.0 8.32	INMCM 25.61	MIROC-M 38.92
4	IAP 7.48	MIROC-M 19.36	MRI 64.49	GISS-E-H 17.40	CSIRO-MK3.0 83.11	NCAR-CCSM 10.99	MIROC-M 54.77	MRI 13.25	CCCMA T47 67.64	IAP 28.78	CCCMA T63 8.42	GISS-E-H 28.44	MIROC-H 39.16
5	GISS-E-R 7.54	CSIRO-MK3.0 23.06	CSIRO-MK3.0 71.22	CSIRO-MK3.5 17.52	IAP 88.01	GISS-E-R 11.40	GISS-E-H 71.45	GISS-E-R 13.34	MIROC-M 75.45	INMCM 33.63	INMCM 8.79	CSIRO-MK3.5 32.89	GISS-E-R 40.45
6	NCAR-CCSM 8.09	MIROC-H 23.11	MIROC-H 74.40	INMCM 17.88	CCCMA T63 91.98	IAP 12.05	NCAR-CCSM 76.68	CSIRO-MK3.5 15.61	CSIRO-MK3.0 91.69	CSIRO-MK3.0 37.89	MIROC-M 8.80	GISS-E-R 36.21	GISS-E-H 46.28
7	CCCMA T63 8.14	CCCMA T47 27.57	NCAR-CCSM 77.98	MIROC-H 18.44	NCAR-CCSM 111.92	MIROC-M 12.71	CSIRO-MK3.0 82.70	NCAR-CCSM 17.43	IAP 93.96	CCCMA T47 41.08	CCCMA T47 9.64	MIROC-M 38.21	CSIRO-MK3.0 53.62
8	IPSL 9.06	IAP 31.62	CCCMA T47 84.78	CSIRO-MK3.0 19.02	GISS-E-H 119.14	CCCMA T47 13.00	CCCMA T47 85.91	CCCMA T63 19.79	IPSL 96.84	CSIRO-MK3.5 42.10	IAP 10.83	IPSL 40.73	NCAR-CCSM 55.48
9	MIROC-H 9.67	GISS-E-R 32.35	GISS-E-R 102.01	IPSL 20.39	IPSL 138.23	MRI 13.29	IPSL 105.08	CSIRO-MK3.0 19.84	CSIRO-MK3.5 110.29	GISS-E-H 42.22	GISS-AOM 11.37	MIROC-H 45.09	IPSL 56.05
10	CCCMA T47 9.76	IPSL 33.57	MIROC-M 104.46	CCCMA T47 21.41	MRI 156.97	IPSL 13.54	MRI 113.30	GISS-AOM 20.86	NCAR-CCSM 118.84	MRI 48.02	NCAR-CCSM 12.40	CSIRO-MK3.0 46.12	CSIRO-MK3.5 59.14
11	INMCM 10.24	NCAR-CCSM 36.75	IPSL 107.88	CCCMA T63 22.62	GISS-E-R 166.88	GISS-AOM 13.68	CSIRO-MK3.5 176.51	GISS-E-H 36.42	GISS-AOM 127.44	IPSL 49.82	GISS-E-H 14.00	GISS-AOM 48.61	GISS-AOM 59.55
12	MRI 10.26	MRI 40.79	GISS-E-H 134.80	NCAR-CCSM 27.00	GISS-AOM 173.04	INMCM 13.73	GISS-AOM 204.57	IPSL 44.31	MRI 147.98	CCCMA T63 52.68	IPSL 14.34	IAP 60.22	CCCMA T47 91.12
13	GISS-AOM 10.65	INMCM 56.27	INMCM 1029.61	MRI 29.26	INMCM 375.02	MIROC-H 15.71	GISS-E-R 250.71	INMCM 94.98	INMCM 159.75	NCAR-CCSM 54.90	MRI 14.43	NCAR-CCSM 71.19	MRI 132.39
14	GISS-E-H 12.08	GISS-AOM 57.58	GISS-AOM 14761.49	GISS-AOM 30.13	CCCMA T47 799.46	GISS-E-H 19.59	INMCM 259.12	CCCMA T47 782.40	CCCMA T63 216.66	GISS-AOM 57.27	MIROC-H 19.39	MRI 72.81	CCCMA T63 158.58

The models are ordered by Δ_{SS} (the Euclidian distance from perfect skill score). Each model is represented with different colour and Δ_{SS} is provided below the name of the model (lower values are better).

although not always, better (e.g. CSIRO-MK3.0, CCCMA_T47, CCCMA_T63) or poorer (e.g. GISS-EH, IPSL) in almost all regions.

Table II shows the same as Table I except that both the annual rainfall and potential evaporation metrics are considered. The overall findings are relatively similar to those represented in Table I. The models that are consistently good over most regions include CSIRO-MK3.0, MIROC-M and IAP. The addition of potential evaporation metrics to the Δ_{ss} can significantly change the relative order of the models at a given region. For instance, for the MDB, the CCCMA_T47 is ranked second when only rainfall metrics are considered and is tenth when both rainfall and potential evaporation metrics are included. As it can be seen from Figure 2, CCCMA_T47 reproduces the observed mean rainfall relatively well but fails to reproduce the mean and the C_V of PET.

6. Drought projections with and without consideration of model reliability

The results presented in Tables I and II can be employed as guidance for selecting models to be used in projecting future drought intensity based on rainfall and RDI. Here, the drought intensity is defined as the percentage area of a region affected by a drought event. Figures 4 and 5 show the simulated percentage area experiencing drought in each of the 12 regions based on rainfall and RDI, respectively. The solid lines represent the multi-model mean, while the shading shows the range between the lowest and highest 10% of the model results. All results are shown as 30-year average values. Each column shows projections based on a different sample of models (either the top five, top seven, top nine or all 14 models). Quantitative values of drought intensity for 30 years centred on 2030, 2050 and 2070 are also presented in Tables III and IV. It must be noted that, given the drought definition used in this study (Section 3), each region has an average of about 5.6% of the area experiencing drought simulated over the period 1900–2007.

Figure 4 and Table III suggest that the areal extent of drought, based on the simulated rainfall index of all 14 models, is likely to increase in most regions in the future. The increase is clearly seen over South West Western Australia (SWWA), West New South Wales (NSW), East NSW, MDB, Victoria (Vic.) and Tasmania, and is less clear over the North West, Qld East Coast and Central Qld. For example the mean area increases from 5.6% in 1900–2007 to 15.5, 20.1 and 24.4% for 2030, 2050 and 2070, respectively, for SWWA and to 6.6, 8.7 and 9.8%, respectively, for West NSW (Table III). In some regions (i.e. SWWA, South West, West NSW, East NSW, MDB, Tasmania), omitting the poorer models leads to a much greater increase in the areal extent of drought in the future. According to the top five GCMs (defined by this metric), the mean area affected by drought by 2030, 2050 and 2070 for SWWA is 17.0, 23.6 and 29.2%, respectively (Table III). Over North Qld, the better models tend to suggest a clearer decrease in drought intensity. Using all 14 models, the mean area affected by drought is 5.4, 4.6 and 3.8%, by 2030, 2050 and 2070, respectively, while according to the top five models it is 4.4, 2.6 and 2.1%. Relatively similar results are also obtained from the projected areal extent of drought based on simulated RDI (Figure 5 and Table IV).

The sample of better models can largely reduce the range of model-to-model uncertainty in some regions including North Qld, SEQ, East NSW and MDB, particularly for longer future projections (e.g. 2050 and 2070). As an illustration, by 2030 the range of projected area affected by drought over the East NSW region (Table III) is 2.6–10.3%, based on all 14 models, and is 1.1–10.2% based on the top five models, whereas by 2070 the range is 1.4–16.8%, based on all 14 models, and is 4.3–16.7% based on the top five models. Another example is, by 2030 the range of projected area affected by drought over the North Qld (Table IV) is 2.2–13.0%, based on all 14 models, and is 1.2–12.5% based on the top five models, while by 2050 the range is 3.5–11.7% based on all models and is 3.5–5.1% based on the top five models.

The reduction in range of uncertainty could be simply due to the reduction of sample size and not necessarily due to the use of the better performing models. To examine this matter, in Figure 6 we plot frequency distribution of the range of drought projections from all 14 models (black lines) against that based on all combinations of five randomly chosen models (dashed lines). In addition, the doted lines show the frequency distribution of the range of drought projections based on the top five models. Overall, the reduction of sample size, from 14 to 5 models, does not largely change/reduce the spread of the uncertainty distribution but it shifts the mean of the distribution toward lower uncertainty values. For some regions (e.g. North West, Qld East Coast, Central Qld and West NSW), the range of uncertainty based on the top five models is not smaller compared to that of 14 models and five randomly chosen models. However, for some regions including North Qld, East NSW, MDB and Vic., there is an indication that the use of only the top five models can produce a smaller range of uncertainty in comparison to that of all 14 models and five randomly chosen models. Similar results are also found in the case of drought projections based on the RDI (not shown here).

7. Discussion and conclusions

This paper assesses the relative abilities of 14 out of 23 GCMs used in the IPCC's 4th Assessment Report to simulate various 1951–2006 observed rainfall and PET characteristics. It also explores how the choice of GCMs used in a study can influence regional drought projections. The drought projections are based on annual rainfall and the RDI time series.

For the purpose of the study, the evaluation of the GCMs is focussed mainly on the annual rainfall and PET,

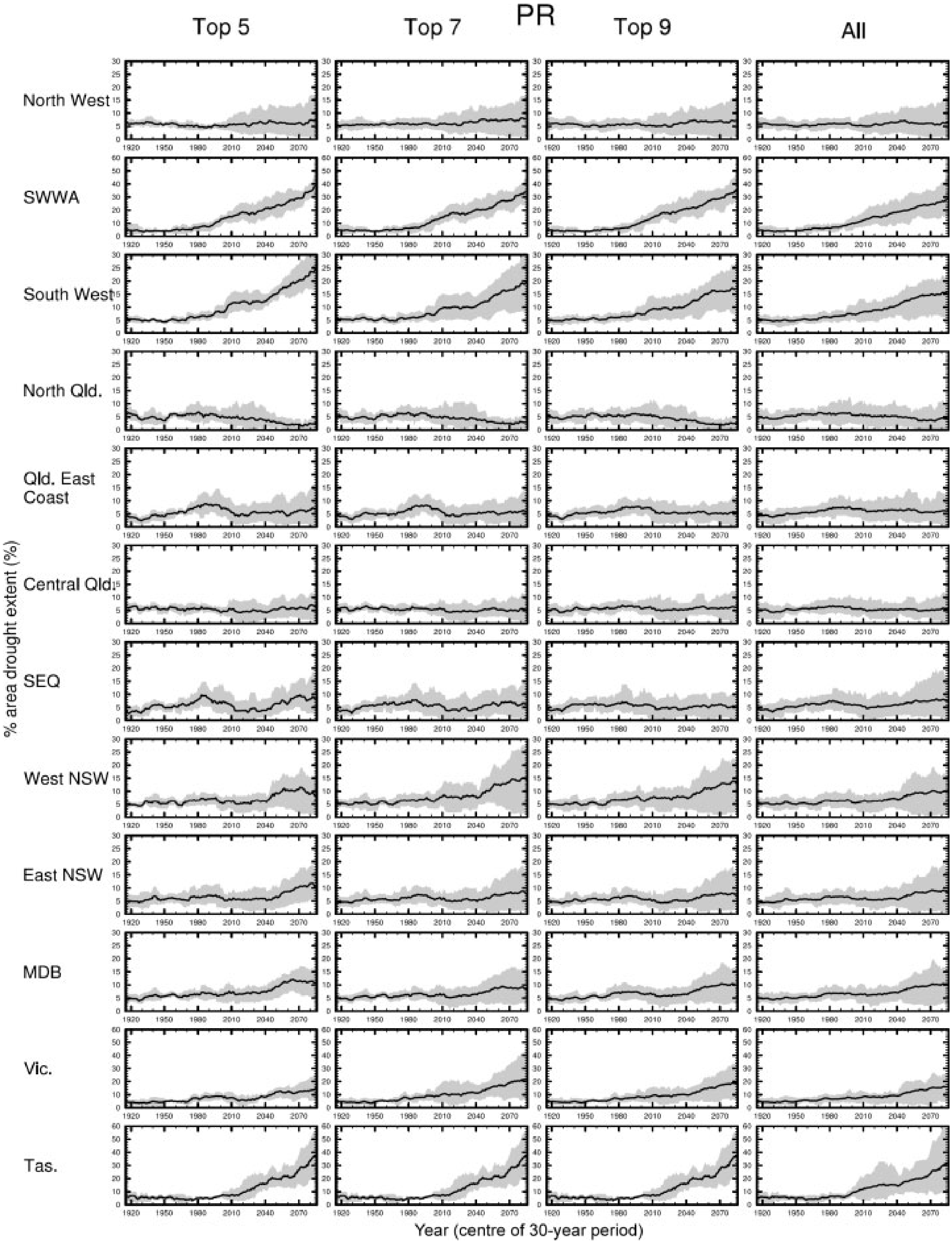

Figure 4. Simulated percentage area with drought in 12 regions based on rainfall. The simulations were based on different sample of models. The solid lines are the multi-model means, while the shading shows the range between the lowest and highest 10% of model results, all smoothed by 30-year average.

and the characteristics that are used to evaluate the model are the spatial patterns of the mean, the coefficient of variation (C_V) and the linear long-term trend at the national and 12 regional levels. However, similar analyses can be easily applied or extended to any other GCM, to any other climate variables (e.g. temperature, mean sea-level pressure), to any other time scales (e.g. seasonal and daily), to any other characteristics (e.g. standard deviation, extreme value) and/or to any region depending on the purpose and/or application of a particular study. The output of such different analyses may or may not be similar to the results found in this study. Thus, it must be noted that the 'better' and/or 'poorer' models we refer to here are only relative to the metrics used in this study.

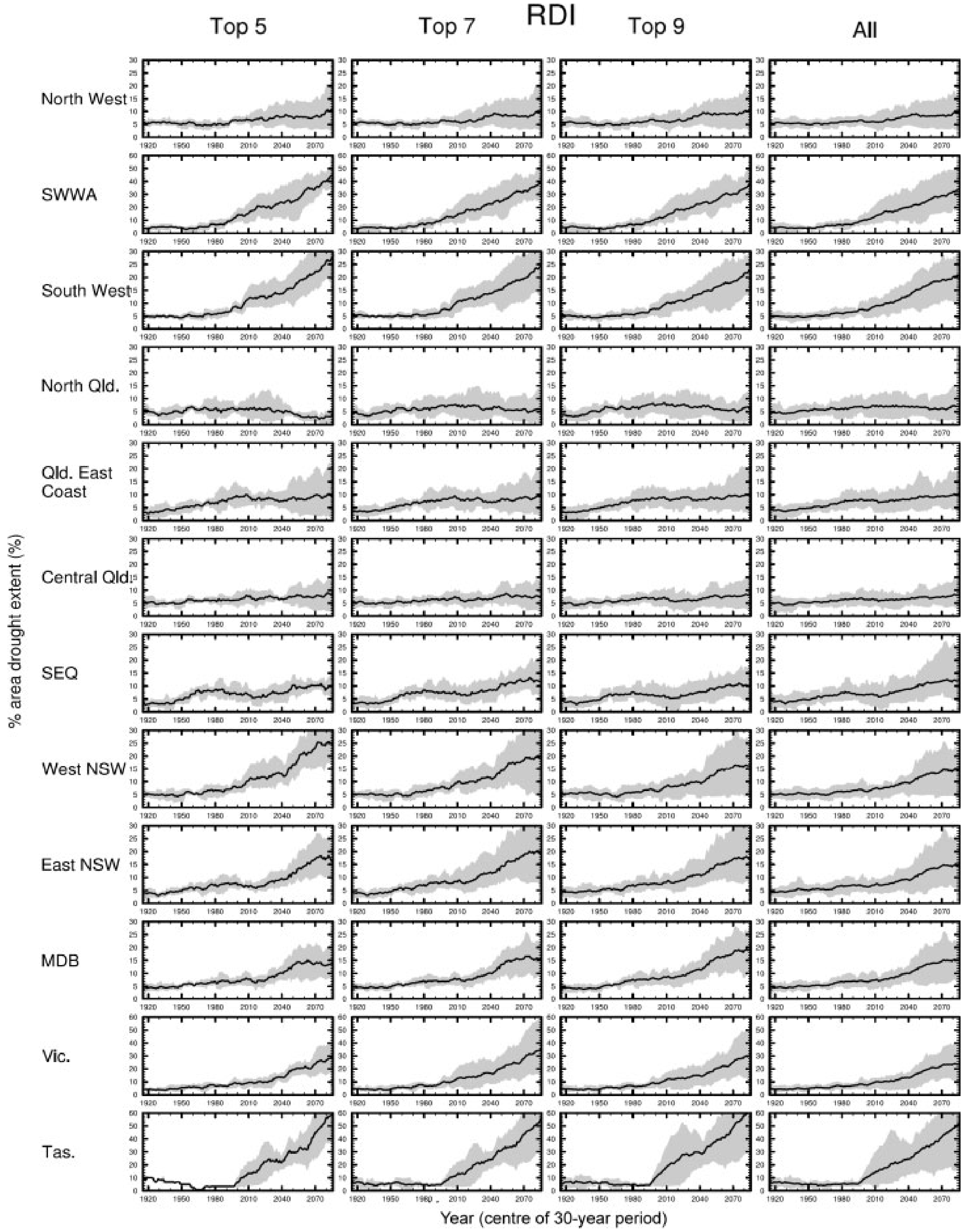

Figure 5. Simulated percentage area with drought in 12 regions based on RDI. The simulations were based on different sample of models. The solid lines are the multi-model means, while the shading shows the range between the lowest and highest 10% of model results, all smoothed by 30-year average.

Our results indicate that some GCMs can generally reproduce the observed spatial mean annual rainfall and PET across Australia, and there is a tendency for GCMs to underestimate/overestimate the observed values. The same is true in the case of the annual C_V, whereby the GCMs simulate relatively smaller inter-annual rainfall and PET variability. Most GCMs fail to reproduce the observed rainfall and PET trends over most regions. This implies that, although a given GCM is able to simulate the observed mean climatology, it may not necessarily be able to simulate the observed inter-annual variability and/or long-term trend. The inclusion of other statistics representing basic climate parameters such as variance, covariances and trend in GCM evaluation

Table III. Simulated percentage area having drought based on rainfall for 2030, 2050 and 2070 for different sample of models.

Region	Top 5			Top 7			Top 9			All		
	10th	Mean	90th	10th	Mean	90th	10th	Mean	90th	10th	Mean	90th
2030												
North West	2.2	6.1	11.6	2.4	6.5	10.9	1.5	5.8	10.3	2.0	6.1	10.1
SWWA	10.0	17.0	23.3	10.0	16.5	23.2	10.0	17.8	24.7	7.3	15.5	23.3
South West	9.3	11.9	16.1	5.0	9.9	15.1	5.4	9.8	14.0	5.7	9.4	12.7
North Qld	0.4	4.4	10.7	0.7	4.3	10.5	0.9	3.9	8.8	1.1	5.4	9.2
Qld East Coast	1.8	5.8	9.7	1.0	4.9	8.7	1.3	5.6	9.9	2.2	6.4	11.7
Central Qld	0.7	5.1	9.4	0.7	4.7	9.0	0.8	5.3	8.7	1.6	5.2	8.2
SEQ	0.7	4.7	10.7	1.0	5.0	11.3	1.3	5.1	10.7	1.6	5.5	11.2
West NSW	2.7	6.1	8.8	3.3	7.9	13.3	3.6	7.6	11.6	3.4	6.6	9.5
East NSW	1.1	5.7	10.2	1.7	5.7	10.0	2.0	5.3	9.8	2.6	5.7	10.3
MDB	3.2	7.2	9.8	2.3	6.1	9.6	2.8	6.0	9.5	3.3	6.5	9.9
Vic.	3.2	6.1	9.5	3.3	10.7	19.7	3.3	9.4	14.8	3.1	8.4	12.1
Tas.	5.5	12.1	21.7	5.5	12.1	21.7	5.5	12.1	21.7	4.0	14.7	30.7
2050												
North West	2.1	6.2	11.9	2.2	7.2	11.6	1.8	6.7	11.4	2.0	6.5	12.0
SWWA	13.3	23.6	34.7	12.9	21.0	32.8	13.1	22.4	35.2	8.7	20.1	32.9
South West	12.5	15.1	17.9	5.0	12.2	17.3	5.3	12.7	16.6	4.7	12.6	17.9
North Qld	0.8	2.6	4.9	0.9	2.9	4.9	0.9	2.9	5.0	1.1	4.6	8.4
Qld East Coast	1.1	6.1	12.4	1.3	5.8	10.3	1.4	5.9	8.2	1.7	6.8	14.8
Central Qld	2.0	5.3	9.7	2.5	5.3	8.6	3.1	6.1	11.2	2.5	5.5	10.4
SEQ	2.3	6.5	12.7	1.3	6.0	11.7	1.5	5.6	10.0	2.2	6.9	11.0
West NSW	4.1	9.5	14.2	5.7	10.3	15.2	1.7	9.5	14.7	2.0	8.7	14.2
East NSW	2.3	6.8	11.0	0.8	6.3	10.9	1.0	6.4	10.9	1.5	7.3	11.7
MDB	5.1	9.4	12.4	2.6	7.6	12.3	2.8	8.2	12.5	3.0	8.7	12.7
Vic.	7.4	12.1	15.2	8.5	14.4	19.6	4.7	12.2	17.5	2.4	11.7	20.1
Tas.	13.8	19.6	25.7	13.8	19.6	25.7	13.8	19.6	25.7	9.8	17.7	26.7
2070												
North West	1.1	6.4	13.9	1.2	7.7	13.8	1.0	7.1	13.7	1.0	6.1	13.7
SWWA	21.7	29.2	35.3	18.3	27.5	34.6	18.3	28.8	37.1	14.1	24.4	35.7
South West	15.5	20.2	26.5	7.8	16.6	24.6	8.1	16.2	22.8	7.2	14.8	20.3
North Qld	0.5	2.1	4.2	0.7	2.5	4.5	0.0	2.2	4.2	0.2	3.8	9.6
Qld East Coast	1.2	6.3	12.9	1.8	5.8	11.3	1.3	5.2	9.6	1.8	5.6	9.5
Central Qld	2.5	5.9	10.6	2.2	5.0	9.7	2.2	5.8	10.0	2.1	5.1	9.1
SEQ	5.2	9.4	15.3	1.5	7.1	13.0	1.3	6.1	10.7	1.9	7.5	16.2
West NSW	2.0	10.8	16.6	2.8	13.6	22.3	0.7	12.4	19.6	0.5	9.8	16.7
East NSW	4.3	10.3	16.7	1.5	8.2	16.4	1.6	8.0	16.1	1.4	8.9	16.8
MDB	6.8	11.4	16.3	2.7	8.9	16.0	2.9	10.0	16.6	2.4	9.9	16.8
Vic.	6.4	12.3	18.6	7.1	19.1	33.3	4.6	17.0	27.8	1.9	14.9	23.3
Tas.	15.6	26.5	38.0	15.6	26.5	38.0	15.6	26.5	38.0	10.1	23.9	42.0

Results are presented as the multi-model mean and the 10th–90th percentile.

against the observation can also be useful, particularly for differentiating the capability of GCMs to simulate the present-day climate.

At the national level, there is relatively little difference between the better and poorer GCMs, but at the regional level we start to see a distinction in the skill scores, particularly over small regions. Although there are GCMs that are consistently good/poor in most regions, the order of the better/poorer GCMs in different regions is not always the same and a GCM that is better in a given region may be poorer when evaluated in another region and vice versa. The addition of potential evaporation metrics to the overall skill scoring, as opposed to the rainfall metrics alone, may change the relative order of the GCMs for a given region. All these findings suggest that determining a 'better' model is not straightforward exercise. There is a need for assessing GCMs at a regional level and using a variety of metrics if GCMs are to be used for different applications in different regions. Alternatively, the evaluations can be made on the basis of how well the models represent particular aspects of the ocean-climate system that drive the climate of the region such as the monsoons, the ENSO, etc. The major differences in the modelled precipitation and PET across different regions and the changes in the skill score order depending on whether precipitation only or both variables are used suggest that some of the models fail to capture some of the important drivers of these processes. This effect is exacerbated by the limited size of some of the regions studied.

Once the skill scores for each region and each metric are tabulated, there are options for treating the GCM

Table IV. Simulated percentage area having drought based on RDI for 2030, 2050 and 2070 for different sample of models.

Region	Top 5			Top 7			Top 9			All		
	10th	Mean	90th	10th	Mean	90th	10th	Mean	90th	10th	Mean	90th
2030												
North West	3.7	7.3	12.1	3.8	6.9	11.5	3.9	7.1	10.9	3.7	7.4	12.4
SWWA	9.8	18.9	29.4	11.3	18.2	29.2	12.9	18.8	29.1	7.0	17.4	29.4
South West	8.2	12.6	19.0	8.6	12.1	17.0	7.0	11.6	16.2	5.9	11.0	15.9
North Qld	1.2	5.8	12.5	1.8	6.6	14.6	2.4	7.0	13.5	2.2	7.1	13.0
Qld East Coast	5.9	8.5	11.3	5.5	8.5	12.1	5.7	9.0	12.9	3.5	7.9	13.2
Central Qld	5.5	7.5	9.8	3.6	6.8	9.5	1.7	6.3	9.2	2.5	6.3	8.7
SEQ	4.0	7.2	10.8	4.3	7.9	12.8	3.0	6.8	12.7	3.6	8.0	13.1
West NSW	7.3	11.8	18.8	6.7	10.5	16.1	5.0	9.1	13.3	5.2	8.6	10.7
East NSW	5.9	8.3	12.2	6.1	10.7	18.3	6.3	10.2	16.4	5.1	8.4	13.2
MDB	5.9	8.5	11.8	6.1	8.6	11.8	6.2	9.9	13.6	5.7	8.7	11.9
Vic.	4.7	10.4	16.2	4.7	14.6	28.1	4.2	13.3	22.9	3.7	11.4	16.9
Tas.	11.2	22.5	33.8	9.8	20.6	32.8	10.3	27.1	46.7	7.3	20.9	41.7
2050												
North West	3.5	7.6	13.1	3.8	8.4	14.3	4.1	8.9	13.8	3.6	8.3	13.2
SWWA	9.3	24.7	41.1	10.7	25.0	40.6	12.0	23.4	40.0	7.0	22.4	40.6
South West	8.5	15.7	22.6	6.5	15.3	22.2	6.2	14.8	21.6	6.5	15.4	23.0
North Qld	3.5	4.3	5.1	3.6	6.3	10.5	3.7	6.6	9.5	3.5	6.7	11.7
Qld East Coast	2.8	9.1	17.1	3.2	8.5	14.6	3.5	9.1	15.1	3.5	9.4	19.5
Central Qld	3.9	7.5	11.7	3.9	8.0	13.5	3.7	7.6	13.3	3.9	7.4	12.7
SEQ	6.5	10.4	14.5	7.1	10.9	15.8	3.2	9.1	15.8	3.9	10.7	15.9
West NSW	11.5	16.8	22.2	7.8	14.4	21.3	4.1	12.3	20.5	4.7	11.9	18.9
East NSW	7.8	12.0	17.7	8.4	14.5	23.8	8.6	13.4	22.8	4.3	11.3	19.6
MDB	7.7	13.2	19.1	9.0	13.5	18.8	10.3	14.9	21.2	5.3	12.3	19.3
Vic.	14.7	19.4	23.8	10.8	20.7	30.7	6.6	17.6	27.7	6.4	17.0	25.3
Tas.	20.5	29.2	37.8	20.9	31.0	39.6	21.8	34.8	46.0	14.8	30.5	43.0
2070												
North West	3.3	8.1	15.2	3.2	8.0	15.2	3.2	9.0	15.2	3.3	8.4	15.1
SWWA	28.0	35.0	44.3	27.2	32.9	42.5	24.0	30.6	40.7	16.1	29.1	47.5
South West	15.9	22.3	31.6	10.6	19.6	29.6	8.9	18.4	27.7	11.0	18.9	27.7
North Qld	1.2	3.1	5.4	1.3	6.0	12.1	1.3	5.8	9.1	1.4	6.3	11.7
Qld East Coast	1.8	9.7	20.0	2.7	9.0	18.1	3.6	9.5	16.8	4.9	9.4	14.8
Central Qld	2.4	7.5	13.5	3.4	7.6	12.9	3.0	7.6	12.3	4.1	7.4	11.7
SEQ	8.7	10.2	11.9	8.7	11.8	16.5	6.0	10.0	14.5	7.5	11.8	24.4
West NSW	15.1	23.3	33.8	7.0	18.5	30.8	4.8	15.7	27.8	4.4	14.2	23.5
East NSW	10.0	17.2	25.8	8.3	18.7	32.2	8.6	17.1	30.8	6.7	14.4	26.7
MDB	7.6	13.9	21.0	8.9	15.8	22.9	10.1	17.9	26.0	6.2	14.7	23.7
Vic.	14.6	23.7	33.4	13.1	28.1	46.6	13.5	25.2	40.7	12.4	22.6	34.6
Tas.	25.0	45.0	65.0	22.1	43.7	66.4	22.8	49.0	70.0	16.0	41.5	70.0

Results are presented as the multi-model mean and the 10th–90th percentile.

projections. One option is to select or reject the model according to a certain criteria (e.g Smith and Chandler, 2009). One can (1) include any GCM that has a skill score better than a given threshold, or (2) rank the GCMs according to the skill score and then, for example, select only the top half of the sample projections. A second option is to include all the available GCM projections but use the skill score to weight each of the GCMs in the final analysis (Watterson, 2008).

In this study, we rank the GCMs according to their skill score and then use a certain threshold to select those GCMs for inclusion in the drought projections. Overall, it is suggested that the drought affected area simulated by all 14 GCMs is likely to increase, and omitting the poorer GCMs leads to a much clearer change in most regions. This also true over the North Qld region where the poorer GCMs tend to mask an otherwise strong decrease in drought intensity. The exclusion of the poorer GCMs tends not only to result in a clearer sign of the likely change but also to result in a smaller range of model-to-model uncertainty in some regions. Given that projections are commonly used for risk management, it is hoped that the reduction in the range of uncertainty can be useful to the end users of those projections (policy, adaptation and mitigation groups), particularly for those dealing with water management.

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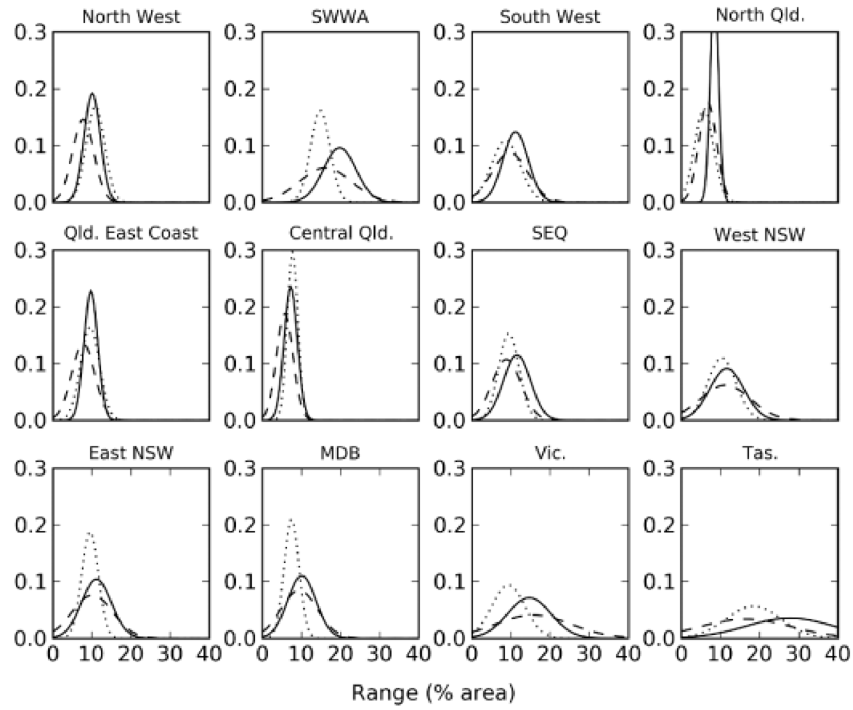

Figure 6. Frequency distribution of the range of projections based on all 14 models (black lines), five randomly chosen model (dashed lines) and the top five models (dotted lines). Drought projections are based on rainfall time series.

(WGCM) for their roles in making available the WCRP CMIP3 multi-model dataset. Support of this dataset is provided by the Office of Science, U.S. Department of Energy. This paper is based on the research partially funded by the South-Eastern Australian Climate Initiative (SEACI) Project and the Australian Climate Change Science Project (ACCSP). We also wish to thank Freddie Mpelasoka for providing some of the data used in this study, Kevin Hennessy for useful discussion, Ian Smith for constructive comments in the internal peer reviewing process of this paper and three anonymous reviewers for their constructive comments.

Appendix A. RDI Formulation

The initial value of annual RDI (α_o) is calculated as

$$\alpha_o = \sum_{j=1}^{12} P_{ij} / \sum_{j=1}^{12} \mathrm{PET}_{ij}, \quad i = 1 \text{ to } N, \quad j = 1 \text{ to } 12 \tag{A1}$$

in which P_{ij} and PET_{ij} are the rainfall and potential evaporation of the jth month of the ith years and N is the total number of years of the available data. The normalized RDI can then be calculated as:

$$\mathrm{RDI}_n^{(i)} = (\alpha_0^{(i)}/\overline{\alpha_0}) - 1 \tag{A2}$$

and the standardized RDI is calculated as:

$$\mathrm{RDI}_{\mathrm{st}}^{(i)} = (y_i - \overline{y_i})/\hat{\boldsymbol{\sigma}} \tag{A3}$$

where the $\overline{\alpha_0}$ is the arithmetic mean of α_0 values calculated for the N years of data and in which y_i is the $\ln(\alpha_0^{(i)})$, $\overline{y}_i$ is its arithmetic mean and $\hat{\sigma}$ is the standard deviation of y_i. The above formulation is based on the assumption that α_0 values follow a lognormal distribution.

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