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Coupled model simulations of current Australian surface climate and its changes under greenhouse warming: an analysis of 18 CMIP2 models

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Coupled climate models have been extensively used to further our understanding of the dynamics and physics of the Earth's climate system and the potential changes of regional and global climates in the future, especially due to human activities such as fossil fuel burning and land-use activities. Nevertheless, there are still large uncertainties in our knowledge of the glob-

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al climate system and in our representations of such a complex system. The confidence of our projected future climate change, therefore, inevitably depends on how well the current climate is simulated by coupled climate models and how large the scatter is among the model simulations of current and future climates. As one of the diagnostic subprojects within the Coupled Model Intercomparison Project phase II (CMIP2), we present an evaluation of 18 CMIP2 coupled model simulations over the Australian region.

Monthly rainfall and surface air temperature climatologies over the Australian region have been derived from the 18 CMIP2 control simulations and compared with observations from the Australian Bureau of Meteorology. The gross spatial patterns of austral summer rainfall (DJF) are reasonably simulated by the majority of the models. However, there are significant model errors in simulating the intensity and location of the heavy Australian monsoon rainfall in the north and eastern parts of the continent, with about half of the models showing more than 100 mm/month biases and a number of models simulating wrong locations of the monsoon rainfall. The seasonal cycle of the surface temperature is reasonably reproduced in the models although there are biases of around 2-4 °C present in the model simulated surface air temperature climatology.

Based on the 80-year model simulations of perturbed climate, with 1% per year increase of atmospheric CO_2 concentration, the changes of surface air temperature and precipitation have also been analysed. The average annual surface temperature change in the last 20-year period of the model simulations against the model control simulations over the Australian region varies from 1.00 °C to 2.18 °C, with an ensemble average of 1.59 °C and ± 0.33 °C scatter measured by one standard deviation. The models give a mixed signal in predicting averaged Australian rainfall changes, with some models simulating more than 3 mm/month increase while others show more than 4 mm/month decrease with on average no change. The spatial distributions of the model-simulated surface temperature and precipitation changes have also been analysed. Surface temperature is increased over the whole continent in all models, while the changes in precipitation show large spatial variations. The ensemble mean model shows decreases in winter rainfall across southern Australia and over northwestern Australia during summer. Increased rainfall is simulated over parts of eastern Australia during winter, extending further north during summer. Besides the analysis of changes in mean climate, the potential impacts of global warming on Australian climate variability is explored in a preliminary way by analysing the changes in tropical Australian precipitation correlations with surface temperature variations over four key oceanic regions. Results suggest that the influence of tropical and subtropical sea-surface temperature (SST) forcing on the Australian climate may change under greenhouse warming.

Introduction

Coupled climate models have been extensively used to further our understanding of the dynamics and physics of the Earth's climate system and the potential changes of regional and global climates in the future, especially due to human activities such as fossil fuel burning and land-use activities (e.g. Houghton et al. 2001). Nevertheless, there are still large uncertainties in our knowledge of the global climate system and in our representations of such a complex system. The confidence of projected future climate change depends to some extent on how well the current climate is simulated by the coupled climate models and how large the scatter is among the model simulations of current and future climates. A series of international modelling intercomparison projects have been established to identify the strengths and weaknesses of current climate models, to encourage further model development and improvement, and to help quantify the uncertainty in the model predictions of future climate change, especially with regard to the increase in global mean surface temperature (see Zhang et al. (2002) and references therein; Cess et al. (1989); Mitchell et al. (1989)). The Coupled Model Intercomparison Project (CMIP) (Meehl et al. 2000) was established in 1995 under the auspices of the World Climate Research Programme's Joint Scientific Committee and the International Research Programme on Climate Variability and Predictability – Working Group on Coupled Models with the aim of providing climate scientists with a set of coupled global circulation model (CGCM) simulations under standardised boundary conditions. While the initial phase of CMIP – called CMIP 1 – focused on the 'control run' of the CGCMs (i.e. constant external forcing), the subsequent phase – CMIP 2 (started in 1997) – collected output from both the control run and an idealised perturbation run in which the CO_2 concentration increases at the rate of 1% (compounded) per year.

A large number of CMIP diagnostic subprojects have been established, exploring differences among the models and seeking to identify aspects of the simulations in which 'consensus' in model predictions or common problematic features exist. As one of the diagnostic subprojects within CMIP2, this paper presents a preliminary analysis of 18 CMIP2 coupled model simulations over the Australian region. While Covey et al. (2003) have given a global overview of CMIP2 model simulations, this study is focused on the Australian region. The aim is to present information on how well the models simulate present day Australian climate and what changes might occur as a result of increase in a 1% per year atmospheric CO_2 level (with observed changes over the past 20 to 30 years amounting to a 0.5 % per year compounded increase) .

The Australian continent extends from the tropics to mid-latitudes, and poses a particular challenge for climate models because of the naturally occurring gradients in surface air temperature and precipitation. The Australian tropics are strongly influenced by the surrounding oceans, and are subject to a strongly varying seasonal cycle of precipitation and surface pressure, dominated by the Australian component of the Asian-Australian monsoon (e.g. McBride 1998). Total precipitation in northern and eastern Australia is strongly influenced by the El Niño Southern Oscillation (ENSO), showing marked interannual variability. Winter conditions in tropical Australia, on the other hand, are subject to mild and relatively dry, southeast trades. Southern regions are subject to eastward moving mid-latitude cyclones. The mean location of the cyclone belt varies seasonally from south of the continent in summer, to the southern portion of the continent in winter, with consequent seasonality of temperature and precipitation. Central parts of the continent are predominantly dry, with occasional precipitation episodes penetrating from the north and south. Other distinctive features such as northwest cloudbands contribute to mid-continental precipitation. Topography is generally low, although the eastern ranges and parts of central Australia have a significant impact on regional temperatures and precipitation. These patterns of precipitation, namely monsoonal in the north, Mediterranean in the southwest, 'mid-latitude' in the southeast, and dry in the centre, are important features to capture in climate models.

As part of an earlier Atmospheric Model Intercomparison Project Phase 2 (AMIP2) subproject, Zhang et al. (2002) reported an analysis of sixteen models in their simulations of key surface climate and surface fluxes in the Australian region. Significant model deficiencies in their simulations of rainfall and surface temperature climatologies were identified. Similarly Harvey and McAvaney (2002) intercompared AMIP2 models in their simulations of the double-jet structure in the southern hemisphere. Using observed SST conditions, the AMIP2 model integrations may represent an 'upper limit' in the capability of current atmospheric GCMs to simulate Australian current climate. The main aim of this study is to evaluate how well basic aspects of the Australian climate are simulated in the fully coupled experiments. CMIP2 offers a unique opportunity to examine how a broad range of coupled models represent the key features of the current Australian region climate. It also provides an opportunity to assess how these important features change under greenhouse warming in these models. Coupled climate model simulations have been used earlier to assess the impact of climate change in Australia and determine our confidence in these simulations (Pittock and Wratt 2001). The IPCC assessment of vulnerability reports (Watson et al. 1998; McCarthy et al. 2001) noted particular concern for Australia from possible changes to the timing, intensity and location of tropical monsoon systems, and location and intensities of mid latitude weather systems and the subtropical anticyclone belt.

We have analysed 18 CMIP2 model simulations (see Table 1 for an overview of all models) of surface air temperature and precipitation over the Australian region. Additional attention is focused on the tropical Australian region, where the Asian-Australian monsoon system dominates. The main deviations of some models from the CMIP 2 protocol with regard to the two fields under consideration are: Model 18 had prescribed sea ice (i.e. not interactive), Model 16 has 75 years instead of 80 years in both runs, and Model 15 has only three years in the control run. Even though there are good arguments for excluding Models 15 and 18 from this report because of the reasons mentioned above, we have included them where appropriate (i.e. they were not used to determine the 'average model' and 'ensemble', but appear on some figures). A more detailed documentation of all CMIP2 models is available at http://www-pcmdi.llnl.gov/cmip/Table.htm and links therein. Note that these model results in many cases do not reflect the most recent model development in each of the modelling groups.

We use the Australian Bureau of Meteorology's observational precipitation dataset created from high quality stations as described in Lavery et al. (1997) as well as surface air temperature data in the model evaluation. Daily average surface air temperature was generated by combining T_{max} and T_{min} from high-quality observational datasets from the National Climate Centre of the Australian Bureau of Meteorology. The usage of $(T_{max}+T_{min})/2$ to estimate daily average temperature in Australia has recently been compared with averages from regular fixed-hour observations (Trewin 2004) and only a slight inhomogeneous difference was noted.

Standard model statistics such as model climatological biases, root mean square errors (rmse), and spatial correlations are calculated for the 18 model simulations. When assessing change in correlations between Australian rainfall and tropical SST, we generated for each 80-year time series of de-trended DJF anomalies 200 new series randomly selected from the original one. This Monte Carlo technique resulted in 200 random correlations allowing the estimation of the 95 per cent confidence level to the original correlation coefficients. Changes between model control and perturbed simulations are taken as significant if the confidence intervals of the corresponding correlation coefficients don't overlap.

Model simulated current surface climatology over Australia

This section will describe the general features of model climatologies over the Australian region. These are compared to observed climatologies from the Australian Bureau of Meteorology datasets for surface air temperature and precipitation for the period

Table 1. Participating CMIP2 coupled GCMs.

Code	*Model Version*	*Research Institutes*
bmrc	BMRCa	Bureau of Meteorology Research Centre, Melbourne, Australia
ccc	CGCM1	Canadian Centre for Climate Modeling and Analysis, Canada
ccsr	CCSR/NIES2	Centre for Climate System Research / National Institute for Environmental Studies, Japan
cerf	ARPEGE/OPA2	Centre European de Recherche et de Formation Avancee en Calcul Scientific, France
csir	CSIRO Mk2	Commonwealth Scientific and Industrial Research Organization, Melbourne, Australia
ech3	ECHAM3/LSG	Deutsches Klima Rechen Zentrum, Hamburg, Germany
ech4	ECHAM4/OPYC	Max-Planck Institut für Meteorologie, Hamburg, Germany
gfdl	GFDL_R30_c	Geophysical Fluid Dynamics Laboratory, NOAA, USA
giss	GISS2	Goddard Institute for Space Studies, NASA, USA
iap	GOALS	Institute of Atmospheric Physics / Laboratory for Atmospheric Sciences and Geophysical Fluid Dynamics, China
inm	INMCM	Institute of Numerical Mathematics, Russian Academy of Science, Russia
lmd	IPSL-CM2	Institute Pierre Simon LaPlace – Laboratoire de Meteorologie Dynamique, France
mri	MRI2	Meteorological Research Institute, Japan
ncarcsm	CSM	National Centre for Atmospheric Research (NCAR) – Climate System Model, Boulder, USA
nrl	NRL2	Naval Research Laboratory, Monterey, USA
pcm	DOE PCM	Department of Energy Parallel Climate Model / NCAR, USA
ukmo3	HadCM3	Hadley Centre, United Kingdom Met Office, UK
yonu	YONU	Yonsei University, Seoul, S. Korea

1950 to 2000. Each model output grid was re-gridded to a common 2.5° x 2.5° grid before applying a land-sea mask and analysis procedures.

Bias over the Australian continent

Figures 1 and 2 show the bias of the seasonally averaged climatologies (DJF only) for surface air temperature and precipitation from the 18 CMIP 2 models against the observed climatologies. Also included is the multi-model ensemble mean, which is generated by simply averaging all the model simulations for the same period.

During the austral summer, the observed rainfall climatology displays heavy rainfall in tropical Australia and eastern coastal regions generated by the summer monsoon system. Figure 1 shows that more than half of the models show substantial overestimation of the rainfall climatology, by up to approximately 120 mm/month, with high precipitation generally penetrating far too south towards inland Australia. This deficiency is also reflected in the multi-model ensemble mean. There is no coherent pattern in the distribution of model biases, with overestimations occurring in tropical Australia in some models and northwest Western Australia in other models. This result was also evident in the AMIP2 results discussed by Zhang et al. (2002). There is a general tendency that if a model underestimates rainfall, it is more likely to do so in the tropics as this is where precipitation amounts are largest. Additionally, some models have a systematic negative bias over almost the entire continent (bmrc, ccsr, csir, giss). Note that about five of the models failed in simulating the gross feature of monsoon rainfall in the region. As found by Ebert (2001) and Zhang et al. (2002), a simple averaging of all the model simulations (at each grid point) to produce the 'poor-man's' ensemble mean tends to produce the best overall results.

Because the analysis has been done at 2.5° resolution, there could be a contribution of model bias from this coarse resolution: for example the simulation of rainfall in northeast Australia is most likely deficient due to coarse resolution of most GCMs, whereas the large-scale displacement of monsoonal rainfall in northwest Australia is most likely due to deficient large-scale circulation in the tropics, which may be related to the Walker circulation being affected by a cold tongue bias in the sea-surface temperature simulated by the CMIP2 models.

Fig. 1 **Precipitation bias in summer (DJF) for all 18 CMIP2 simulations. Units: mm/month.**

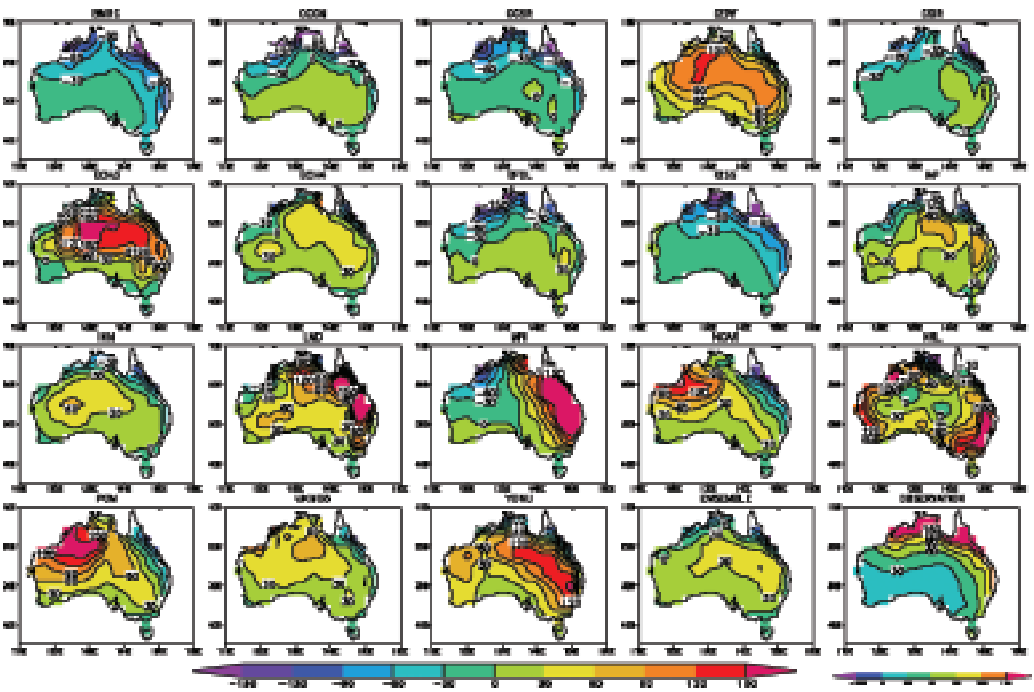
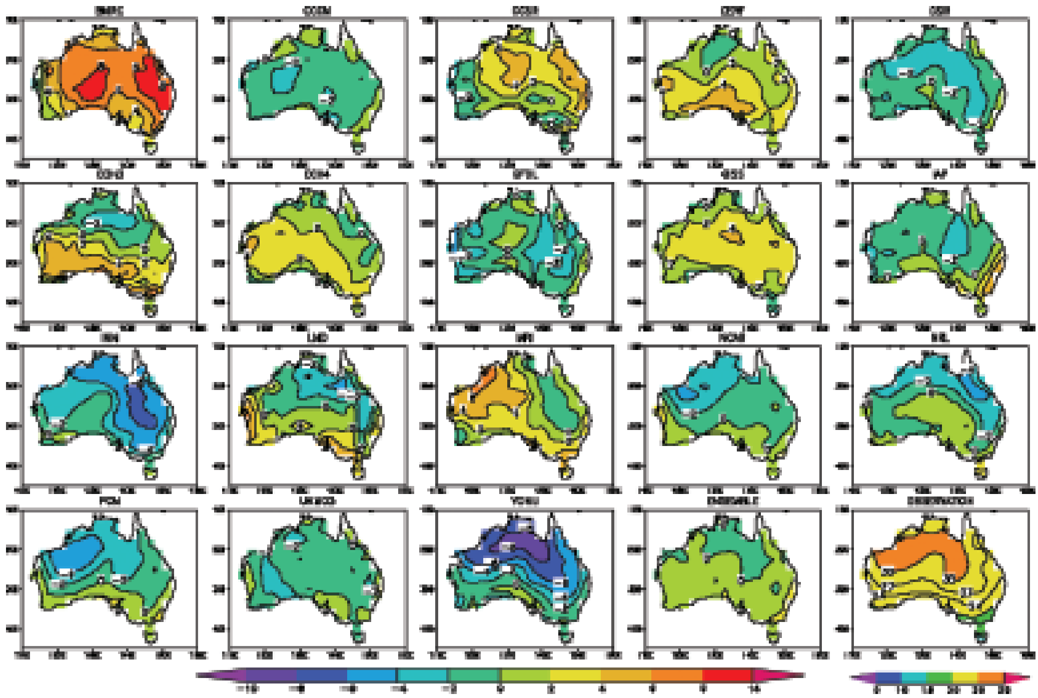


Fig. 2 Temperature bias in summer (DJF) for all 18 CMIP2 simulations. Units: °C.



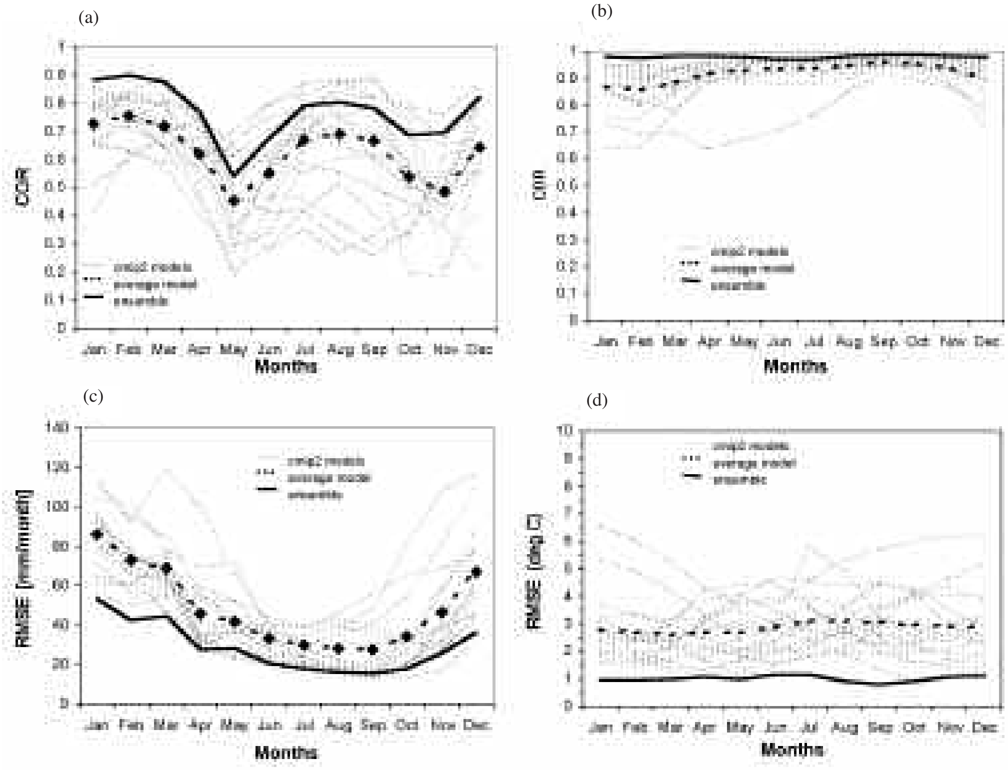
Biases tend to have the same sign in winter (JJA) (not shown here) as they do in summer (DJF), although the size of the bias is lower in winter than in summer. Following the southward shift of the rainfall belt, the general tendency of underestimation switches from the tropics in summer to the mid-latitudes along the east and west coasts of the continent in winter.

Although there are large biases present in Fig. 1, the spatial pattern of precipitation climatology and its seasonal variation is overall reasonably simulated by the 18 CMIP 2 models (Fig. 3(a)). Most models show a correlation above 0.5 for all seasons, although there are considerable differences between models and within seasons. In particular, the Australian summer monsoon does not coincide with markedly increased spatial correlations of the simulated climatologies, indicating a mixed representation of the seasonal migration of the rainfall pattern within the models. The spatial correlations during winter are comparable to summer, while most of the low correlations occur during the spring and autumn seasons. This is probably related to a decreased north-south gradient of precipitation in the transition seasons. The ensemble mean model (created by averaging all models at each grid-point before calculating the statistic) and the average model (average of all model results from the statistic) are shown as well.

Figure 3(c) shows the corresponding area-averaged root mean square error (rmse) of the 18 model climatologies over Australia. In accordance with the results from the bias calculations, the rmse during summer is higher than in winter and the general deviation from the average model is greater in summer as well. In December, for example, the range of rmse for the models varies between 30 and 120 mm/month – a result of the frequent under/overestimation of rainfall climatology during this season. Again, results from the ensemble mean outperform most of the individual models, especially with regard to the rmse. The reason for this could be twofold: the calculation of the ensemble mean (a) usually decreases outlying extremes relative to individual members; and (b) tends to cancel out systematic errors of opposite sign. The ensemble averaging process could also create a smoothed spatial distribution leading to a higher spatial correlation with observations.

As with the rainfall analysis, surface air temperature climatology in the Australian region was analysed and compared against the observational data from the Australian Bureau of Meteorology. Figure 2 shows the bias of the seasonally averaged temperatures during the austral summer (DJF), indicating that there is no common pattern of the surface temperature bias in the models. Some models have a negative bias

Fig. 3 Spatial correlation and root mean square error (rmse) of precipitation (a and c) and temperature (b and d) climatologies simulated by 18 CMIP2 models. Also shown is the ensemble mean model (heavy solid) and average (heavy dashed) of the 18 models.

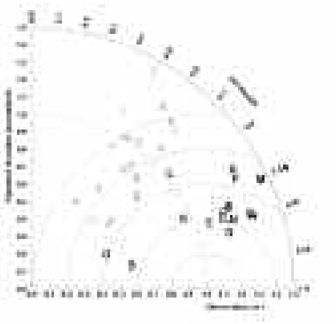


of -2°C to -4°C over parts of the, or the entire, Australian continent. One model has a systematic positive bias of up to +8°C and another has a negative bias of –6 °C, while several models show a mixture of positive and negative bias. Again, the ensemble mean of all models (labelled 'Ensemble' in Fig. 2) gives one of the best results, showing a slight positive bias over most of Australia. In winter (JJA – not shown here), more than half of the models show a negative bias of -2 to -6°C. Meanwhile, there are positive biases over a central band through Australia in a number of models, with larger biases towards inland areas. In general, if a model overestimates surface air temperature in summer, it is likely that it also overestimates in winter. In both seasons some models show a spatial pattern in the temperature bias that seems to be associated with a similar pattern in their precipitation bias over Australia.

The spatial pattern of surface air temperature climatology and its seasonal variation is reasonably simulated by most of the 18 CMIP 2 models (Fig. 3(b)). The greatest variation occurs during the summer season (with a range in correlation of 0.65 to 0.97 around an average correlation of just under 0.9), while for the remainder of the year, most models show a higher spatial correlation of above 0.9. Most of the low correlations occur during the summer season, coinciding with a slight negative bias of these models over central Australia. Figure 3(d) shows the corresponding area-averaged rmse of the 18 model climatologies over Australia. In accordance with the results from the bias calculations, the rmse during summer is very similar to that in winter with one model (bmrc) having a systematic positive bias for all seasons. Overall, the average rmse is around 4°C or less throughout the year. Note that one model (yonu) stands out with a low spatial correlation and a rather high rmse during the summer months. This is also the only model with partly fixed boundary conditions applied to the control and perturbed runs (see previous section).

The strong seasonality of the pattern correlation as shown in Fig. 3(b) might be due to the stronger north-south temperature gradient in winter compared with other seasons, which is picked up much more readily

Fig. 4 Taylor plot for CMIP2 models temperature (capital letters) and precipitation (small letters). Observational values are at (1,1) and the ensemble value is S and s respectively. The dashed circles centred around the observation represents the root mean square error (rmse) for the models.



by the models. The ensemble mean model outperforms all individual models for both temperature bias (~ 1 °C for all seasons) and spatial correlation (above 0.97 for all seasons).

The skill of the models in simulating spatial characteristics of the Australian temperature climatology is enhanced in comparison to precipitation, with most models showing a higher correlation and less seasonal variation. The exception for this occurs in DJF, when some models show a marked drop in the correlation.

Summarising the overall performance of the models with regard to bias and rmse error, Fig. 4 shows a Taylor plot (Taylor 2001) of the simulated precipitation and temperature climatologies. It depicts the normalised standard deviations for all model control runs compared to observations (distance from origin), including the spatial pattern correlations to the observations (azimuth position) and rmse (dashed circles – indicating distance away from observations at (1,1)). In general, modelled temperature variability (indicated by capital letters for each model) is more closely correlated with observed variability than is precipitation (indicated by small letters for each model) and also shows a smaller rmse for most models. Interestingly, temperature variability is usually higher in the models compared with the observations (except for two models and the ensemble mean model 'S'), while the modelled variability in precipitation varies strongly between models with slightly more than half showing lower variability than observed. The ensemble mean model (letter 'S' for temperature and 's' for precipitation) shows a high correlation together with markedly lower than observed variability. One reason for the higher spatial correlation of temperature could be a more homogeneous temperature field across Australia.

Seasonal cycles over the tropical and the whole Australian regions

In this section we compare the seasonal cycles of precipitation and surface temperature in the model simulations with observations. One of the key components of this CMIP2 diagnostic subproject is to analyse simulations of the Australian monsoon. In Fig. 5 we show the precipitation and surface air temperature seasonal cycles over three regions (land only): the whole Australian continent (left panels; lat = (45°S – 10°S), lon = (110°E – 155°E)), the 'top end' tropical Australian region (centre panels; lat = (20°S – 10°S), lon = (120°E – 155°E)), and extra-tropical Australia (right panels; lat = (45°S – 20°S and 110°E – 155°E)).

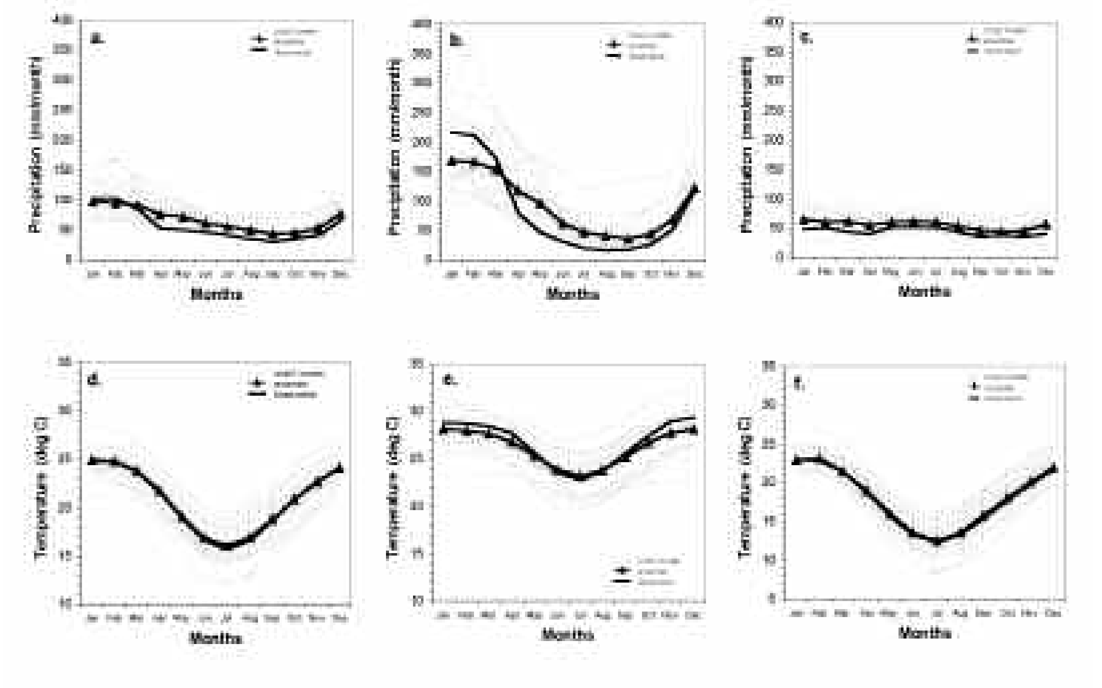
The dominant role of the Australian monsoon leads to similar precipitation seasonal patterns over the entire Australian continent and over the tropical region. However, the precipitation seasonal cycle is much clearer and stronger in the tropical region. When comparing the simulated seasonal cycles with the observations, the differences become apparent. Averaged over the entire Australian continent, most of the models overestimate the precipitation over the entire seasonal cycle and even the model ensemble mean shows an overestimation of about 20-40 mm/month for most seasons. In contrast, over the Australian tropical region, most models underestimate the summer rainfall seasonal cycle with the difference between observed and average model being around 50 mm/month. This is consistent with a feature seen in the bias analysis i.e. the Australian summer rainfall penetrates too far into the inland region. Also more pronounced is the overestimation of tropical Australian rainfall for all other seasons, especially during spring. Again, the multi- model ensembles mean gives a better simulation than most of the individual models, resembling the observed cycles more closely.

In extratropical Australia (Fig. 5(c)), the seasonal cycle for precipitation does not indicate marked seasonality with most models on average overestimating rainfall.

The seasonal cycles of surface air temperature for both the Australian continent (Fig. 5(d) and the separate regions (tropical: Fig. 5(e) and extratropical: Fig. 5(f)) are reasonably simulated in the models, largely following the excursion of the sun. The biases in most models behave consistently throughout the year: there is a 7-8°C temperature scatter among the models. The multi-model ensemble mean underestimates the observed seasonal surface air temperature seasonal cycles over tropical Australia by 1°C during the six months surrounding summer, while there is almost no difference with the observations over the entire Australian continent.

In summary, (a) simulated precipitation seasonal

Fig. 5 Seasonal cycles for precipitation (a, b, c) and temperature (d, e, f) for all 18 CMIP2 models for the whole Australian continent (left panels), tropical Australia (centre panels) and extratropical Australia (right panels). The panels include observations (heavy solid) and ensemble mean (solid marked).



cycles show large variation (from model to model) and large deviation from observed (typically 50 mm/month over tropical Australia) during summer and extending into spring; (b) simulated surface air temperature seasonal cycles show large systematic variations between models with a consistent deviation from observed of up to ± 3-4°C throughout the year.

The overall simulations of current climate by the CMIP2 models show considerable spread in quality: while the gross spatial patterns of austral summer rainfall (DJF) are reasonably simulated by the majority of the models, there are significant model errors in simulating the intensity and location of the heavy Australian monsoon rainfall in the north and eastern parts of the continents. The seasonal cycle of the surface temperature is reasonably reproduced.

Model simulated surface climate changes

Figure 6(a) indicates that all simulations show significant warming trends, with a high linear correlation with time, i.e. most temperature increases are close to linear. However, the surface temperature warming rate shows quite notable differences among the models, with one of the models showing a warming of 2.18 °C averaged over the final twenty years, while another warms by only 1.0 °C in the same period. This variability is illustrated in Fig. 6 which highlights two example simulations (UKMO3 and BMRC).

The surface air temperature results in Fig. 6(a) are consistent (although with relatively greater spread) with those shown elsewhere for global change of surface air temperature simulated by CMIP 2 models (Covey et al. 2003) and in the IPCC 2001 report (Houghton et al. 2001). The models reach about 1.6°C mean surface warming over Australia by the time CO_2 has doubled around year 70. This is shown in more detail in the last column of Table 2, where the averages of years 61-80 are listed for each model. The multi-model ensemble value is 1.6 °C and all but one of the models are within ± 30% of this value.

The time evolution of the Australia-averaged change in precipitation relative to the control run is quite different. There is hardly any change at all in most models. Some models show slight increases and others slight decreases in rainfall. In Fig. 6(b) there are two examples of CMIP 2 simulations highlighted

Fig. 6 **The time evolution of the Australia averaged annual temperature (top) and precipitation (bottom) change relative to the control run of the CMIP2 simulations. Highlighted are two examples for each field. Also shown is the ensemble mean of all models.**

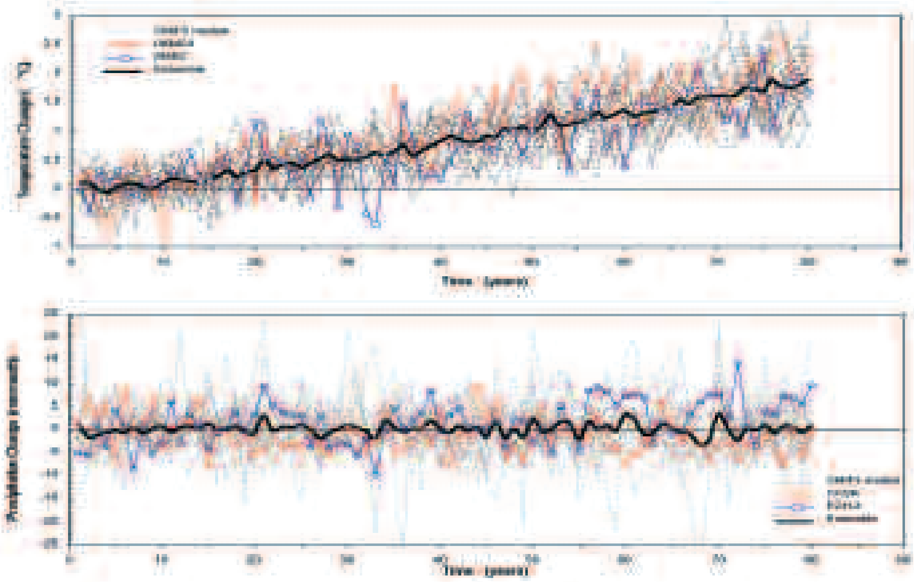


Table 2. **Linear regression statistics of the time evolution of the annual Australia-averaged temperature change relative to the control run of CMIP 2 simulations.**

Model	*Slope* [°C/y]	*STD of slope* [°C/y]	R^2	*Last 20 years:* [°C]
BMRC	0.022	0.002	0.61	1.53
CCCM	0.029	0.001	0.88	1.86
CCSR	0.019	0.002	0.63	1.39
CERF	0.024	0.001	0.84	1.51
CSIR	0.027	0.002	0.77	1.76
ECH3	0.026	0.002	0.75	1.56
ECH4	0.020	0.001	0.71	1.24
GFDL	0.033	0.002	0.78	2.11
GISS	0.026	0.001	0.84	1.63
IAP	0.036	0.001	0.90	2.18
INM	0.015	0.001	0.66	1.00
LMD	0.029	0.001	0.90	1.89
MRI	0.019	0.001	0.70	1.35
NCAR	0.021	0.002	0.69	1.35
PCM	0.018	0.002	0.63	1.23
UKMO3	0.028	0.002	0.75	1.83
YONU	0.019	0.001	0.88	1.18
ENSEMBLE	0.025	0.0004	0.98	1.59 AVG 0.33 STD

representing a slight decrease (ccsr) and an increase (ech3). The ensemble mean shows a non-significant slight negative trend with time. Details of each models linear regression analysis are shown in Table 3. Note that some models show a slightly higher initial positive or negative value (at t=0).

The precipitation results in Fig. 6(b) are quite different to those shown elsewhere for global change of precipitation simulated by CMIP 2 models (Covey et al. 2003) and in the IPCC 2001 report (Houghton et al. 2001). The global picture shows an increase in precipitation for almost all models of up to 6 mm/month in the last 20-year average (Covey et al. 2003). This is not the case over Australia where the models reach anywhere between approximately ± 7 mm/month in the year (61-80) average with the ensemble sitting very close to zero (but with a relatively large standard deviation of almost 3.5 mm/month) as shown in Table 3. This implies that the soil moisture reduces in these models as the climate warms. This seems to be a robust feature in most models represented here. It highlights the importance of detailed analysis of regional climate change simulations, with the possibility of highly different precipitation responses to global warming in different regions.

When examining the spatial distributions of changes in surface air temperature and precipitation over Australia relative to the control runs, the difference between the models becomes apparent. Figure 7

Table 3. Linear regression statistics of the time evolution of the annual Australia averaged precipitation change relative to the control run of the CMIP2 simulations.

Model	*Slope ([mm/months]/y)*	*STD of slope*	R^2	*Last 20 years: [mm/mon]*
BMRC	-0.05	0.04	0.02	-1.46
CCCM	-0.01	0.03	0.00	0.24
CCSR	-0.02	0.03	0.00	-2.64
CERF	0.12	0.06	0.05	6.61
CSIR	-0.08	0.05	0.03	-1.83
ECH3	0.09	0.04	0.06	4.80
ECH4	-0.02	0.03	0.01	-1.17
GFDL	0.00	0.04	0.00	0.56
GISS	-0.09	0.03	0.15	-4.85
IAP	0.03	0.05	0.01	-1.91
INM	0.01	0.03	0.00	2.06
LMD	-0.09	0.04	0.05	-6.81
MRI	0.12	0.05	0.08	3.55
NCAR	0.05	0.03	0.02	-0.61
NRL	-0.02	0.03	0.00	0.72
PCM	-0.06	0.07	0.01	-2.11
UKMO3	0.06	0.02	0.07	3.25
YONU	0.00	0.01	0.00	-0.30
ENSEMBLE	-0.05	0.04	0.02	-0.09 AVG
				3.42 STD

shows the changes in surface air temperature for the summer season – focusing on the last twenty-year (61-80) averages, when the CO_2 concentration has doubled.

For most CMIP2 models, there are reasonably uniform overall patterns of warming in both summer and winter seasons (JJA not shown here). Nevertheless, models tend to show some difference in the locations where greatest warming occurs. There is a general tendency for the majority of the models to have greater warming in the inland regions than near the coasts. The shift of the warming patterns between summer and winter seasons in each of the models is also relatively small, indicating a remarkably uniform response in temperature changes across seasons when CO_2 has doubled. Confirming this, the ensemble mean model correlation between summer and winter temperature change is quite high at around 0.8.

In contrast to the homogeneity seen in surface temperature changes, the precipitation response to global warming has large spatial variations over Australia (Fig. 8 for DJF and Fig. 9 for JJA). There is no common region where all models simulate an increase or decrease in rainfall. Some models simulate quite substantial changes for summer (ech3, iap, lmd, ncar_csm) over certain areas. In general, increases in rainfall are simulated more often over eastern Australia and slightly more in the tropics in both seasons, as indicated by the results from the ensemble mean model in both figures. In winter there is a tendency for a reduction in precipitation broadly across southern Australia. This decrease of precipitation in the sub-tropical belt has also been noted in the last IPCC assessment report (Houghton et al. 2001), for both the all-Australian annual mean precipitation as well as the two subsections (NAU=Northern Australia, SAU=Southern Australia). The shift of the patterns between summer and winter seasons in most of the models is quite significant and the corresponding seasonal pattern correlations are very small, suggesting a strong shift in seasonal patterns.

The most recently published climate change projections for Australia (CSIRO 2001) showed the spatial distribution of seasonal temperature and precipitation changes based on the IPCC Special Report on Emissions Scenarios (SRES) (IPCC 2000). While the SRES scenarios include other forcing besides an increase in atmospheric CO_2 , the spatial patterns of increases in temperature are similar to the CMIP2 ensemble model with Western Australia showing most of the increase in temperature by the time CO_2 has doubled. The CSIRO projections do not show central tendencies but overall ranges of the change, which somewhat limits a comparison to our results. This is particularly the case when comparing changes in DJF precipitation.

The ensemble averaged changes in rainfall for DJF and JJA show the following tendencies:

- DJF season: decrease in rainfall in northwestern and northeastern Australia, and perhaps parts of Victoria and South Australia. Increase in rainfall along a band covering northern New South Wales, southern Queensland and reaching further northwest into the Northern Territory.
- JJA season: decrease in rainfall across all of southern Australia, including southwest Western Australia, South Australia, Victoria, Tasmania, and southern parts of New South Wales. Increase in rainfall over central eastern Australia, covering southwest Queensland and northern New South Wales.

Changes in the role of tropical oceans in influencing Australian climate variability

Australian climate is significantly affected by the tropical SST forcing related to the El Niño Southern Oscillation (ENSO) and Indian Ocean conditions (Nicholls 1989, 1995; Power et al. 1999; Drosdowsky

Fig. 7 Spatial distribution of temperature change for DJF from the 1%CO_2 runs (yr61-80). Units: °C.

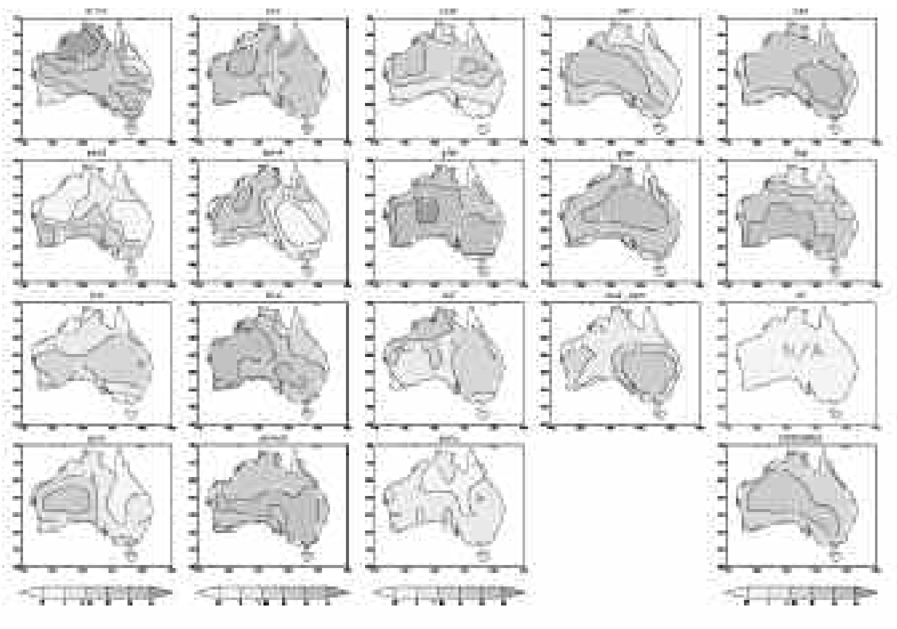


Fig. 8 Spatial distribution of precipitation change for DJF from the 1%CO_2 runs (yr61-80). Units: mm/month.

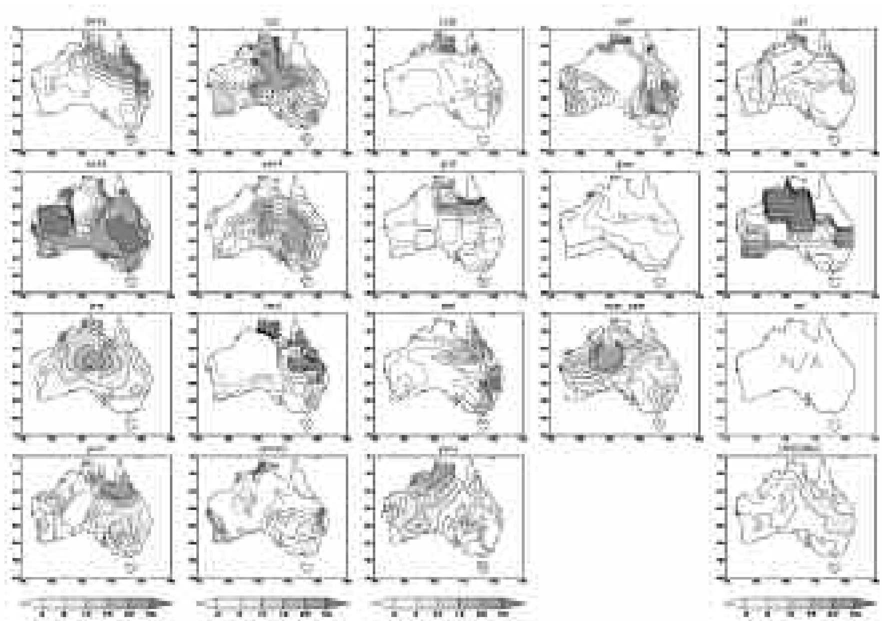
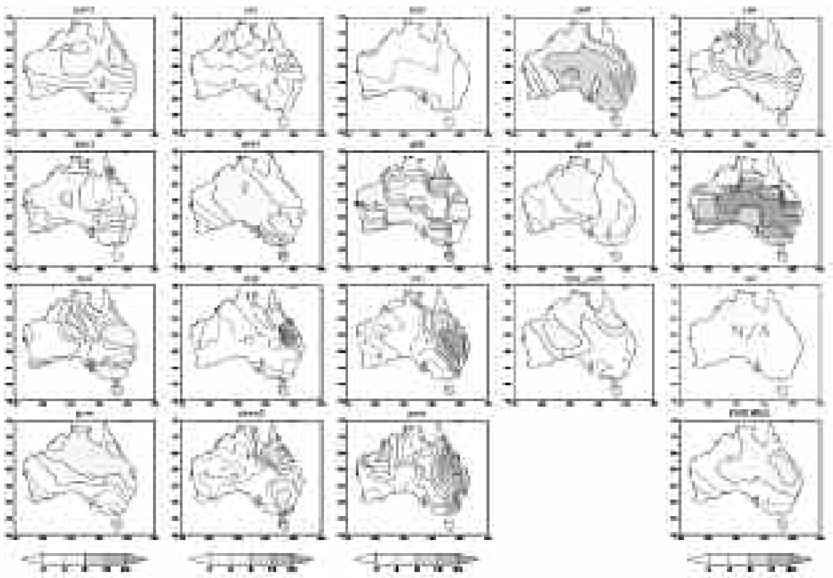


Fig. 9 Spatial distribution of precipitation change for JJA from the 1%CO_2 runs (yr61-80). Units: mm/month.



1993; Drosdowsky and Chambers 2001). Here, we examine: (a) if there are significant correlations between precipitation in tropical Australia (usually dominated by the summer monsoon system), and SST conditions in a number of key regions; and (b) if such correlations change between the CMIP2 model control and perturbed simulations. Four key areas are examined (see Fig. 10). These areas are: Niño3.4 which is a centre of action for ENSO and exhibits a known high correlation with precipitation in Australia, the western Pacific Ocean (WPO) warm pool area which affects the Australian monsoon, and the Indian Ocean (Area7, index area defined by Mullan (1998)) and western Indian Ocean (WIO) areas. Here we examine the correlation coefficients between SST averaged over these areas with model-simulated rainfall over tropical Australia (10°S – 20°S and 120°E – 155°E).

Note that there is no CMIP2 model SST output for the analysis. Instead, we have used model simulated 2-metre surface air temperature as an approximation of SST conditions. Even though there are some differences between these two fields, the high correlations between surface air temperature and SST suggest that this approximation will not significantly affect the conclusions in this section.

Because of its known high correlation with tropical precipitation in Australia, the Niño3.4 variability (expressed as the year-to-year (DJF) standard deviation of SST (in °C)) is a very important assessment for model performance. Figure 11 shows the Niño3.4 variability within all models compared with observation (indices from the NOAA Climate Prediction Centre, 2004) for both the control and perturbed runs. Besides the fact that nearly all the models show a weaker variability than observed, for most models, there is little difference between the runs, i.e. a 1% compounded CO_2 increase does not change significantly the tropical SST variability. The fact that almost all models underestimate the variability is also consistent with the underestimation of interannual variability we have seen (not shown here).

Following the examination of Niño3.4 variability simulated in the coupled models, the correlation of tropical Australian precipitation with SST conditions over key areas will be discussed in the following section.

Firstly, the correlations between surface air temperature from key areas shown in Fig. 10 and tropical Australian rainfall (representing the Australian monsoon) are computed for all CMIP2 models for both the control runs and the 1% increase in CO_2 per year runs. Only the last 40 years of the transient run have been used for this statistic because we are interested in the strength of this relationship at a time when the

Fig. 10 Grid boxes used in the correlation analysis (WPO = Western Pacific Ocean, WIO = Western Indian Ocean, WLD = Index area defined in Drosdowsky (1996), Area7 = Indian Ocean index area defined by Mullan (1998)).

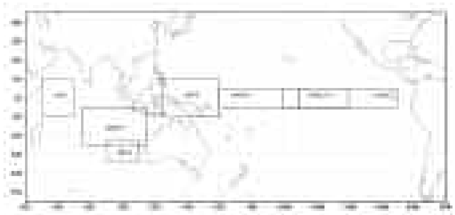
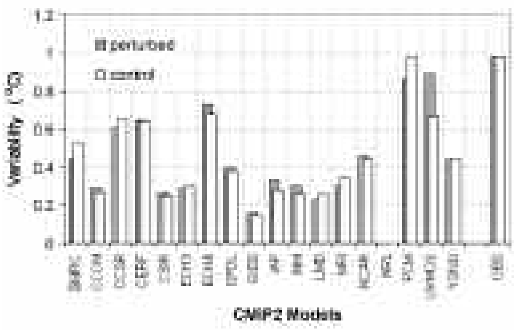


Fig. 11 Niño3.4 variability simulated by the CMIP2 models compared with observations (here: NOAA's Climate Prediction Centre NCEP indices data at http://www.cpc.ncep.noaa/data/ indices/index.html). Shown is the year-to-year (DJF) standard deviation (in °C) for model control runs (empty bars) and perturbed runs (dark bars) – bars furthest to the right depict the observations. Shown is the standard deviation in °C.



climate has already undergone a change. The results for Niño3.4, Western Pacific Ocean (WPO), Indian Ocean (Area7) and the Western Indian Ocean (WIO) are shown in Fig. 12. The corresponding results from the validation data sets (NCEP reanalysis for surface air temperature; Australian Bureau of Meteorology data for precipitation; time span 1950-2000) have been added as dashed lines in Fig. 12 for comparison.

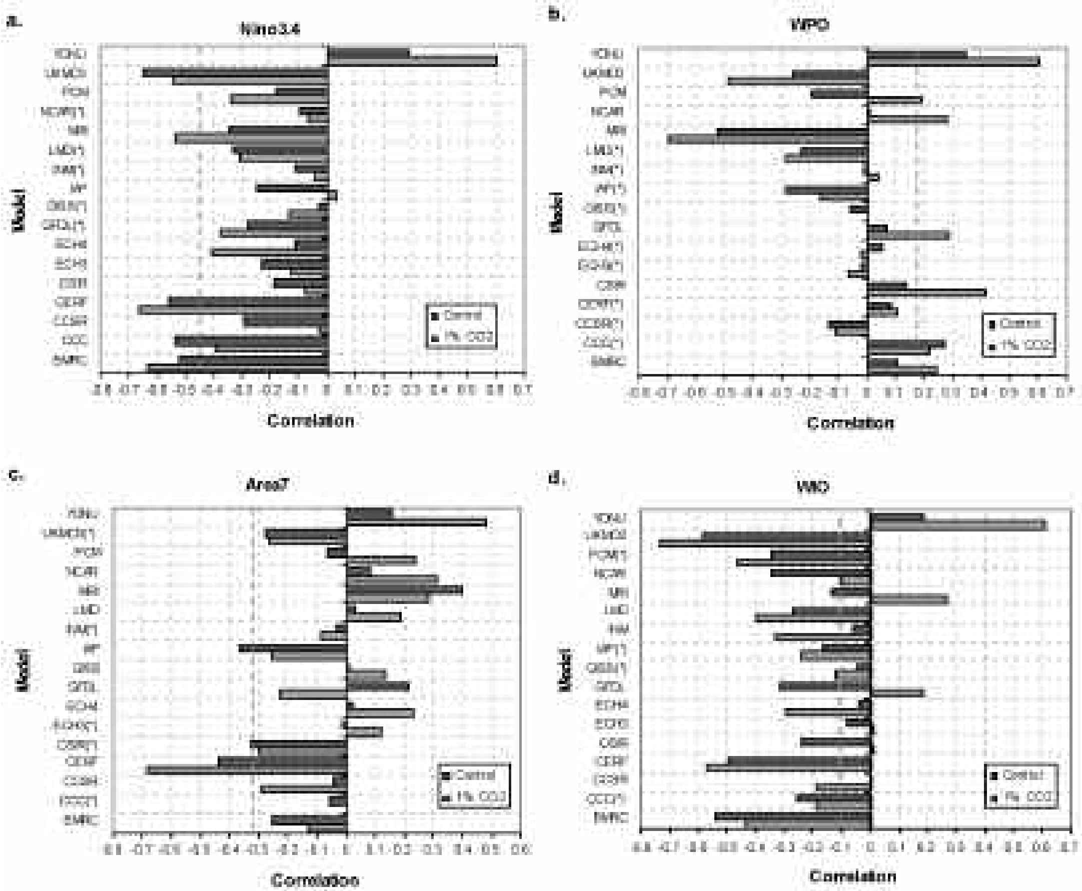
- Niño3.4: Based on the Monte Carlo calculations, the significance threshold for the control run correlations ($n = 78$, $\alpha = 5\%$) lies at ± 0.22, and the perturbed run correlations ($n = 40$, $\alpha = 5\%$) lies at ± 0.304. Most simulations show a negative correlation in the control as in the observations, but the strength varies from weak insignificant (giss) values to strong highly significant values (bmrc, cerf, ukmo3). There are 10 models that have a non-significant correlation in either control or perturbed run with 6 of them (csir, ech3, giss, inm, ncar-csm, pcm) unable to establish a significant correlation in both runs.
- WPO: The observed weak positive correlation in this area is only simulated by half of the CMIP2 models, while two of the models give stronger opposite correlations.
- Area7: As shown by a number of studies, the Indian Ocean plays a key role in Australian climate variations (Drosdowsky 1993; Frederiksen and Balgovind 1994; IOCIP 2000). This is underlined by the observed correlation shown in Fig. 12. Nevertheless, most models fail to either simulate a comparable strength or even the same sign, with six models simulating a positive correlation in their control runs. Of the 18 CMIP2 models, five of them (bmrc, cerf, csir, iap and ukmo3) show a correlation comparable to the observations in their control run.
- WIO: In contrast with results in the more eastern parts of the Indian Ocean (represented by Area7 here), the observed correlation for the Western Indian Ocean section is simulated quite strongly by most models (similar to the Niño3.4 case). This is quite striking because the observations point to a very weak negative correlation, which is seen by only one third of the models control runs.

Finally, the changes of correlations in the model perturbed runs, compared with their control simulations, were carefully examined by the scatter between 200 Monte Carlo random correlation calculations from both control and perturbed simulations. Again, only the last 40 years of the transient run has been taken into account. In Fig. 12, any model with an asterisk (*) indicates that the difference between correlations simulated in the control run compared with the perturbed run is not significant.

Figure 12a shows that all but one of the models retain the sign of the correlation between Niño3.4 surface temperature and tropical Australian rainfall as in their control runs. However, under greenhouse warming, most models simulate statistically significant changes in the magnitude of correlations between Niño3.4 surface temperature and tropical Australian precipitation. About half of the models show a stronger negative correlation in their perturbed runs compared with the control run, while the other half have either weaker correlations, or an opposite sign.

Over the western Pacific Ocean (WPO), half of the

Fig. 12 Correlation coefficients for gridbox averaged SST to tropical Australia precipitation correlations in both the control (dark) and 1%CO_2 (light) run of the simulations. Shown are the correlations for Nino3.4 (a), WPO (b), Area7 (c) and WIO (d). Observations are shown by the dashed line. Not significant differences between control and perturbed run correlations are indicated by (*) next to the model name.



models simulated statistically significant changes in their correlations, with about half of them strengthening their correlations under climate change conditions. Similar model behaviours are also seen in the results of the eastern Indian Ocean (Area7) and western Indian Ocean (WIO), with half of the models showing enhanced correlations.

Discussion and conclusions

This paper has presented a preliminary analysis of 18 CMIP2 models in simulating Australian climate and its potential changes under greenhouse warming (CO_2 forcing only). We also investigated whether the influence of tropical SST (via approximation of 2 m surface air temperature) on Australian rainfall has varied in the model control and perturbed simulations.

Rainfall and surface air temperature monthly climatologies over the Australian region have been derived from the model monthly datasets in their control simulations (i.e. with constant CO_2 concentration), and compared with observations from the Australian Bureau of Meteorology. The gross spatial patterns of austral summer rainfall (DJF) can be reasonably simulated by the majority the models. There are, however, significant model errors in simulating the intensity and location of the heavy Australian summer monsoon rainfall in the northern and eastern parts of the continent. About half of the models show more than 100 mm/month biases and a number of models simulated wrong locations of the monsoon rainfall. The model errors in the Australian winter (JJA) rainfall simulations are relatively small compared with the results in DJF, partly because rainfall totals are smaller in winter. There are 2-4°C biases present in the model simulated surface air temperature climatology, however the seasonal variation of the surface temperature climatology is reasonably reproduced in the models.

By way of summary, the Taylor diagram in Fig. 4 (Taylor 2001) suggests that Australian surface temperature is more reasonably simulated by the CMIP2 model control simulations than the rainfall. No single model consistently gives a better result in all respects. Results from a simple multi-model ensemble are better overall than most individual models in both simulations of surface temperature and precipitation. The interannual variability of simulated precipitation and temperature is too weak. This is at least partly due to an underestimate of ENSO-driven variability in the models.

Based on the 80-year model simulations of perturbed climate, with 1% per year increasing atmospheric CO_2 concentration, the changes of surface air temperature and precipitation have also been analysed. The Australia - averaged annual surface temperature change between the control and transient runs in the last 20-year period of the model simulations over the Australian region varies from 1.00°C to 2.18°C, with the multi-model ensemble average of 1.59°C, with a standard deviation of 0.33°C. All of the models simulate warming over Australia at most locations. Australia-averaged rainfall averages, on the other hand, are not consistent. Some models simulate more than 3 mm/month increases while some show decreases of 4 mm/month or more.

Surface temperature increased over the entire continent in almost every model, while the changes in precipitation show quite large spatial variations. The ensemble mean model shows decreases in winter rainfall across southern Australia and over northwestern Australia during summer. Increased rainfall is simulated over parts of eastern Australia during winter, extending further north during summer.

Besides the analyses of changes in mean climate, the potential impacts of global warming on Australian climate variability have been explored in a preliminary way by measuring the changes of tropical Australian (de-trended) precipitation correlations with surface temperature variations over four key oceanic regions. Results suggest that the influence of tropical and subtropical SST forcing on Australian climate may change under greenhouse warming, with the majority of the models showing statistically significant changes in correlation coefficients, although being roughly evenly split as to the sign of the change.

Coupled model development has moved on since the submission of data to the CMIP2 program and a similar analysis needs to be carried out with more recent model versions.

Acknowledgments

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