NARCliM

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Choosing GCMs

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Choosing GCMs

1. GCM performance from literature

Many studies have evaluated the performance of GCMs over south-east Australia using different variables and metrics. Here we build on the meta-analysis of Smith & Chandler (2010). First, more recent evaluations over Australia, not covered in Smith & Chandler (2010) are added to the analysis for a total of 11 studies (see Table 1). Then a fractional demerit point was calculated to indicate the models over-all performance. The lower the fractional demerit the better the performance.

Table 1: Summary of model assessments

Assessment region		Australia							MDB		SE Australia	
Model	**Fractional Demerit**	**A**	**B**	**C**	**D**	**E**	**F**	**G**	**H**	**I**	**J**	**K**
UKMO-HadCM3	0	0	Yes	6	608							179
CSIRO-Mk3.5	0						5	1				207
GFDL-CM2.1	0.111	0	Yes	2	672	Yes			No	Yes	0.72	184
GFDL-CM2.0	0.125	0	Yes	2	671	Yes			No	Yes		252
MIROC3.2 (hires)	0.125	0	Yes	7	608		12	9	Yes			201
CSIRO-Mk3	0.182	1	No	7	601	Yes	1	2	Yes	No	0.73	214
UKMO-HadGEM1	0.2	0	No	2	674							163
ECHAM5/MPI	0.222	0	Yes	1	700	Yes			No	No	0.79	173
MIUB-ECHO-G	0.222	0	No	4	632	Yes			Yes	No	0.78	174
INM-CM3.0	0.222	1	No	7	627		9	11		Yes	0.75	192
NCAR CCSM3	0.273	0	No	2	677	No	4	6	No		0.68	245
CNRM-CM3	0.286	0	No	4	542					No	0.73	196
FGOALS-G1.0	0.3	2	No	2	639	No	8	4	Yes		0.66	251
MIROC3.2 (medres)	0.364	2	Yes	7	608	Yes	11	3	Yes	No	0.6	255

CCCM3.1(T63)	0.375	1		10	478		2	7	No		0.72	241
MRI-CGCM2.3.3	0.455	1	No	3	601	No	10	12	Yes	Yes	0.41	437
CCCM3.1(T47)	0.455	1	No	8	518	No	3	10	Yes	No	0.77	186
GISS-ER	0.5	0	No	8	515	Yes	6	5	No	No		238
BCCR-BCM2.0	0.5	5		5	590	Yes			No			485
GISS-AOM	0.667	1	No	8	564	No	7	13	Yes		0.6	326
IPSL-CM4	0.8	2	No	14	505	No	13	8	Yes		0.48	394
NCAR PCM	0.833	3	No	11	506						0.64	309
GISS-EH	1	5	No	14	304		14	14				487

A number of rainfall criteria failed (Smith and Chandler 2010), **B** satisfied ENSO criteria (Min et al. 2005; van Oldenborgh et al. 2005), **C** demerit points based on criteria for rainfall, temperature and MSLP (Suppiah et al. 2007), **D** M-statistic representing goodness of fit at simulating rainfall, temperature and MSLP over Australia (Watterson 2008), **E** satisfied criteria for daily rainfall over Australia (Perkins et al. 2007), **F** order of model based on the total skill scores for each rainfall metric (Kirono, et al 2010), **G** order of model based on the total skill scores for each of rainfall and PET metric (Kirono, et al 2010), **H** satisfied criteria for daily rainfall over MDB region (Maximo et al. 2008), **I** satisfied criteria for MSLP over MDB region (Charles et al. 2007), **J** combination of RMSE of mean annual rainfall across south-east Australia and mean NSE (rainfall > 1mm) comparing GCM-simulated and observed daily rainfall distribution with equal weights (Vaze et al 2011), **K** RMSE of mean annual rainfall over south-east Australia (Chiew, et al 2009)

Demerit points are added to a GCM in two ways. For evaluations which provided a binary pass/fail outcome any fail equals one demerit point. For evaluations that provide a continuous measure, any GCM that falls in the 25% worst performing GCMs receives one demerit point. All demerit points across the published studies are totalled for each GCM. Since not every GCM was present in every study this demerit total is then divided by the total number of studies the GCM appeared in to calculate the fractional demerit. In this way fractional demerit scores of 0.5 or above indicate that the GCM was amongst the 25% worst GCMs at least half of the time. These consistently worst performers were then removed from further analysis.

2. GCM Independence

In the method of *Abramowitz and Bishop* [2010] the model independence is defined based on the correlation of model errors. For precipitation, mean temperature, the daily time series for each event is bias corrected using the BAWAP observations, to produce an anomaly time series. These time series are then used to create the model error covariance matrix. *Abramowitz and Bishop* [2010] are able to show that the coefficients of a linear combination of the models that optimally minimizes the mean square error depends on both model performance and model dependence. The solution of this minimization problem can be written in terms of the covariance matrix already constructed. The size of the coefficients assigned to each model reflects a combination of model performance and independence. That is, the models with the largest coefficients are the best performing/most independent models in the ensemble.

These coefficients are calculated for each variable and then averaged to give the overall performance/independence of each model (Table 2).

Table 2: The absolute GCM independence coefficient for each model.

models	temperature	precipitation	average	rank
miroc3_2_medres	0.3524954	0.03638067	0.38887607	1
ukmo_hadgem1	0.1360727	0.06942903	0.20550173	2
inmcm3_0	0.16053	0.04361571	0.20414571	3
gfdl_cm2_0	0.07290747	0.1077916	0.18069907	4
mpi_echam5	0.07039613	0.09215108	0.16254721	5
mri_cgcm2_3_2a	0.06236396	0.084668	0.14703196	6
miub_echo_g	0.08682907	0.0413819	0.12821097	7
gfdl_cm2_1	0.02902377	0.0799438	0.10896757	8
cccma_cgcm3_1	0.02332552	0.07327753	0.09660305	9
ukmo_hadcm3	0.03306758	0.06017381	0.09324139	10
csiro_mk3_5	0.005901015	0.08603905	0.091940065	11
csiro_mk3_0	0.03983158	0.0502712	0.09010278	12
ncar_ccsm3_0	0.00908887	0.07265306	0.08174193	13
cnrm_cm3	0.006109701	0.05134836	0.057458061	14

3. GCM future changes

The projected future changes of all the reasonably well performing GCMs are considered equally probable future changes. As such we want to choose models that sample from this future change space, while being as independent as possible. The GCM independence rankings are plotted in the future precipitation/temperature change space in Figure 1.

Based on these criteria the ideal GCM choice would be

1. MIROC (1)
2. HadGEM (2)
3. GFDL 2.0 (4)
4. CCCMA (9)

Due to many groups not keeping all the required data to run the WRF model, alternative choices have to be made. The GCM choice used in practice is

1. MIROC (1)
2. ECHAM5 (5)
3. CCCMA (9)
4. CSIRO mk3.0 (12)

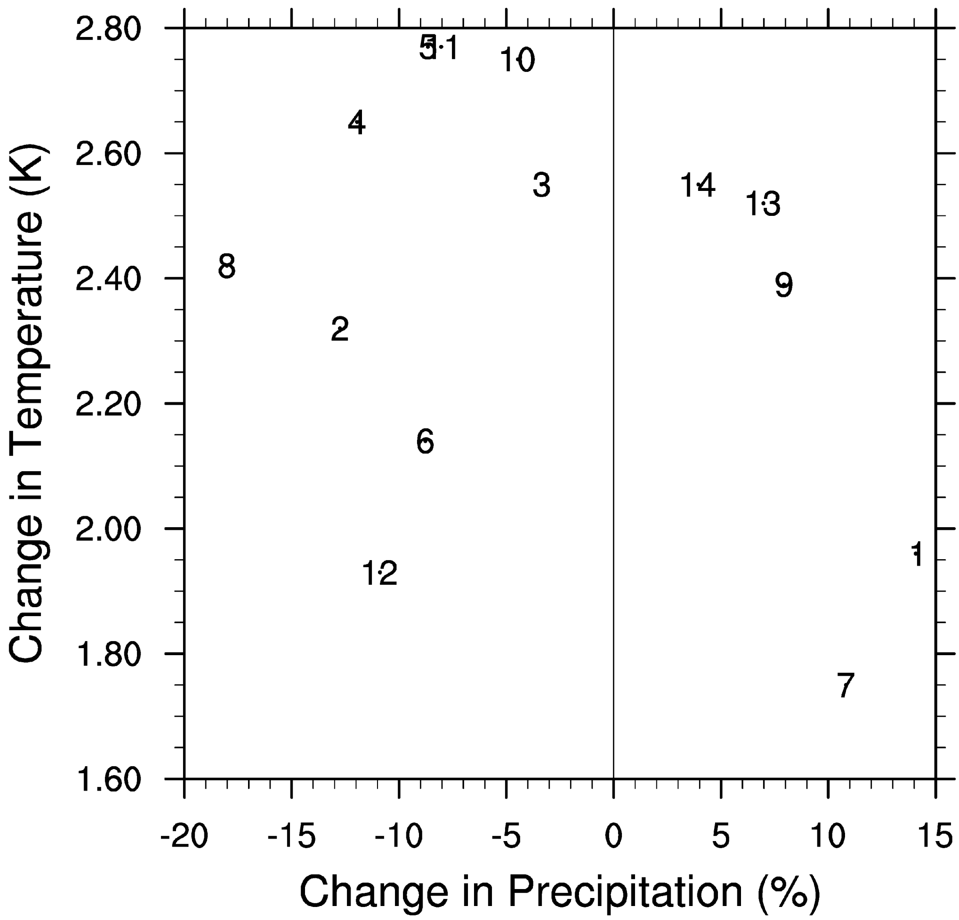

Figure 1: Future change space for the GCMs numbered by their independence rank given in Table 2. The change is between the mean of 1990-2009 and the mean of 2060-2079.

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