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Multi-Model Projections of Temperature and Rainfall under Representative Concentration Pathways in Zimbabwe

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ABSTRACT

We describe climate changes (temperature and rainfall) by mid-century in Zimbabwe based on projections of 10 global climate models using the newly developed Representative Concentration Pathways (RCPs.) We used a multi-model ensemble of Coupled Model Inter-comparison Project 5 (CMIP5) global climate model outputs for the mid-century (2040-2070) period relative to the 1980-2010 baseline. The projections were based on the moderate (RCP4.5) emission scenario and the highest (RCP8.5) emission scenario. Projected time series of monthly minimum and maximum temperature indicated a warmer climate that was consistent across all models. The models showed a large spread of rainfall change projections under both scenarios, however there was a high level of agreement in the direction of rainfall change by almost all models in some months. Model convergence was assessed using probability density functions (PDFs) to establish the consistency in predictions from the ensemble. The shapes of PDFs for temperature showed that the 10 models predicted similar trends while those of rainfall showed that models only agreed at the extremes of the distribution. We performed an analysis of variance (ANOVA) test at 5 % level of significance to quantify the level of consistency in predictions. Results of ANOVA indicated significant ($p = 0.000$) differences among the 10 models in predicting minimum and maximum temperature. The results also showed significant differences between the two emission scenarios. For rainfall, there were significant ($p = 0.000$) differences between the 10 models but there were no significant ($p = 0.531$) differences between the two emission scenarios.

Keywords: *analysis of variance, climate change, emission scenario, multi-model ensemble.*

1. INTRODUCTION

Projections of future climate provide important information for risk assessment and adaptation planning. Thus, accurate climate change projections are important for developing appropriate and effective adaptation strategies and better targeted global emissions reduction goals (Ramirez-Villegas et al., 2013). Global climate models (GCMs) are at the heart of climate projections (Pitman and Perkins, 2008) and they have been viewed as our principal tools for projecting future climate (Houghton et al., 2001). Randall et al. (2007) concluded that there is now considerable confidence that coupled GCMs provide credible quantitative estimates of future climate change, particularly at continental scales and above. However, challenges still prevail in GCM predictions of future climate. The main challenge as viewed by Tebaldi and Knutti (2007) is lack of verification. The predictive skill of a model is usually judged by comparing the predicted outcome with observations (Knutti et al., 2006; Chiew et al., 2009; Mitchell, 2003; Whetton et al., 2005; Suppiah et al., 2007), however, simulating the past and present correctly does not guarantee that the model will be correct in predicting the future. While there is a lot of evidence for GCMs to be trusted for the future (e.g. Knutti et al., 2002, 2003, 2005, 2006; Murphy et al., 2004; Annan et al., 2005b; Frame et al., 2005; Meinshausen, 2005; Piani et al., 2005; Stainforth et al., 2005; Hegerl et al., 2006; Schneider von Deimling et al., 2006), there is no definitive proof of model skill in projecting future climate (Tebaldi and Knutti, 2007). For projections of future climate, considering time scales of decades and longer, there is no verification period, and strictly, there will never be any, even if we wait for a century (Tebaldi and Knutti, 2007). It is therefore difficult to judge whether a climate model is skilful or not in its predictions of the future. Räisänen (1997) was probably the first one (Tebaldi and Knutti, 2007) to explicitly advocate the need for quantitative GCM comparison and the importance of inter-model agreement in assigning confidence to the predictions of different models. Many other coordinated efforts have been made to try and quantify GCM skill in predicting future climate. Tebaldi et al. (2005) evaluated climate models with respect to the present-day climatology and the inter-model consistency in predictions. In another study, a climate prediction index was defined by Murphy et al. (2004) that included many fields against which different GCMs were compared. However, it is not clear which fields are important for a model to give a credible climate change response (Tebaldi and Knutti, 2007). In addition, it is also unclear how the different diagnostics should be weighted. An alternative approach was proposed by Tebaldi and Knutti (2007) in which they suggested combining GCMs in a weighted average (or in which subsets of GCMs could be used). This would see some GCMs assigned zero weight, where the model weight is determined by some measure of model performance. Tebaldi and Knutti (2007) however argue that a unique way of defining a metric for model performance for predicting future climate does not exist. The difficulty in quantifying model performance for predicting future climate therefore still stands. In this paper we analyse projections of two main variables: air temperature and rainfall in Zimbabwe based on the new Coupled Model Inter-comparison Project 5 (CMIP5) global climate models under Representative Concentration Pathways (RCP) scenarios. Chaturvedi et al. (2012) assessed CMIP5-based climate change projections of temperature and precipitation for India and reported a potential warming in the range 3.3-4.8 °C towards the end of the 21st century relative to pre-industrial times. The warming was accompanied by an increase in all-India precipitation from 6 % to 14 % compared to the 1961-1990 baseline. Xu and Xu (2012) used CMIP5 model outputs to analyse future climate changes under RCP scenarios and reported a potential warming in all regions across China in the period 2011-2100 while precipitation was found to decrease during the period 2011-2040 in southern parts of the country. In this paper, the projections are based on a multi-model ensemble of CMIP5 global climate model outputs for the mid- century (2040-2070) period relative to the 1980-2010 control period. We present the methodology is section 2 followed by results and discussion in section 3. Finally, conclusions are summarized in section 4.

2. DATA AND METHODOLOGY

We carried out the study in Mutoko district in Zimbabwe. The climatic variables used were rainfall R, maximum air temperature T_{max} and minimum air temperature T_{min}. The choice of these three variables was partly based on data availability. The following data were used: (a) Observed daily fields obtained from the Zimbabwe Meteorological Services Department (ZMSD) for the period 1980-2010. (b) Global climate model data generated by statistical downscaling of the observed fields. Downscaling was done at the Climatic Systems Analysis Group (CSAG) of the University of Cape Town, South Africa to generate station scale climate projections for the periods 1980-2010, 2010-2040, 2040-2070 and 2069-2099 under the RCP4.5 and RCP8.5 climate change scenarios. Table 1 gives an overview of the associated institution and the atmospheric model component of the GCMs used in the study.

Table 1: Information of the 10 coupled global climate models used in this study

Model name	Modeling centre (or group)	Resolution (degrees) latitude x longitude
Beijing Normal University Earth System model (BNU-ESM)	College of Global Change and Earth System Science, Beijing Normal University, China	2.810 x 2.810
Canadian Earth System Model version 2 (CanESM2)	Canadian Centre for Climate Modelling and Analysis, Canada	2.810 x 2.810
Centre National de Recherche Météorologiques Climate Model version 5 (CNRM-CM5)	CNRM/Centre Europeen de Recherche et Formation Avancees en Calcul Scientifique, France Calcul Scientifique, France	1.410 x 1.410
Flexible Global Ocean-Atmosphere-Land System Modelspectral version 2 (FGOALS-s2)	State Key Laboratory of Numerical Modeling for Atmospheric Sciences and Geophysical Fluid Dynamics, Institute of Atmospheric Physics, Chinese Academy of Sciences, China	1.670 x 2.810
Geophysical Fluid Dynamics Laboratory Earth System Model (GFDL-ESM2G)	NOAA Geophysical Fluid Dynamics Laboratory	2.000 x 2.500
Geophysical Fluid Dynamics Laboratory Earth System Model (GFDL-ESM2M)	NOAA Geophysical Fluid Dynamics Laboratory	2.000 x 2.500
Model for Interdisciplinary Research on Climate-Earth System, version 5 (MIROC5)	The University of Tokyo, National Institute for Environmental Studies and Japan Agency for Marine-Earth Science and Technology	1.417 x 1.406
Atmospheric Chemistry Coupled Version of Model for Interdisciplinary Research on Climate-Earth System (MIROC-ESM-CHEM)	Japan Agency for Marine-Earth Science and Technology, The University of Tokyo and National Institute for Environmental Studies	2.857 x 2.813
Model for Interdisciplinary Research on Climate-Earth System (MIROC-ESM)	Japan Agency for Marine–Earth Science and Technology, The University of Tokyo and National Institute for Environmental Studies	2.857 x 2.813
Meteorological Research Institute Coupled General Circulation Model version 3 (MRI-CGCM3)	Meteorological Research Institute, Japan	1.132 x 1.125

We then analysed climate projections for the period 2040-2070 relative to the 1980-2010 baseline based on the 10 CMIP5 global climate models listed in Table 1.

a. Projected Anomalies

Using downscaled historical (1980-2010) daily data, we calculated monthly mean values for T_{max}, T_{min} and R for each climate change scenario. We also calculated monthly mean values for the same variables and scenarios using projections for the period 2040-2070. The anomalies were then calculated as the absolute difference (2040-2070) minus (1980-2010) for each model and variable to depict the magnitude of change.

b. Probability density functions (PDFs)

Model convergence was assessed using probability density functions (PDFs) to establish the consistency in predictions from the 10 models. We calculated PDFs for each of the variables T_{max}, T_{min} and R using downscaled GCM projections for the period 2040-2070 under RCP4.5 and RCP8.5. The data were binned into bins of 0.1 mmday^{-1} width for R and 0.1°Cday^{-1} width for T_{max} and T_{min}. An advantage of using PDFs (Pitman and Perkins, 2008) is that models can be compared across whole distributions rather than at a selected priority point such as the mean. We then performed a two-way analysis of variance (ANOVA) test using MINITAB to quantify the level of consistency in predictions. The two factors under consideration were the model and scenario (RCP4.5 and RCP8.5).

3. RESULTS AND DISCUSSION

a. Projections of T_{max} and T_{min}

Monthly time series plots of temperature anomalies are shown in Figure 3.1 to Figure 3.4

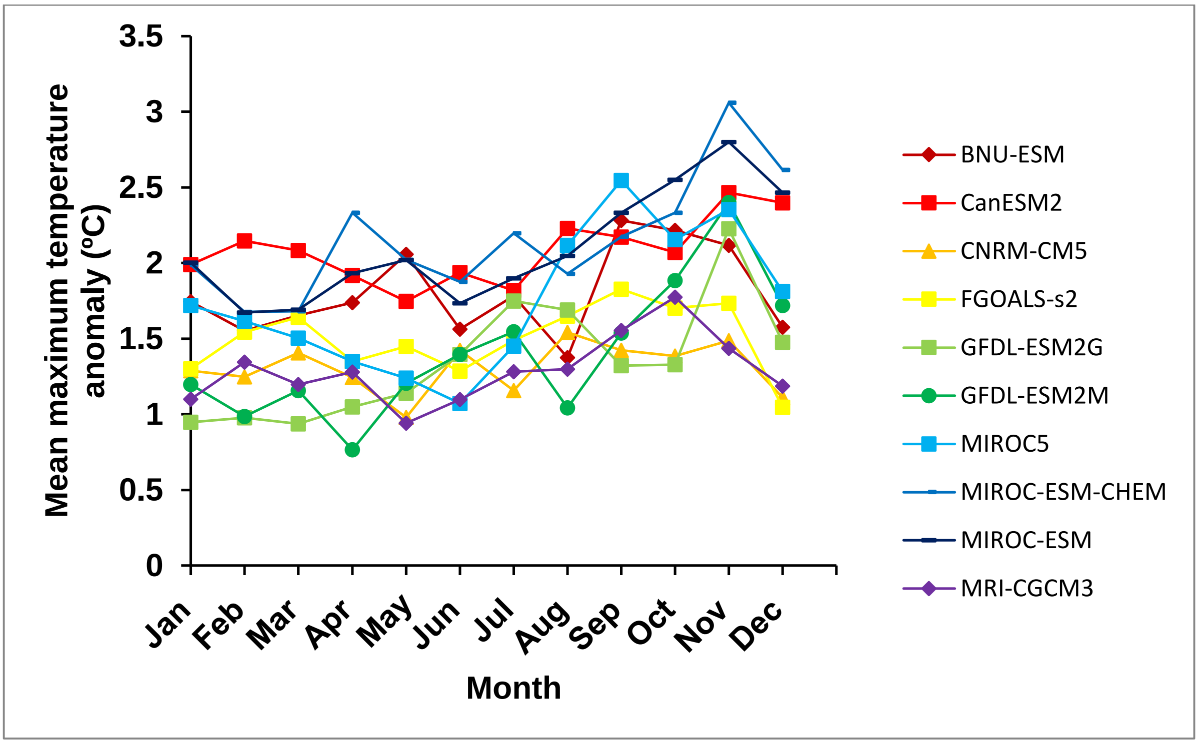

Figure 3.1 Projected mean monthly anomalies for T_{max} for the period 2040-2070 under RCP4.5

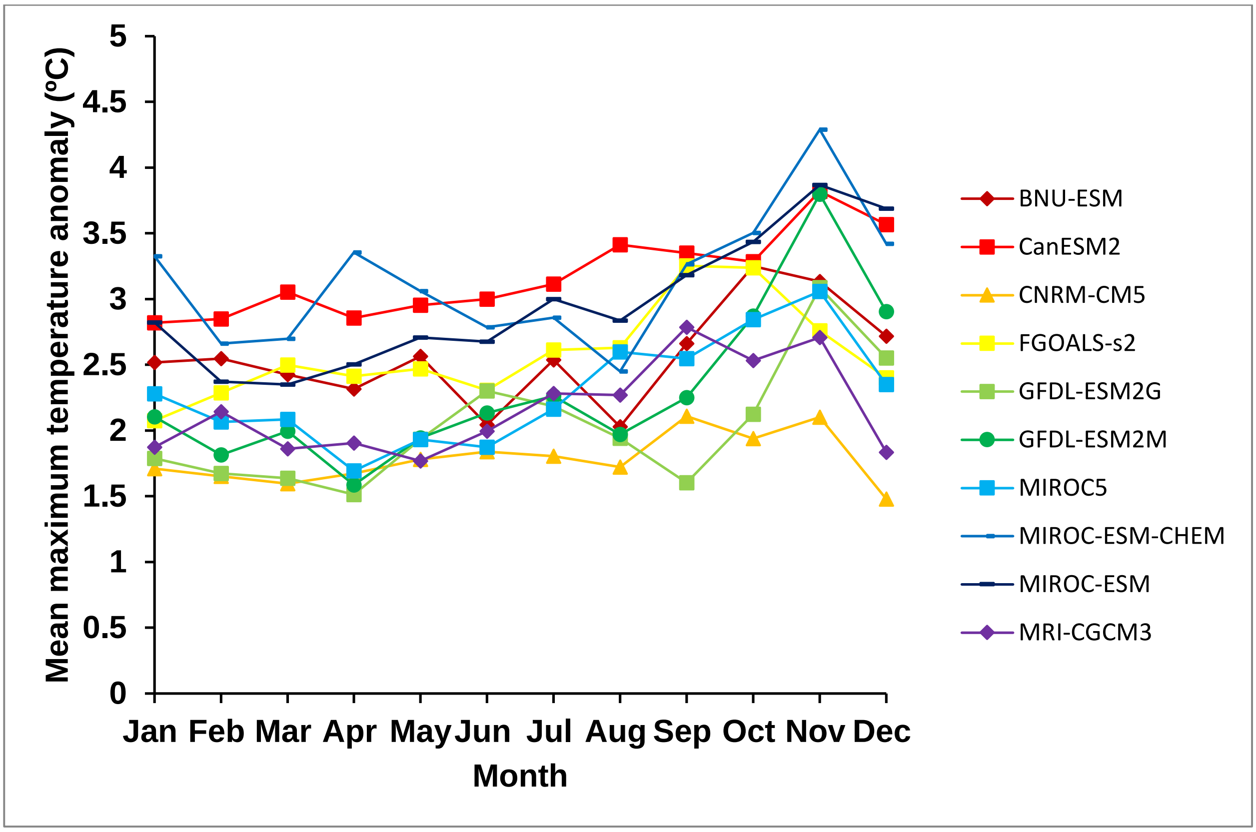

Figure 3.2 Projected mean monthly anomalies for T_{max} for the period 2040-2070 under RCP8.5

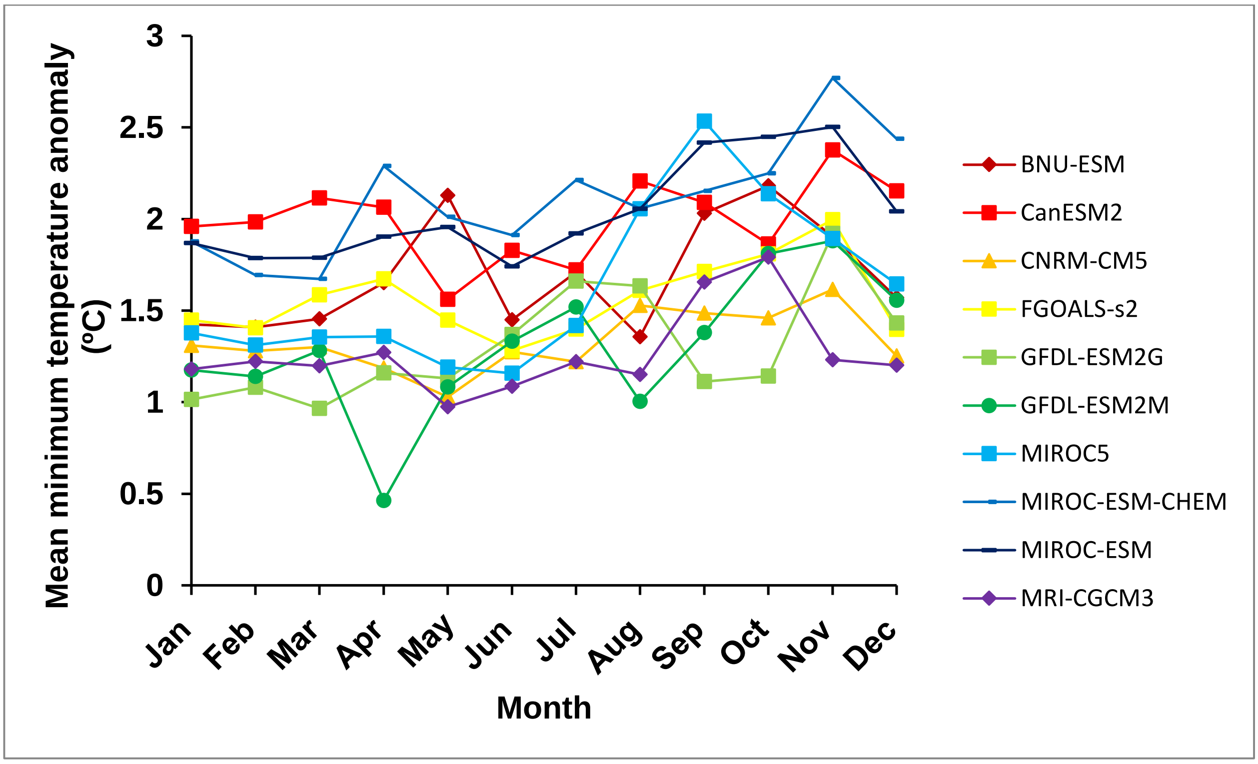

Figure 3.3 Projected mean monthly anomalies for T_{min} for the period 2040-2070 under RCP4.5

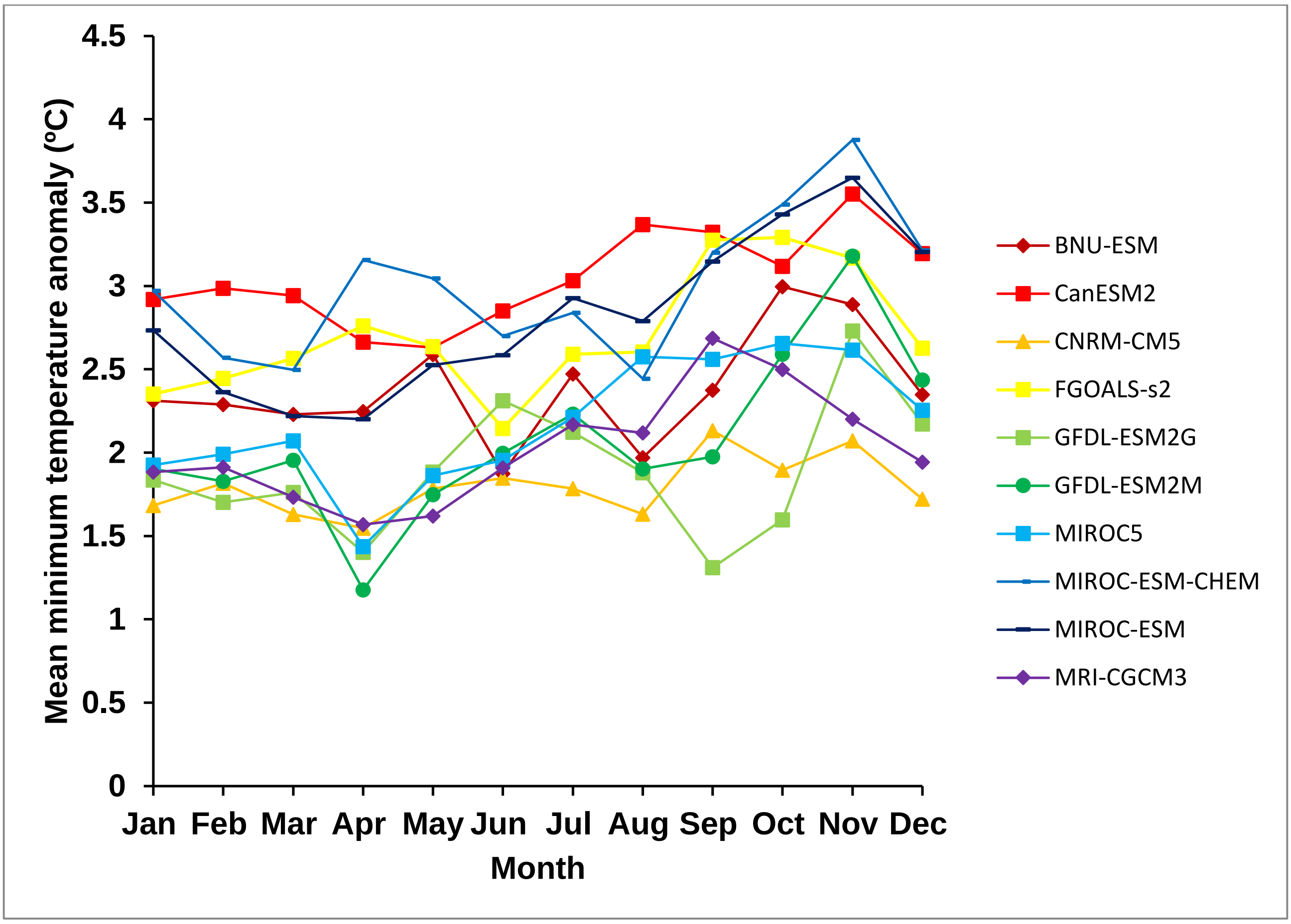

Figure 3.4 Projected mean monthly anomalies for T_{min} for the period 2040-2070 under RCP8.5

Figure 3.1 and Figure 3.2 show the CMIP5 model ensemble-based mean monthly temperature changes projected for the 2040-2070 period relative to the 1980-2010 period for T_{max} under RCP4.5 and RCP8.5 scenarios respectively. The ensemble projected an increase in temperature in the range 1-2.5 °C under RCP4.5 and 1.5-3.5 °C under RCP8.5 for the period 2040-2070 above the 1980-2010 baseline. Temperature changes for T_{min} are in the range 1-2.3 °C under RCP4.5 and 1.5-3.3 °C under RCP8.5 for the same periods as shown in Figure 3.3 and Figure 3.4 respectively. The models projected a consistent warming trend of about 1.5 °C under RCP4.5 and about 2 °C under RCP8.5. This warming is consistent with literature. RCP8.5 is a highly energy-intensive scenario (Van Vuuren, 2011) and therefore is associated with higher temperature rise than the intermediate RCP4.5 scenario.

b. Projections of *R*

Monthly time series plots of rainfall anomalies are shown in Figure 3.5 and Figure 3.6

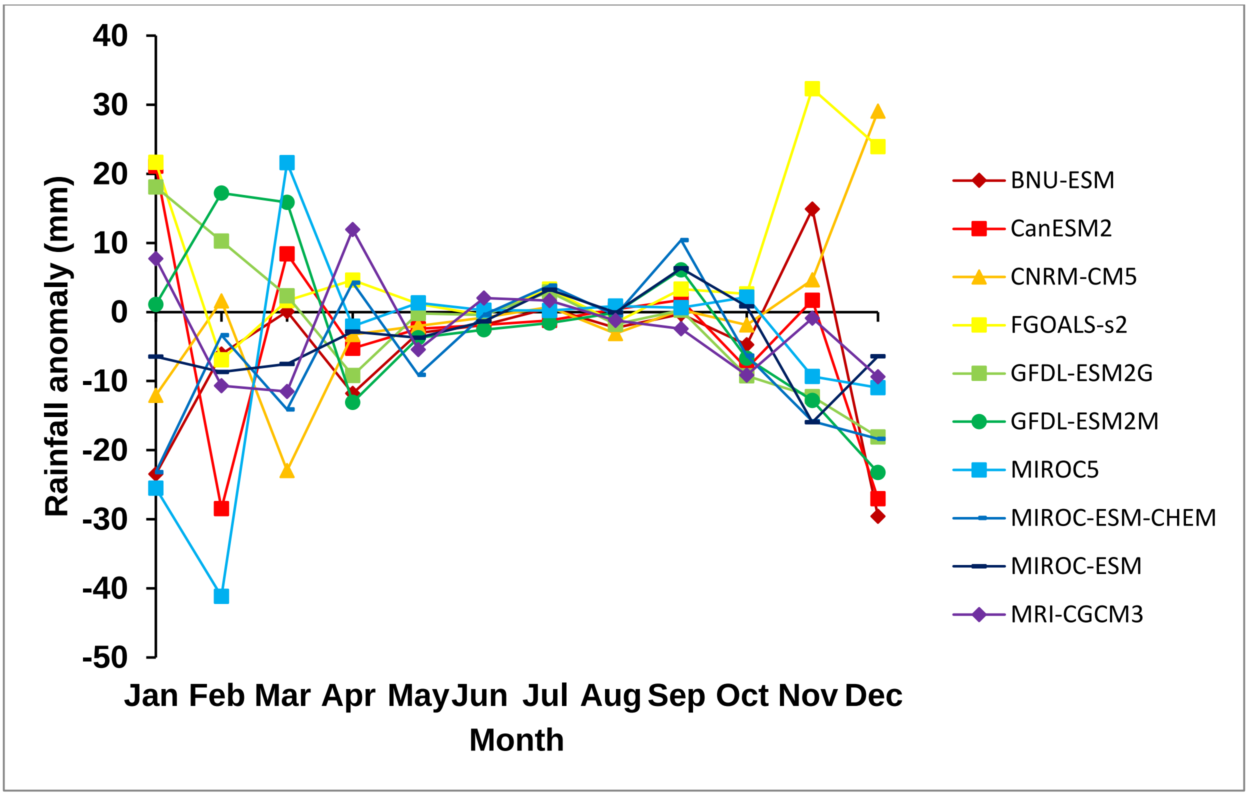

Figure 3.5 Projected mean monthly anomalies for *R* for the period 2040-2070 under RCP4.5

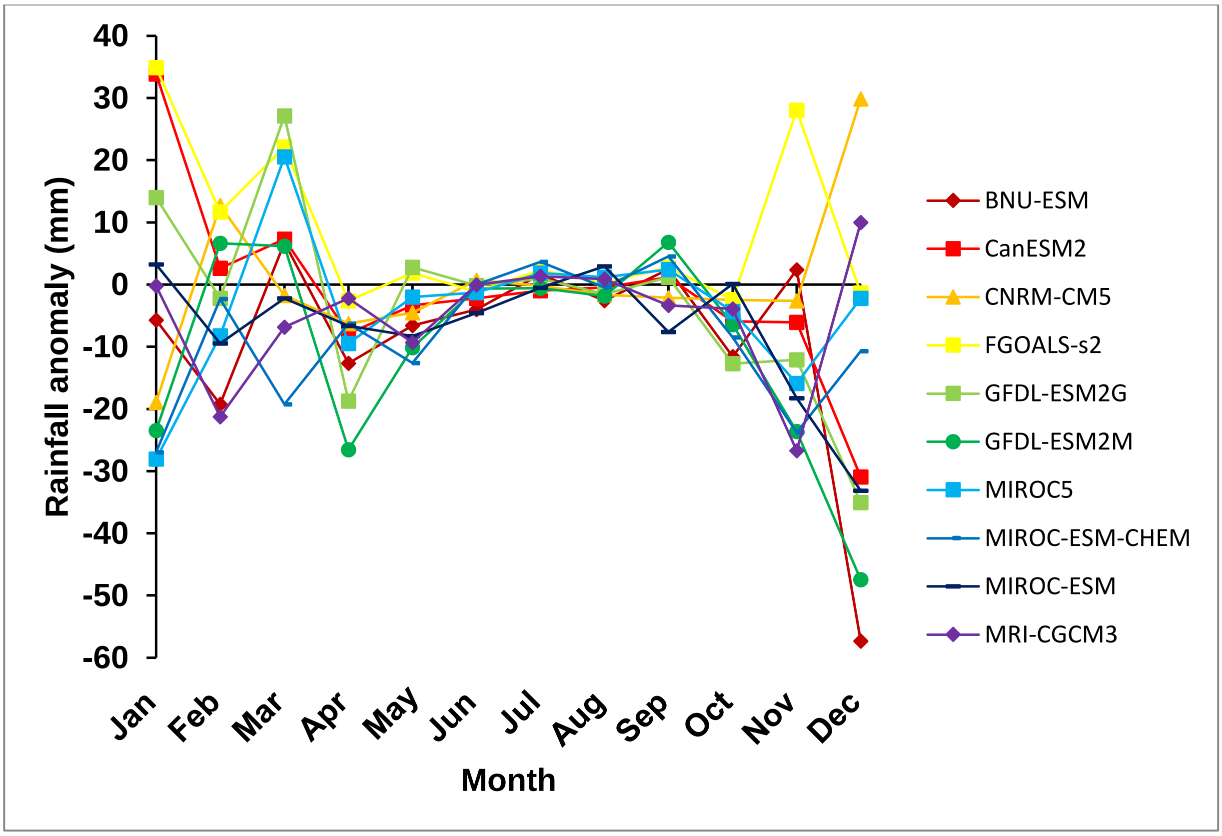

Figure 3.6 Projected mean monthly anomalies for *R* for the period 2040-2070 under RCP8.5

Figure 3.5 and Figure 3.6 show the CMIP5 model ensemble-based mean monthly rainfall changes projected for the 2040-2070 period relative to the 1980-2010 baseline under RCP4.5 and RCP8.5 scenarios respectively. The figures show a wide variation in GCM predictions as evidenced by a large spread of rainfall change projections under both scenarios mainly in the months of January-April and October-December. Figure 3.5 shows that under RCP4.5, about seven out of 10 models predicted a reduction of rainfall for the 2040-2070 period in the months of October-December. The same models predicted a similar trend under the higher emission scenario as shown in Figure 3.6. Overall, there is a higher level of agreement in the direction of rainfall change by almost all models in the months of October-December as compared to the months of January-April under both scenarios.

c. Analysis of PDFs for T_{max} and T_{min}

PDFs are shown in Figure 3.7 to Figure 3.10

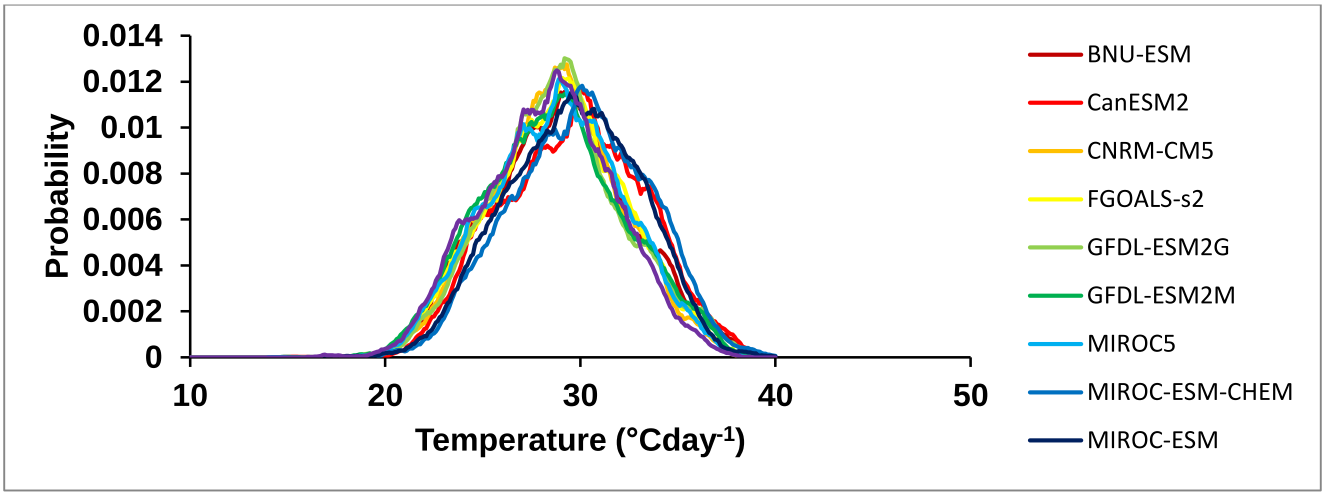

Figure 3.7 PDF for T_{max} for the period 2040-2070 under RCP4.5

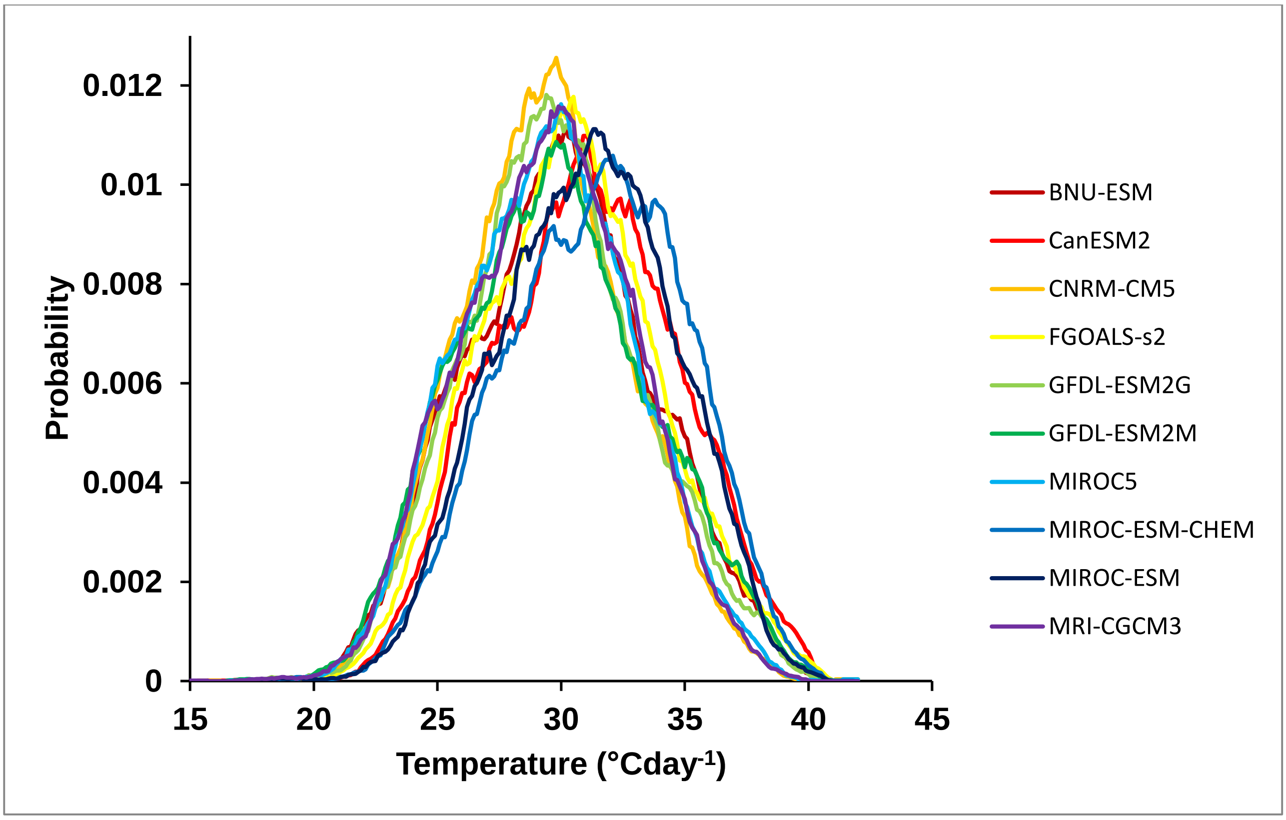

Figure 3.8 PDF for T_{max} for the period 2040-2070 under RCP8.5

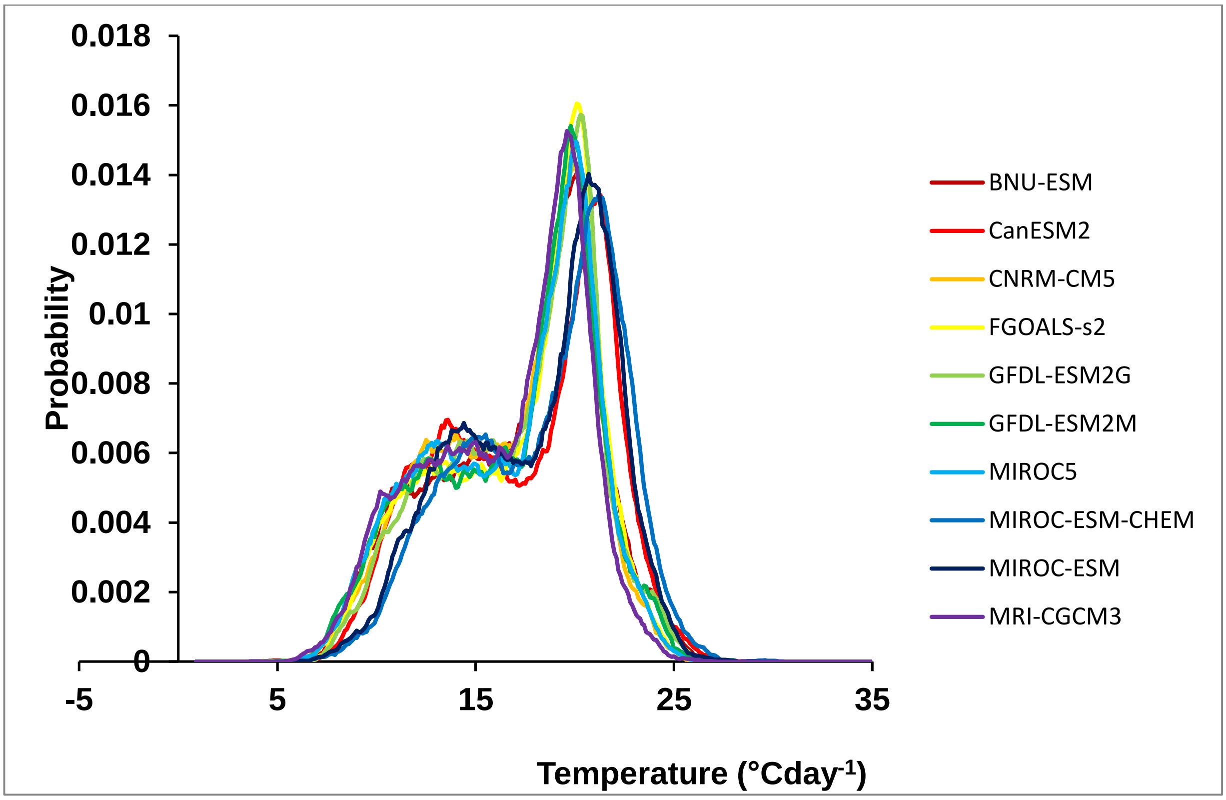

Figure 3.9 PDF for T_{min} for the period 2040-2070 under RCP4.5

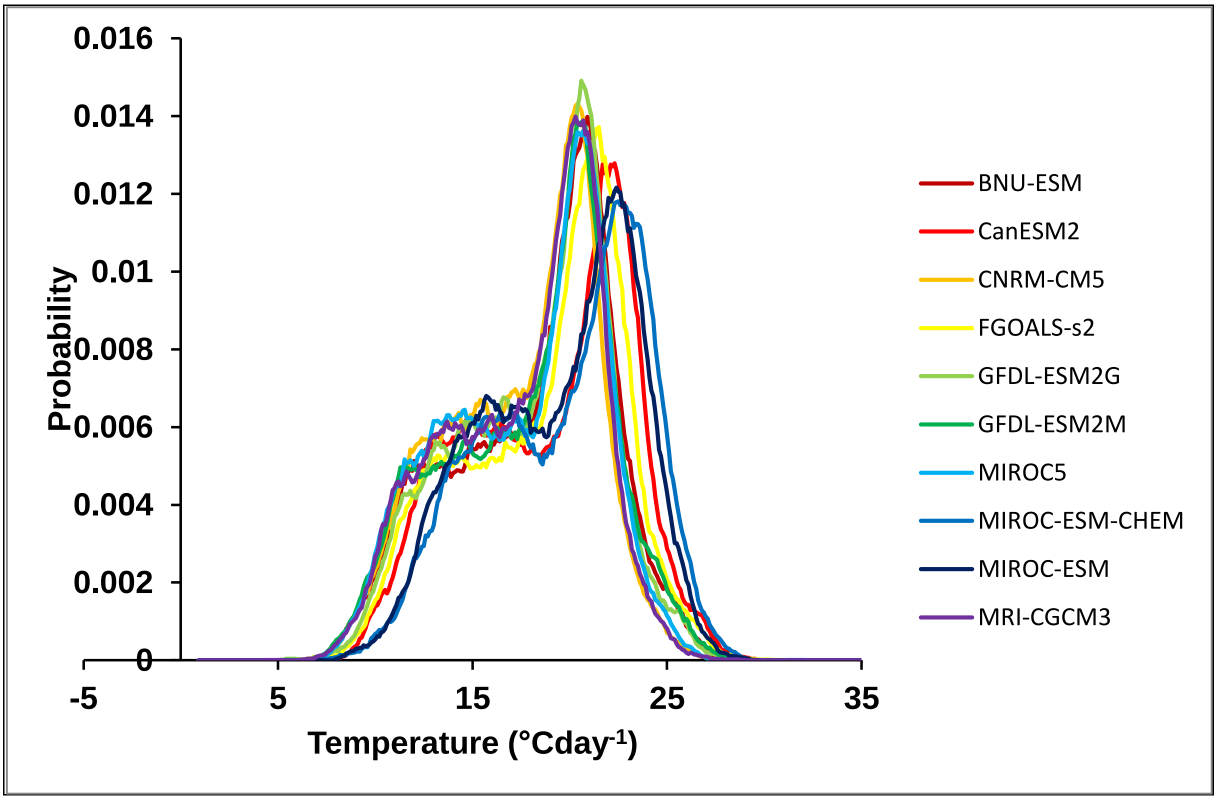

Figure 3.10 PDF for T_{min} for the period 2040-2070 under RCP8.5

PDFs for T_{max} and T_{min} are shown in Figure 3.7 to Figure 3.10 for each climate change scenario. Overall, the shapes of the PDFs are in agreement with each other, an indication that the 10 model predict similar trends by mid-century. However, a closer examination of the PDFs reveals some groups of models with very similar PDFs. For example Figure 3.10 presents effectively two different groups of models. One group consists of the MIROC-ESM and MIROC-ESM-CHEM models and the other of five models namely: MRI-CGCM3, GFDL-ESM2M, GFDL-ESM2G, MIROC5 and BNU-ESM. In Figure 3.9, three groups can be identified: MRI-CGCM3 and GFDL-ESM2M group, MIROC-ESM, MIROC-ESM-CHEM and CanESM2 group and the last group consisting of the FGOALS-s2 and GFDL-ESM2G models. It is interesting to note that in some cases, models from the same institution fall in the same group for example the MIROC-ESM and MIROC-ESM-CHEM in Figure 3.10 are both from Japan (see Table 1) while GFDL-ESM2M and GFDL-ESM2G are both NOAA models. This shows some level of consistency in predictions by these models.

d. Analysis of PDFs for *R*

PDFs are shown in Figure 3.11 and Figure 3.12

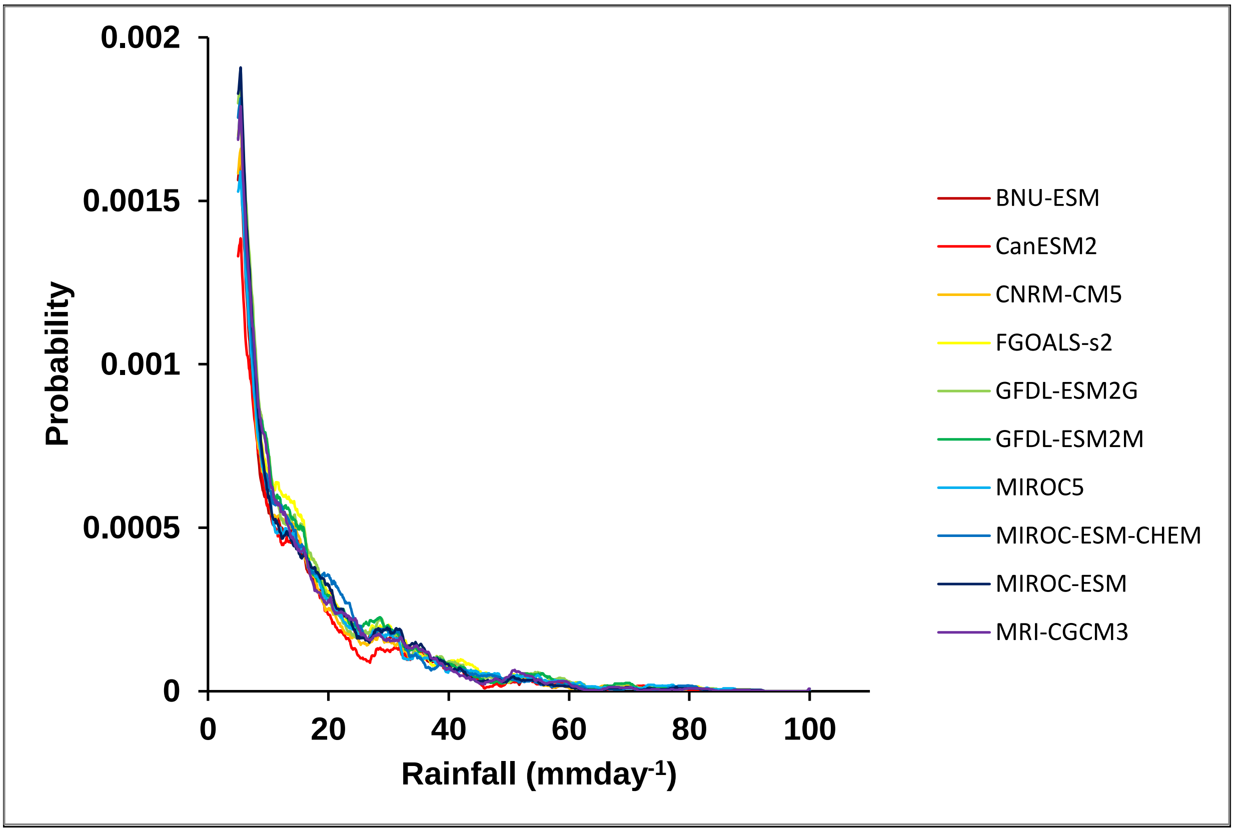

Figure 3.11 PDF for *R* for the period 2040-2070 under RCP4.5

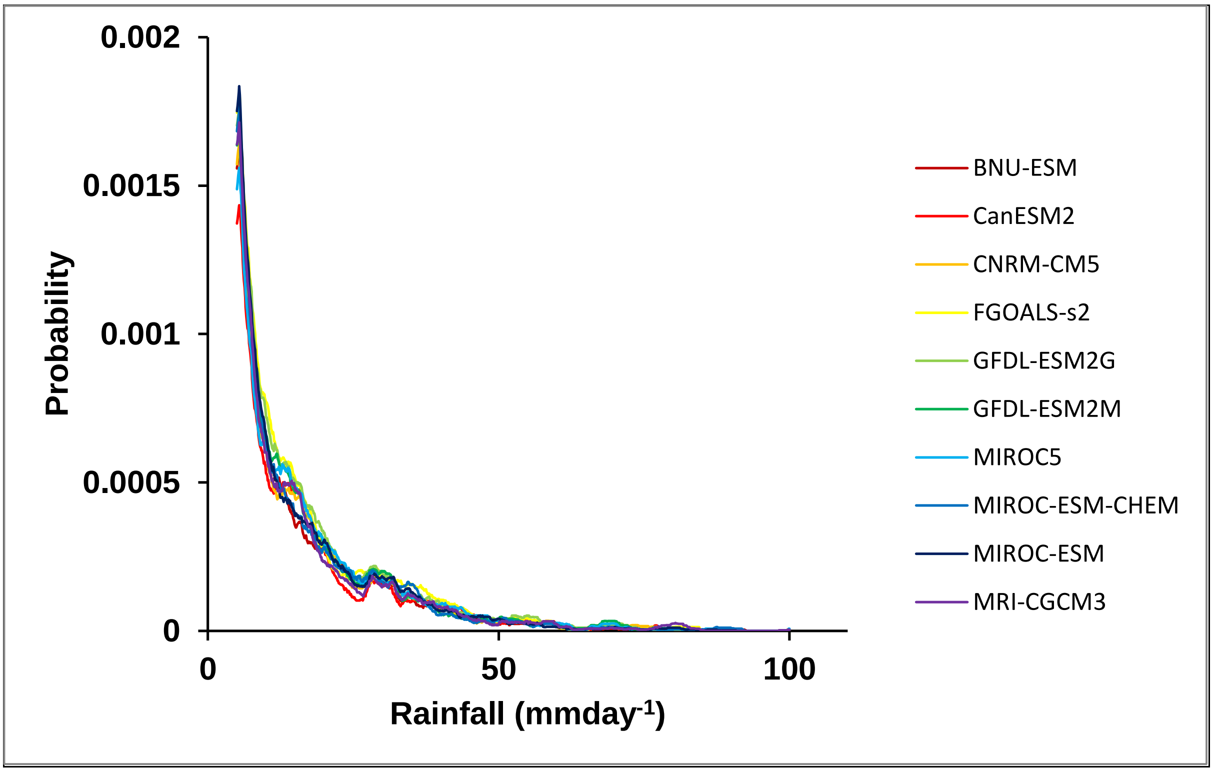

Figure 3.12 PDF for *R* for the period 2040-2070 under RCP8.5

PDFs for *R* are shown in Figure 3.11 and Figure 3.12 respectively for the two climate change scenarios. Models tend to agree at the extremes of the distribution as shown by the PDFs clustering in these regions. In between the extremes, PDFs are widely separated indicating some level of disagreement in predictions. Rainfall is difficult to predict than temperature (Pitman and Perkins, 2008) and it is expected that there would be considerable uncertainty in the projections of rainfall using climate models.

e. Two-way analysis of variance (ANOVA) test

Table 2: Quantitative measures of the performances of the 10 global climate models for predicting minimum temperature under the two climate change scenarios

Source	DF	SS	MS	F	P
Model	9	91975	10219.5	642.32	0.000
RCP	1	66865	66865.4	4202.68	0.000
Interaction	9	4830	536.7	33.73	0.000
Error	226440	3602697	15.9		
Total	226459	3766368			

There are significant differences among the 10 models in predicting minimum temperature (p = 0.000) at 5 % level of significance. Significant differences were also observed between the two scenarios (RCP4.5 and RCP8.5) in predicting minimum temperatures (p = 0.000) as shown in Table 2.

Table 3 Quantitative measures of the performances of the 10 global climate models for predicting maximum temperature under the two climate change scenarios

Source	DF	SS	MS	F	P
Model	9	77113	8568.1	685.92	0.000
RCP	1	70462	70462.4	5640.83	0.000
Interaction	9	5011	556.8	44.57	0.000
Error	226440	2828575	12.5		
Total	226459	2981162			

There are significant differences among the ten models in predicting maximum temperature (p = 0.000) at 5 % level of significance. Significant differences were also observed between the two scenarios (RCP4.5 and RCP8.5) in predicting maximum temperatures (p = 0.000) as shown in Table 3.

Table 4: Quantitative measures of the performance of the 10 global climate models for predicting rainfall under the two climate change scenarios

Source	DF	SS	MS	F	P
Model	9	6251	694.556	11.78	0.000
RCP	1	23	23.096	0.39	0.531
Interaction	9	456	50.659	0.86	0.561
Error	226440	13353341	58.971		
Total	226459	13360071			

There are significant differences among the 10 models in predicting rainfall (p = 0.000) at 5 % level of significance. However, there are no significant differences between the two scenarios (RCP4.5 and RCP8.5) in predicting rainfall (p = 0.531) as shown in Table 4.

4. CONCLUSIONS

Analyses of projections of air temperature and rainfall were carried out based on the new Coupled Model Inter-comparison Project 5 global climate models under Representative Concentration Pathways scenarios. Lack of verification of future projections over time scales of decades or more makes it difficult to judge the performance of climate models in predicting future climate. The level of agreement of models may therefore partly provide an idea of what the climate is likely to be because the future is unknown. It is thus obligatory for researchers to provide knowledge on what makes the projections of two climate models agree or disagree. New methods are necessary that can better assimilate the variability of global climate model output. The scientific community is likely to benefit from new methods of combining multi-model ensembles as well as physical and statistical methods that take model uncertainties into account.

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