Evaluation of 21st Century CMIP5 GCM Outputs for Climate Change Impact Assessments in Shire River Basin in Malawi

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Abstract

Data scarcity globally has impeded our understanding of hydrological processes. This study was aimed at evaluating skills of models in reproducing past climate in the Shire River Basin (SRB) in Malawi for future climate impact assessments. The study used data, simulated by Global Climate Models (GCMs), participating in the Coupled Model Intercomparison Project Phase 5 (CMIP5). A total of 52 models were considered comprising a mixture of models in the Representative Concentration Pathways of RCP4.5 and RCP6.0. The mean annual bias, correlation, extreme precipitation indices obtained from the RClimdex package of R software program and frequency distributions were used to quantify the accuracy of the GCM simulations. On the precipitation indices, emphasis was placed on the frequency indices (number of heavy precipitation days (RR ≥ 10 mm), R10mm, number of very heavy precipitation days (RR ≥ 20 mm), R20mm, number of extremely heavy precipitation days (RR ≥ 25 mm), R25mm, Consecutive Dry Days (RR < 1 mm), CDD and Consecutive Wet Days (RR ≥ 1 mm), CWD and on the intensity indices (daily maximum precipitation, RX1day, 5-day maximum precipitation, RX5days, annual total wet-day precipitation, PRCPTOT and very wet days, (R95P). Study results have revealed that there is variation in the performances of individual models and that the overall performance of the models over the SRB is generally low. Some individual models perform better than the multi-model ensemble. Results have also shown the better performance of the following models: ACCESS1-3_rcp45_r1i1p1, BNU-ESM_rcp45_r1i1p1, CSIRO-Mk3-6-0_rcp45_r3i1p1, CSIRO-Mk3-6-0_rcp45_r8i1p1 and GFDL-ESM2G_rcp45_r1i1p1 of medium-low emission pathway, RCP4.5, in replicating the historical extreme precipitation for Shire River Basin.

1.0 Introduction

Data scarcity globally has impeded our understanding of hydrological processes. The situation is even worse in developing countries such as Malawi. In addition, there is a general agreement by scientists across the globe, that climate is changing and will continue to do so in the future. The extent and direction of change is very uncertain. This development is very worrisome to hydrologists and water managers, in their quest to design and construct hydraulic structures such as barrages, canals, bridges, dams, embankments, reservoirs and spillways. Consequently, there has been a plethora of climate change studies in an attempt to understand the change and come up with proper mitigation and adaptation measures. These studies are periodically done by the Intergovernmental Panel on Climate Change (IPCC), which conducts simulations for future climate caused by different emission scenarios. These studies have culminated into reports such as the Third, Fourth and Fifth Assessment Reports, termed AR3, AR4 and the recent AR5, respectively. In order to properly project future climate change, Global Climate Models (GCMs) are commonly used (Libanda & Nkolola, 2019). Knowledge of how climate will change in the future and the impacts this change might bring, is very vital for planning purposes.

In the recent past, the 21st century climate projections from GCMs participating in the World Climate Research Programme's CMIP3 have been used to assess climate change impacts at regional and local scales. Currently, CMIP5 is into force and as such, and most simulations are being undertaken using these new generation GCMS. This is because these simulations provide the basis for many of the conclusions in the recent Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report (AR5) (IPCC, 2013).

GCM simulations often give a myriad of model outputs, with varying capabilities; intended to accurately reproduce the past and predict the future. Owing to this huge number of outputs, selecting the best performing model has oftentimes posed a big challenge. To avert this challenge, evaluation of model outputs has often been used. Since the future climate change is very uncertain, it is often preferred to test the models in their capabilities to reproduce the past climate and this gives confidence in the models in predicting the future climate.

To understand the performance of CMIP5 GCM simulations, there have been so may evaluations that have been undertaken by different studies with differing objectives. Using 22 CMIP5 historical simulations of precipitation over East Africa (EA), Ongoma et al., (2018) noted that there is huge variation in the performance of individual models and that the overall performance of the models in that region is generally low. These findings are consistent with another study by Rupp et al. (2013), who also noted that there exist differences in the performance of models between regions of the United States. In some studies, it was discovered that model performance was dependent on model resolution (Akurut et al., 2014). This, therefore, requires some modification of the resolutions, if the model performance is to be fairly improved. In some studies, it has been observed that CMIP5 models perform better in some precipitation events including relatively intense events such as wet days (Koutroulis et al., 2016). It must be noted that when it comes to representing observed precipitation on short spatial and temporal scales, GCMs have limits. For instance, Mehran et al., (2014) reported poor reproduction of the observed precipitation over arid regions and certain subcontinental regions across the globe. When evaluating GCM model outputs, which are intended to be selected and applied to climate change impacts, there are always uncertainties. Accordingly, there is need to minimize these uncertainties as much as possible in order to have credible simulations. One way of achieving this is the use of ensemble mean of models. In some cases, the ensemble mean of models have demonstrated close approximation of the mean of the ensemble values with the observation (Nyeko et al., 2011). Woldemeskel et al., (2012) found that the model uncertainties were consistent using a number of groups of models, where ensemble run uncertainty was found to be more important in precipitation simulation than that in temperature. In addition, substantial improvement of the simulation of precipitation was achieved using multimodel ensembles of the CMIP5 and this provided a more realistic fine-scale features tied to local topography and land use (Nikiema et al., 2016). Despite the promise offered by the ensemble means for their reliability in offsetting the downside of individual model runs, there are also some discrepancies in their performance. In some cases, using fully-coupled models of the CMIP5 historical experiments, a study by Yang et al., (2014) observed the underestimation and overestimation of long and short rains, respectively, in East Africa.

Vincent et al., (2014) determined the nature of recent observed climate changes and projected future changes for Malawi, using a combination of GCM ensembles driven by RCP4.5 and RCP8.5 scenarios of IPCC's AR5. In addition and using 11 GCMs and 21 RCMs, Erika & Reay, (2018) found that the current models are suitable for projecting temperature trends but not precipitation and that future plans will need to consider a range of future precipitation scenarios. Furthermore, using 18 CMIP5 historical simulations of precipitation over Malawi, to examine the performance against rain gauge data, Libanda & Nkolola, (2019) found that in general, most models poorly simulated the spatial standard deviation. In addtion, it was also found that while the selected models were well performing, they were also riddled with a myriad of deficiences. Owing to these findings, modelling improvement was therefore recommended for Malawi. .

Even though the above studies have demonstrated that the evaluation GCMs ability in replicating the observed climate in different regions globally has been conducted, very few have focused on Malawi in general and SRB in particular. The current study focuses on the SRB in Malawi. The SRB lies in the Sub-saharan Africa (SSA) and the SSA has been identified as being particularly vulnerable to future climate change due to its high exposure and low adaptive capacity (Niang et al., 2014). In addition, the SRB's hydrological system represents Malawi's most important water resource that provides essential water to key developmental sectors such as hydro-power generation, agriculture, public water supply, fisheries and navigation (International Water Association, 2011).

From the foregoing, the climate change impacts for Malawi and the SRB have been sparesly studied and mostly using the outdated greenhouse gas emission scenarios. In addition, most studies on climate change impacts for the basin, have focused on the averages; no much coverage has been done on the extremes, which are worrisome. Analysis of extreme rainfall events that were analysed at 43 stations across Malawi by Ngongondo et al., (2014) revealed a

decrease in total annual rainfall, annual maximum 1-day and 5-day rainfall amount, number of heavy and extreme rainfall days. However, there was an increase in the consecutive number of wet and dry days. Studies on the current latest generation CMIP5 GCM simulations, the ones that motivate this paper, have not been extensively covered, thereby leaving a knowledge gap. It is believed that these latest GCM simulations provide fewer uncertainties while offering better and more reliable predictions. Owing to the identified gaps, this study therefore aims at assessing the ability of the current state-of-the-art 21st century GCM simulations, archived by CMIP5 in reproducing the past climate (precipitation) for the Shire River Basin (SRB) in Malawi. The assessment culminates into the selection of models that fairly reproduce that past precipitation and can therefore be used for future impact assessments.

2.0 Data And Methods

2.1 Study Area

This study was conducted in the SRB in Malawi (Fig. 1). Shire River is one of the tributaries of the Zambezi River and is the longest and largest river in Malawi. It is home to over 3 million people; flows from Lake Malawi for a distance of about 700km to its confluence with the Zambezi River in Mozambique and 95% of the Shire River is in Malawi and the remaining 5% is in Mozambique. Shire River provides water for more than 95% of Malawi's hydroelectric power generation, agriculture (e.g., small- and large-scale irrigation schemes in the lower Shire), fisheries, navigation, tourism and urban water supply (90% of the water supplied to Blantyre, Malawi's commercial capital. The basin has been identified as being particularly vulnerable to future climate change due to its high exposure and low adaptive capacity.

2.2 Data and Sources

This study used two sets of precipitation data namely: the historical (observed) data and CMIP5 GCM dataset.

The historical (control) data was the observed daily data for PCPT of thirty (30) historical years from 1961 to 1990 over the SRB. The precipitation data was averaged from 20 precipitation stations spatially distributed within the study area (Fig. 1). This data was obtained from the Department of Climate Change and Meteorological Services in the Ministry of Natural Resources and Environmental Affairs (MONREA) in Malawi. The CMIP5 GCM-simulated data that was used in this study was also for the thirty (30) years span of 1961–1990 (for control period). This was termed the GCM control simulated data. Table 1 gives detailed information about 30 CMIP5 GCMS which were disintegrated into 52 GCM runs (due to model ensembles) used in this study. A combination of medium-low (RCP4.5) and medium-high (RCP6.0) emission scenarios were used after abandoning GCM outputs from the highest (8.5) and lowest (2.6) representative pathways, owing to their perceived mismatch with the study region.

2.3 Overview of GCM control

This study concentrated on precipitation since it is one of the most important inputs into the hydrological cycle. The assessment of 52 CMIP5 GCM runs was carried out over SRB by comparing the model outputs with observed datasets for 1961–1990 precipitation.

2.4 GCM evaluation approach

The most straightforward method to assess the accuracy of climate models is to compare observed climate data with simulated climate outputs (IPCC, 2013). However, Gleckler et al., (2008) noted that many variables and timescales, which can be taken into account, implies that there is no standard set of tests, which can be applied to a climate model to carry out this comparison. In this study, the annual mean bias, correlations, precipitation indices and frequency distribution were used to evaluate the GCM outputs in their capacity in reproducing the observed climate over the SRB.

A total of 52 model outputs driven by medium-low (RCP4.5) and medium-high (RCP6.0) emission pathways, were considered. The extreme pathways of RCP2.6 and RCP8.5 were neglected, owing to their perceived mismatch with the situation in the study area. The GCM control outputs were compared with the observed precipitation for the same period of between 1961 and 1990 (the control period).

In order to measure the inconsistency between the model outputs and the observed dataset, the Root Mean Square Error (RMSE) was used. RMSE has been widely used in climatological and hydrologic studies (Sudheer et al., 2002). Mathematically, RMSE is given as:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(x_{obs,i} - x_{mod,i})^2}{n}} \quad \text{..... Equation 1}$$

where X_{obs} refers to observed values and X_{model} denotes modelled values at time/place *i* (Chai and Draxler, 2014).

Where two variables are being compared, there is need to ascertain the degree of change of one variable against another. In order to do this, the strength and direction between the simulated and observed values was established through the determination of correlation where the correlation coefficient, *R*, was determined (Zaid, 2015).

Considering that this study focuses on extremes, analysis of precipitation extremes, which is the major variable, was done using precipitation extreme indices. The extreme precipitation indices that were analyzed annually were those recommended by the World Meteorological Organization WMO), the Expert Team on Climate Change Detection and Indices (ETCCDI), which has well-defined standard indicators of climate extremes in order to obtain comparable results in different countries. Derivation of these indices was done using the RClimdex package of R software (Zhang & Yang, 2004). Slopes for the simulations were quantified by linear regression (Zaid, 2015). This study used nine (9) extreme precipitation indices (Table 2), categorized into frequency and intensity indices.

When evaluating precipitation extremes, it is sometimes important to determine the optimum fitness of the extreme events by comparing the distribution of the estimates with their corresponding observations of similar return periods. To achieve this, frequency distribution plots were done by using the empirical formula, known as plotting position. From the plots, the quantile versus return period of the simulations were then compared with those of the observations on the same charts. Nyeko et al., (2011) used the same approach in the evaluation of frequency distribution for extremes in the Lake Victoria catchments. To determine the frequency distribution, this study used the Weibull plotting position. For *n* being the number of years of record and *m* the rank assigned to the data after arranging them in descending order of magnitude, where the maximum value is assigned *m = 1*, the second largest value *(m = 2)*, and the lowest value *m = n;* then the return period *T*was computed using the Weibull's formula;

$$T = (n+1)/m \quad \text{..... Equation 2}$$

The probability of exceedance of precipitation values was taken as the reciprocal of the return period, same approach used by Kumar & Bhardwaj, (2015).

Since GCM runs have inevitable uncertainties, minimization of these uncertainties is one way of attaining credible outputs. To achieve this, the multi-model mean ensemble for all model runs was computed..

2.5 Model performance and selection

Selection of good performing models is often the end product of model evaluation from a myriad of GCM runs. As this is not a simple task, mean values are often used. Typically, the model runs should have the skills in replicating the past climate accurately. In this study, selection of the best models was done by analyzing the annual absolute biases, correlations, precipitation indices and frequency distribution of precipitation extremes.

3.0 Results And Discussions

3.1 Mean bias

The annual absolute bias for 52 GCM runs for precipitation is shown in Fig. 2. All GCM runs are positively biased, ranging from 9 to 60mm. There is also overestimation of the observed series with the exception of 2 models, CSIRO-Mk3-6-0_rcp45_r3i1p1 (mod25) and MRI-CGCM3_rcp45_r1i1p1 (mod75). These two best performing models are both for the medium-low emission pathways of RCP4.5. Even though the worst performing models such as CanESM2_rcp45_r2i1p1, CanESM2_rcp45_r3i1p1, CanESM2_rcp45_r4i1p1, CCSM4_rcp45_r1i1p1 and CCSM4_rcp45_r2i1p1 are also from the medium-low emission pathways, they are from a different modelling group presumably of different assumption and model structures.

3.2 Correlations

The correlations of GCMs between the observed and the simulated precipitation are given in Table 3. Based on the accepted guidelines for interpreting the correlation coefficient, (Ratner, 2009), the best models that indicate a strong linear relationship between the observed and the simulated precipitation belong to the medium-low emission pathway and these are CESM1-CAM5_rcp45_r1i1p1 (mod17), IPSL-CM5A-LR_rcp45_r1i1p1 (mod56) and ACCESS1-3_rcp45_r1i1p1 (mod1).

3.3 Synopsis of evaluation of precipitation indices

Table 4 shows a summary of slopes of plots for precipitation indices of GCMs considered and Fig. 3 depicts the same. There is evidence of decrease in the dry spell days (CDD), wet spell days (CWD), total annual precipitation (PRCPTOT) and annual maximum 5-day precipitation (RX5). On the other hand, there is observed increase in the number of heavy precipitation days (R10), extremely heavy precipitation days (R25), annual maximum 1-day precipitation (RX1) and very wet days (R95P). Most indices that were analysed were not statistically significant at $\alpha = 0.05$ level. The above findings are consistent with a study on the analysis of extreme rainfall indices at 43 stations in Malawi where a decrease in PRCPTOT and RX5 was revealed (Ngongondo et al., 2014) and on the analysis of daily precipitation data from 14 south and West African countries over the period 1961–2000, where there was decrease in overall precipitation, average precipitation intensity and increasing dry spell (New et al., 2006).

Both the CDD and CWD of the observations are decreasing by 8 and 6 days per decade respectively (Table 4). The decrease in CWD is less than that of CDD implying that wet days remain wetter while dry days remain drier. The observed slight increase trend in RX1day (0.98mm/decade) is dwarfed by the decrease in RX5day (4.81mm/decade) and the latter seems to have a huge influence on the observed decrease in PRCPTOT. The observed decrease in PRCPTOT of 13mm/decade is coherent with the decrease in CWD and RX5day. Even though heavy precipitation days of R10, R20 and R25 are increasing, this has no major influence on the PRCPTOT, which has demonstrated a relatively large decrease. The increasing number of heavy and extreme precipitation days (R10 and R20) and extreme precipitation days (R25) has potential to bring floods in the region. In terms of the models, most precipitation indices have demonstrated a coarsely equivalent proportion of increasing and decreasing behaviour for all the indicators used in the study area (Fig. 3). The behaviour of R10, R20 and R25 might be explained by intermittent precipitation, which often result to flash floods, which quickly disappear. It is clear from the foregoing that the decreasing PRCPTOT is hugely influenced by the decrease in CWD and monthly maximum consecutive 5-day (RX5day) precipitation. The decrease in PRCPTOT might have also led to decrease in the number of consecutive dry days. This decrease has the potential to cause dry spells for the SRB. The last 5% extreme precipitation series i.e., R95P has shown an increase of

25mm/decade. The increasing number of days for R10, R20 and R25mm has presumably led to this increase. Regarding the simulation skills of GCMs, indices for more than 50% of the models are favourably consistent with the direction of change i.e., decreasing or increasing; the difference being in the magnitude.

3.4 Frequency and Intensity indices

Table 5 and Figs. 4 and 5 summarize of frequency and intensity indices.

Most of the GCM runs are overestimating the dry and wet spells of the observed precipitation as represented respectively by CDD and CWD. However, few models have shown potential to replicate the observed series of all frequency indices. Even though GCMs are over-estimating past precipitation intensity, represented by PRCPTOT, RX1, RX5 and R95P, there is still evidence of a few GCMs' capability in reproducing the past observed intensity (Fig. 5).

3.5 Model ensembles

Figure 6 shows plots of individual GCM runs, observed mean and the ensemble mean of the simulated GCM runs. There is some over-estimation of the GCM ensemble means to the observed mean and this over-estimation can be described by the presence of some outliers as evidenced in 1963, 1974, 1976, 1978, 1985 and 1989. These outliers might have introduced some uncertainties and in order to achieve a closer replica of the ensemble means with the observations, those outliers can be removed.

3.6 Frequency distribution

The annual frequency distributions of the observations, the simulated and ensemble means, for the 30-year period, are shown in Fig. 7. It has been demonstrated from the plots that even though some GCM runs are overestimating the low, medium and heavy precipitation events, there is still some close mimicking of the precipitation quantiles for all the different precipitation events (return periods). This is consistent with a similar study in Lake Victoria catchments (Nyeko et al., 2011). In addition, the model ensemble has shown evidence of over-estimation of the observed in the first 4 years and under-estimation thereafter. However, the extreme events have been fairly captured by the ensembles.

3.7 Summary of acceptable indicators

See Table 6

3.8 Model Performance, Discussion and Selection

Selection of good performing models from a myriad of GCM runs is not a simple task and as such, mean values are normally used. The accurate replication of the past climate by the model runs is considered the perfect signal of good models. In this study, selection of the best models was done by analyzing the annual absolute biases, correlations, precipitation indices and frequency distribution of precipitation extremes.

The GCM evaluation has revealed that most models are over-estimating the observed precipitation. This concurs favourably with a study on the hydrological extremes and water resources in Lake Victoria catchments (Nyeko et al., 2011). From the evaluation, the performance of any individual model has not been consistent for all applied indicators. Libanda & Nkolola, (2019) made similar observations in a study on the variability of extreme wet events over Malawi. The divergent performance can be attributed to differences in models' inherent conditions and internal parameterization made during development each of those models. Additional explanation regarding this behaviour is

dependent on models' sub-grid physics in the atmosphere, ocean, and land domains. To some extent, however, it may also be simply a function of the degree of discretization of the modeling domain. This indicates that the best model(s) for one indicator are not necessarily the same best model(s) for another.

Model evaluation has also revealed that, in addition to over-estimating the observed, there is generally low coherence with observed precipitation. Despite this inconsistency in model performance, models ACCESS1-3_rcp45_r1i1p1, BNU-ESM_rcp45_r1i1p1, CSIRO-Mk3-6-0_rcp45_r3i1p1, CSIRO-Mk3-6-0_rcp45_r8i1p1 and GFDL-ESM2G_rcp45_r1i1p1 have fairly reproduced the observed precipitation and therefore have shown great potential to fairly predict the future climate. Construction of an ensemble of these models would therefore result in reduced performance. This has already been evidenced by the model ensemble findings where it has shown over-estimation of the observed in the first 4 years and under-estimation thereafter indicating over- and under-estimation of the observed low and high precipitation extremes respectively (Fig. 7). Therefore, using a single well-performing model is recommended over ensembles and this was also recommended by Fotso-Nguemo et al., (2018) in another similar study over Central Africa.

4.0 Conclusions On Gcm Evaluation

This study examined the performance of 52 GCM outputs for precipitation, based on the 21st century simulations of the CMIP5 database. It assessed the capability of those models in reproducing the past daily precipitation for the SRB in Malawi. The objective was to select credible model(s) that can be used for future impact assessment for the basin owing to huge number of GCM outputs that were produced. The control outputs from the GCMs were compared with the observed precipitation during the 1961–1990 (the control period) using a number of performance indicators such as the mean annual bias, correlations, precipitation indices and frequency distribution. This study used nine (9) ETCCDI-defined precipitation extreme indices, selected from a suite of 27 indices, defined by RClimDex.

Study results revealed that there is variation in the performances of individual models and that the overall performance of the models over the SRB is generally low. Some individual models perform better than the multi-model ensemble. This is consistent with a study on the evaluation of CMIP5 20th century rainfall simulation over the equatorial East Africa (Ongoma et al., 2018). Results have also shown the better performance of the following models: ACCESS1-3_rcp45_r1i1p1, BNU-ESM_rcp45_r1i1p1, CSIRO-Mk3-6-0_rcp45_r3i1p1, CSIRO-Mk3-6-0_rcp45_r8i1p1 and GFDL-ESM2G_rcp45_r1i1p1 of medium-low emission pathway, RCP4.5, in replicating the historical extreme precipitation for Shire River Basin. This has been observed in most of the 9 precipitation indices that were analysed. This is coherent with a study conducted in Malawi where projected changes using data from 20 Malawi meteorological stations under the CMIP5 showed the range of projected future changes across 10 different-statistically downscaled CMIP5 GCMs for two different RCP pathways (RCP4.5 and RCP8.5) (Vincent et al., 2014).

This study has offered substantial information on well-performing models and the emission scenario pathway to be used for any study in the SRB. The observed discrepancies or biases in model performance can be dealt with by bias correction and/or downscaling of the coarse data from GCM outputs so as to have reliably data for use in future impact assessments.

5.0 Declarations

Conflict of Interest

The authors declare that they have no conflict of interest.

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The authors did not receive support from any organization for the submitted work.

Author's Contribution

All authors contributed to the study. The draft of the manuscript was written by Petros Zuzani and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

Availability of data and material

Data and material for this study is available and can be given upon request.

Code availability

Not applicable.

Ethics approval

The authors of this manuscript are committed to upholding the integrity of the scientific record of this journal and as such they have duly followed the Committee on Publication Ethics (COPE) guidelines. In addition, the authors confirm that this manuscript has not been submitted to more than one journal for simultaneous consideration and that submitted work is original and has not been published elsewhere.

Consent to participate

The author gives consent to all co-authors in taking part towards throughout the whole of the research process.

Consent for publication

The authors give consent to publication of this work.

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7.0 Tables

Table 1: Information about GCMs used

Serial No.	GCM Name	Institution and Country	Model Resolution		Model Ensembles
			Ocean (°lat x °lon)	Atmosphere (°lat x °lon)	
1	ACCESS1-0	Commonwealth Scientific and Industrial Research Organisation and Bureau of Meteorology, Australia	1.0×1.0	1.9×1.2	r1i1p1
2	ACCESS1-3	Commonwealth Scientific and Industrial Research Organisation and Bureau of Meteorology, Australia	1.0×1.0	1.9×1.2	r1i1p1
3	bcc-csm1-1-m	Beijing Climate Center, China	1.0×1.0	2.8×2.8	r1i1p1
4	BNU-ESM	GCESS, BNU, Beijing, China	0.9×1.0	2.8×2.8	r1i1p1
5	CanESM2	Canadian Center for Climate Modeling and Analysis, Canada	1.4×0.9	2.8×2.8	r(1-5)i1p1
6	CCSM4	National Center for Atmospheric Research, Canada	1.4×0.9	2.8×2.8	r(1,2,6)i1p1
7	CESM1-CAM5	National Center for Atmospheric Research, (NCAR) Boulder, CO, USA	1.1×0.6	1.2×0.9	r1i1p1
8	CMCC-CM	Centro Euro-Mediterraneo sui Cambiamenti Climatici Climate Model , Italy	2.0×1.9	0.7×0.7	r1i1p1
9	CMCC-CMS	Centro Euro-Mediterraneo sui Cambiamenti Climatici Climate Model , Italy	2.0×2.0	1.9×1.9	r1i1p1
10	CNRM-CM5	Centre National de Recherches Meteorologiques, France	1.0×0.8	1.4×1.4	r1i1p1
11	CSIRO-Mk3-6-0	Commonwealth Scientific and Industrial Research Organization in collaboration with Queensland Climate Change Centre of Excellence, Australia	1.9×0.9	1.9×1.9	r(1-10)i1p1
12	EC-EARTH	European Earth System Model, Europe	1.0×0.8	1.1x1.1	r(1,12)i1p1
13	FGOALS-g2	The flexible global ocean-atmosphere-land system model, Grid-point Version 2, China	1.0x1.0	2.8x2.8	r1i1p1
14	GFDL-CM3	Geophysics Fluid Dynamics Model, NOAA, USA	1.0x1.0	2.5×2.0	r(1,3)i1p1
15	GFDL-ESM2G	Geophysics Fluid Dynamics Model, NOAA, USA	1.0x1.0	2.5×2.0	r1i1p1
16	GFDL-ESM2M	Geophysics Fluid Dynamics Model, NOAA, USA	1.0x1.0	2.5×2.0	r1i1p1
17	GISS-E2-R	Goddard Institute for Space Studies, NASA, USA	2.5×2.0	2.5×2.0	r6i1p3
18	HadGEM2-AO	National Institute of Meteorological Research/Korea Meteorological Administration, Korea	1.0×1.0	1.9×1.2	r1i1p1
19	HadGEM2-ES	Met Office Hadley Centre, UK	1.0×1.0	1.9×1.2	r1i1p1
20	inmcm4	Institute for Numerical Mathematics, Russia	0.8×0.4	2.0×1.5	r1i1p1
21	IPSL-CM5A-LR	L'Institut Pierre-Simon Laplace, France	2.0×1.9	3.7×1.9	r(1-4)i1p1
22	IPSL-CM5A-MR	L'Institut Pierre-Simon Laplace, France	1.6×1.4	2.5×1.3	r1i1p1
23	IPSL-CM5B-LR	L'Institut Pierre-Simon Laplace, France	2.0×1.9	3.7×1.9	r1i1p1
24	MIROC-ESM-CHEM	Japan Agency for Marine-Earth Science and Technology, Japan	1.4×0.9	2.8×2.8	r1i1p1
25	MIROC-ESM	Japan Agency for Marine-Earth Science and Technology, Japan	1.4×0.9	2.8×2.8	r1i1p1
26	MIROC5	Japan Agency for Marine-Earth Science and Technology, Japan	1.6×1.4	1.4×1.4	r(1-3)i1p1
27	MPI-ESM-LR	Max Planck Institute for Meteorology, Germany	1.5×1.5	1.9×1.9	r1i1p1
28	MPI-ESM-MR	Max Planck Institute for Meteorology, Germany	0.4×0.4	1.9×1.9	r1i1p1
29	MRI-CGCM3	Meteorological Research Institute, Japan	1.0×0.5	1.1×1.1	r1i1p1
30	NorESM1-M	Norwegian Climate Centre, Norway	1.1×0.6	2.5×1.9	r1i1p1

Table 2: The precipitation indices used (Source: Zhang & Yang, 2004)

Serial No.	ID	Indicator name	Description	Units
Intensity Indices				
1	RX1day	Max 1-day precipitation amount	Monthly maximum 1-day precipitation	Mm
2	RX5day	Max 5-day precipitation amount	Monthly maximum consecutive 5-day precipitation	Mm
3	PRCPTOT	Annual total wet-day precipitation	Annual total PRCP in wet days (RR>=1mm)	mm
4	R95P	Very Wet Days	Annual total PRCP when RR>95th percentile	mm
Frequency Indices				
4	R10	Number of heavy precipitation days	Annual count of days when PRCP>=10mm	Days
5	R20	Number of very heavy precipitation days	Annual count of days when PRCP>=20mm	Days
6	R25	Number of days above nn mm	Annual count of days when PRCP>=nn mm, nn is user defined threshold	Days
7	CDD	Consecutive dry days	Maximum number of consecutive days with RR<1mm	Days
8	CWD	Consecutive wet days	Maximum number of consecutive days with RR>=1mm	Days

Table 3: Correlation between the Observed and Simulated Precipitation

Serial No.	Model Code	Model Name	Correlation Coefficient	Rank
1	mod17	CESM1-CAM5_rcp45_r1i1p1	0.76	1
2	mod56	IPSL-CM5A-LR_rcp45_r1i1p1	0.73	2
3	mod1	ACCESS1-3_rcp45_r1i1p1	0.71	3
4	mod12	CCSM4_rcp45_r2i1p1	0.68	4
5	mod59	IPSL-CM5A-LR_rcp45_r4i1p1	0.68	5
6	mod30	CSIRO-Mk3-6-0_rcp45_r8i1p1	0.66	6
7	mod27	CSIRO-Mk3-6-0_rcp45_r5i1p1	0.65	7

Table 4: Summary of Slopes of Plots for Precipitation Indices of GCMs considered

Models	Frequency Indices (Days)															Intensity Indices (mm)											
	CDD			CWD			R10			R20			R25			PRCPTOT			RX1			RX5			R95P		
	Slope	ΔSlope	P	Slope	ΔSlope	P	Slope	ΔSlope	P	Slope	ΔSlope	P	Slope	ΔSlope	P	Slope	ΔSlope	P	Slope	ΔSlope	P	Slope	ΔSlope	P	Slope	ΔSlope	P
Obs	-0.801	0.168	0.000	-0.635	0.100	0.000	0.041	0.070	0.562	0.086	0.032	0.009	0.054	0.021	0.014	-1.304	1.708	0.449	0.098	0.152	0.523	-0.481	0.274	0.086	2.525	0.953	0.011
mod1	0.162	0.523	0.758	-0.088	0.266	0.743	-0.178	0.186	0.347	-0.143	0.099	0.158	-0.106	0.079	0.191	-6.434	4.382	0.153	-0.375	0.363	0.310	-1.298	0.956	0.185	-5.446	2.573	0.043
mod2	0.313	0.387	0.426	-0.238	0.116	0.049	-0.135	0.100	0.187	-0.042	0.084	0.619	-0.020	0.068	0.767	-2.611	4.691	0.582	-0.885	0.908	0.339	1.286	1.618	0.434	-0.524	4.854	0.915
mod4	0.332	0.552	0.553	0.039	0.087	0.657	0.057	0.137	0.679	0.004	0.100	0.968	-0.005	0.089	0.958	5.358	4.637	0.258	0.445	0.296	0.144	2.297	1.032	0.034	3.759	3.889	0.342
mod5	-0.557	0.342	0.115	0.072	0.464	0.878	-0.306	0.269	0.264	-0.057	0.123	0.645	0.018	0.069	0.791	-4.014	5.112	0.439	-0.124	0.194	0.530	-0.053	0.538	0.923	-1.170	2.755	0.674
mod6	0.951	0.565	0.103	-0.614	0.369	0.107	-0.100	0.115	0.390	0.019	0.066	0.774	0.028	0.055	0.610	-4.172	3.666	0.265	-0.621	0.659	0.354	-0.265	1.150	0.820	0.416	3.144	0.896
mod7	0.604	0.592	0.316	-0.177	0.238	0.463	-0.020	0.126	0.876	-0.016	0.070	0.825	-0.063	0.060	0.300	-3.785	4.156	0.370	-0.680	0.783	0.393	-0.652	1.310	0.623	-3.195	3.561	0.377
mod8	0.596	0.499	0.243	-0.003	0.239	0.990	0.054	0.119	0.653	-0.061	0.076	0.426	-0.069	0.067	0.311	-1.455	5.425	0.790	0.800	1.175	0.502	1.253	2.438	0.612	-0.804	4.976	0.873
mod9	0.541	0.658	0.418	0.038	0.226	0.867	-0.184	0.136	0.188	-0.055	0.082	0.507	-0.008	0.061	0.899	-0.243	4.444	0.957	1.164	0.701	0.108	2.348	1.105	0.043	-0.890	3.488	0.800
mod10	1.015	0.652	0.130	-0.159	0.336	0.639	0.244	0.134	0.079	0.089	0.073	0.234	0.107	0.065	0.113	5.250	4.824	0.286	0.774	0.870	0.381	2.044	1.444	0.168	5.006	3.956	0.216
mod11	0.177	0.284	0.539	0.106	0.314	0.737	-0.063	0.161	0.698	-0.059	0.095	0.541	0.024	0.069	0.727	0.639	4.141	0.878	0.458	0.703	0.520	0.928	0.936	0.330	0.370	3.362	0.913
mod12	0.074	0.284	0.797	-0.165	0.218	0.454	0.043	0.187	0.821	-0.079	0.112	0.485	-0.075	0.095	0.383	0.047	4.745	0.992	-0.469	0.712	0.516	-0.540	1.188	0.653	-3.442	4.005	0.397
mod13	-0.054	0.300	0.858	-0.122	0.213	0.569	0.238	0.182	0.201	0.121	0.077	0.127	0.115	0.060	0.065	5.719	4.203	0.184	-0.221	0.588	0.710	0.574	1.490	0.703	4.271	2.724	0.128
mod17	0.034	0.231	0.882	-0.033	0.354	0.925	0.179	0.176	0.317	-0.004	0.078	0.962	0.004	0.065	0.952	3.132	4.318	0.474	0.254	0.502	0.616	-0.091	1.346	0.947	1.128	3.640	0.759
mod19	1.284	0.849	0.142	0.002	0.051	0.969	0.056	0.111	0.619	0.022	0.047	0.643	-0.012	0.034	0.715	0.154	2.414	0.950	-0.152	0.336	0.655	0.401	0.506	0.435	0.499	1.345	0.713
mod20	-0.650	0.662	0.335	0.046	0.060	0.453	0.089	0.144	0.543	-0.026	0.091	0.774	-0.070	0.068	0.312	0.937	3.394	0.784	-0.185	0.208	0.382	-0.060	0.365	0.870	-0.999	2.019	0.624
mod21	0.739	0.623	0.245	0.003	0.395	0.993	-0.115	0.099	0.254	-0.063	0.047	0.193	-0.015	0.044	0.743	-3.043	3.200	0.350	-0.371	0.635	0.564	-1.226	1.007	0.233	-1.650	2.511	0.516
mod22	1.168	0.403	0.007	0.054	0.193	0.783	0.102	0.225	0.654	-0.089	0.145	0.542	-0.117	0.124	0.354	0.869	6.600	0.896	0.002	0.423	0.997	-0.810	1.160	0.491	-0.949	4.046	0.816
mod23	0.077	0.512	0.882	-0.061	0.234	0.795	-0.438	0.171	0.016	-0.132	0.137	0.343	-0.118	0.138	0.399	-9.764	5.462	0.095	-0.303	0.395	0.450	-0.354	1.101	0.750	-2.679	4.687	0.572
mod24	0.637	0.538	0.246	0.089	0.174	0.613	-0.130	0.210	0.541	-0.121	0.189	0.526	-0.148	0.153	0.342	-2.716	7.670	0.726	-0.623	0.312	0.056	-1.538	1.064	0.160	2.155	6.383	0.738
mod25	-0.640	0.425	0.143	-0.274	0.212	0.207	-0.206	0.238	0.393	-0.215	0.163	0.197	-0.160	0.122	0.200	-9.007	6.540	0.179	-0.440	0.301	0.155	-1.968	0.778	0.018	-6.399	3.293	0.062
mod26	-0.629	0.479	0.200	-0.071	0.170	0.680	-0.089	0.186	0.636	-0.055	0.152	0.722	-0.041	0.134	0.762	-0.285	6.246	0.964	1.331	0.497	0.012	1.288	1.837	0.489	4.071	4.393	0.362
mod27	0.965	0.743	0.205	-0.014	0.205	0.948	-0.176	0.255	0.497	-0.072	0.145	0.623	-0.120	0.128	0.354	-3.106	7.565	0.684	0.466	0.294	0.124	0.637	0.964	0.514	1.957	4.209	0.646
mod28	0.260	0.458	0.574	-0.025	0.169	0.885	-0.034	0.182	0.855	0.158	0.157	0.323	0.149	0.135	0.277	5.843	5.577	0.304	0.227	0.284	0.431	0.753	1.011	0.462	5.966	4.045	0.151
mod29	0.127	0.531	0.813	0.059	0.124	0.637	0.025	0.240	0.917	0.063	0.159	0.693	0.074	0.131	0.576	3.562	6.431	0.584	0.437	0.374	0.253	1.361	0.926	0.153	3.976	3.592	0.278
mod30	-0.371	0.357	0.307	-0.069	0.263	0.795	-0.165	0.243	0.504	-0.097	0.172	0.577	-0.058	0.152	0.708	-1.293	7.317	0.861	0.413	0.455	0.373	3.102	1.870	0.109	7.493	5.064	0.150
mod31	-0.735	0.529	0.176	-0.164	0.173	0.351	0.079	0.249	0.753	-0.001	0.152	0.994	-0.013	0.130	0.921	1.318	7.287	0.858	0.028	0.433	0.949	-0.633	1.622	0.699	0.066	4.300	0.988
mod42	0.700	0.481	0.157	0.079	0.281	0.781	-0.005	0.132	0.968	0.040	0.051	0.447	-0.012	0.029	0.677	-1.034	2.659	0.700	0.004	0.094	0.963	-0.026	0.458	0.955	0.280	1.817	0.879
mod43	1.068	0.456	0.027	0.225	0.117	0.064	0.157	0.100	0.130	0.056	0.063	0.379	0.055	0.049	0.267	1.268	2.630	0.634	0.198	0.179	0.278	0.684	0.399	0.097	2.132	1.699	0.220
mod44	0.157	0.318	0.626	-0.959	0.514	0.072	-0.103	0.149	0.490	0.025	0.073	0.731	0.014	0.056	0.805	-3.831	3.605	0.297	-0.548	0.626	0.388	-1.314	1.633	0.428	0.828	3.230	0.799
mod45	-0.101	0.318	0.752	0.651	0.687	0.352	-0.018	0.168	0.915	0.011	0.076	0.882	-0.065	0.052	0.219	-0.663	3.276	0.841	-0.153	0.454	0.739	-1.155	1.534	0.458	-2.077	3.047	0.501
mod46	-0.008	0.504	0.988	0.155	0.536	0.775	0.288	0.250	0.260	0.234	0.093	0.018	0.081	0.044	0.073	6.973	4.994	0.174	0.088	0.569	0.878	0.577	0.944	0.546	5.835	2.776	0.045
mod48	0.281	0.415	0.505	-0.265	0.472	0.580	-0.098	0.234	0.678	0.104	0.124	0.406	0.052	0.066	0.435	0.482	5.305	0.928	0.787	0.515	0.138	0.812	0.839	0.341	4.952	3.268	0.141
mod50	-0.009	0.115	0.938	0.008	0.191	0.969	0.060	0.229	0.795	0.060	0.079	0.454	0.053	0.055	0.339	4.040	5.132	0.438	0.182	0.190	0.349	-0.613	0.474	0.206	0.889	2.435	0.718
mod51	0.023	0.103	0.828	0.184	0.203	0.372	-0.090	0.234	0.704	0.042	0.069	0.547	0.063	0.035	0.088	-1.110	5.150	0.831	0.326	0.138	0.026	0.513	0.418	0.230	0.338	2.350	0.887
mod52	0.278	0.589	0.640	-0.034	0.263	0.897	-0.308	0.194	0.124	-0.068	0.090	0.456	-0.052	0.058	0.379	-7.397	4.252	0.093	-0.646	0.318	0.052	-1.591	0.899	0.088	-4.032	2.686	0.144
mod54	0.570	0.523	0.285	-0.349	0.266	0.200	0.022	0.200	0.913	0.021	0.102	0.835	0.020	0.075	0.796	-3.006	5.079	0.559	0.193	0.283	0.501	0.193	0.833	0.729	0.046	5.079	0.559
mod55	-0.006	0.125	0.959	0.083	0.577	0.887	0.036	0.314	0.911	0.005	0.132	0.971	0.031	0.045	0.497	1.691	5.639	0.766	0.192	0.137	0.171	0.270	0.595	0.654	0.798	3.369	0.814
mod56	-0.201	0.795	0.802	0.261	0.246	0.300	0.002	0.209	0.993	0.006	0.079	0.945	0.041	0.064	0.523	0.441	4.648	0.925	0.580	0.669	0.393	0.264	1.497	0.862	0.174	3.395	0.959
mod57	-0.953	0.941	0.320	0.131	0.312	0.677	0.013	0.145	0.928	-0.035	0.087	0.688	-0.012	0.076	0.878	-1.670	4.042	0.683	-0.179	0.543	0.744	-0.481	1.528	0.755	-1.341	3.554	0.709
mod58	-0.607	0.981	0.541	0.284	0.223	0.214	0.096	0.124	0.444	0.124	0.042	0.006	0.094	0.043	0.038	7.035	2.898	0.022	1.299	0.568	0.030	3.383	1.425	0.025	5.921	2.174	0.011
mod60	-0.201	0.795	0.802	0.261	0.246	0.300	0.002	0.209	0.993	0.006	0.079	0.945	0.041	0.064	0.523	0.441	4.648	0.925	0.580	0.669	0.393	0.264	1.497	0.862	0.174	3.395	0.959
mod61	-0.016	0.346	0.964	-0.190	0.223	0.402	-0.275	0.145	0.068	-0.091	0.086	0.294	-0.084	0.060	0.171	-6.584	4.127	0.122	-0.063	0.807	0.939	-0.895	1.496	0.554	-3.505	3.558	0.333
mod63	0.189	0.708	0.792	0.098	0.255	0.704	-0.060	0.169	0.726	-0.065	0.125	0.609	-0.066	0.112	0.558	-1.534	7.954	0.849	0.306	0.913	0.740	-0.746	2.618	0.778	-2.598	6.813	0.706
mod64	0.206	0.649	0.753	-0.049	0.194	0.801	0.236	0.222	0.297	0.086	0.120	0.490	0.036	0.073	0.627	4.047	5.220	0.445	-0.180	0.146	0.230	-0.252	0.496	0.616	4.047	2.433	0.715
mod66	-0.384	0.474	0.424	-0.056	0.135	0.683	-0.046	0.232	0.843	0.044	0.100	0.664	0.042	0.048	0.390	-2.861	5.270	0.592	-0.009	0.159	0.955	-0.294	0.725	0.688	1.216	1.991	0.546
mod68	-0.209	0.509	0.684	0.059	0.185	0.753	-0.248	0.197	0.218	-0.176	0.143	0.231	-0.089	0.116	0.446	-5.748	5.665	0.319	0.307	0.316	0.340	-0.500	1.164	0.671	1.374	3.736	0.716
mod69	-0.406	0.226	0.083	-0.527	0.182	0.007	-0.226	0.266	0.403	-0.072	0.188	0.704	-0.065	0.143	0.656	-5.821	8.080	0.477	-0.090	0.300	0.766	0.007	0.999	0.995	-1.907	3.969	0.635
mod72	-0.406	0.226	0.083	-0.527	0.182	0.007	-0.226	0.266	0.403	-0.072	0.188	0.704	-0.065	0.143	0.656	-5.821	8.080	0.477	-0.090	0.300	0.766	0.007	0.999	0.995	-1.907	3.969	0.635
mod73	-0.619	0.872	0.483	-0.008	0.083	0.928	-0.117	0.194	0.550	0.063	0.079	0.435	0.056	0.048	0.258	-1.332	3.971	0.740	0.137	0.183	0.458	-0.159	0.395	0.691	1.276	1.588	0.428
mod74	0.544	0.927	0.562	-0.141	0.092	0.136	-0.089	0.138	0.522	0.054	0.073	0.469	0.041	0.053	0.442	-1.096	3.037	0.721	0.209	0.162	0.209	0.341	0.496	0.498	0.825	1.510	0.589
mod75	-0.059	0.355	0.870	0.045	0.117	0.703	-0.184	0.156	0.249	-0.004	0.097	0.969	-0.036	0.073	0.624	-2.313	4.178	0.584	0.443	0.698	0.531	0.632	1.429	0.662	-0.160	3.439	0.963
mod77	-0.061	0.288	0.834	0.210	0.243	0.395	0.152	0.261	0.565	0.056	0.091	0.543	0.034	0.062	0.594	1.599	5.369	0.768	-0.034	0.226	0.880	0.147	0.613	0.812	2.071	3.158	0.517

Table 5: Summary of frequency and intensity indices

Models	Frequency Indices (Days)										Intensity Indices (mm)							
	CDD		CWD		R10		R20		R25		PRCPTOT		RX1		R95		R95P	
	mk	rm	mk	rm	mk	rm	mk	rm	mk	rm	mk	rm	mk	rm	mk	rm	mk	rm
Obs	87	21	47	9	49	18	18	3	11	1	1315	660	96	25	180	66	507	50
mod1	100	21	65	12	57	23	22	5	19	3	1608	830	92	32	273	92	547	64
mod2	125	30	38	14	27	7	15	3	15	2	1450	604	191	41	370	75	991	75
mod4	106	27	26	9	38	12	23	5	19	4	1500	559	108	52	295	73	938	102
mod5	154	31	120	29	73	18	27	1	11	0	1653	629	61	21	204	89	485	69
mod6	136	34	86	13	29	6	15	1	12	0	1170	490	132	24	233	66	665	24
mod7	126	34	64	11	30	8	13	2	11	0	1266	448	138	25	298	78	736	25
mod8	170	35	65	13	30	6	15	0	12	0	1587	483	254	16	470	52	1055	32
mod9	160	36	53	10	31	6	14	0	12	0	1215	521	148	19	264	61	655	51
mod10	58	11	66	8	34	7	14	0	10	0	1304	354	153	15	276	50	618	22
mod11	76	13	80	18	54	21	22	4	12	0	1558	931	162	25	228	75	552	70
mod12	73	12	55	15	60	22	25	4	19	1	1754	925	145	30	284	86	930	66
mod13	58	14	86	18	55	24	18	4	12	0	1594	899	142	25	380	76	577	89
mod17	193	44	85	20	57	19	15	0	13	0	1814	781	172	19	340	62	725	38
mod19	145	44	15	5	40	15	10	1	7	0	1032	420	93	20	153	53	325	27
mod20	140	33	19	4	42	19	21	3	14	0	1184	546	60	23	135	66	443	33
mod21	128	34	92	23	29	13	10	1	9	0	1376	792	126	23	249	64	497	69
mod22	114	28	52	11	82	40	41	13	31	7	2487	1087	110	37	346	127	772	48
mod23	127	33	59	13	76	38	46	15	42	8	2514	1000	108	33	108	33	1077	42
mod24	126	35	44	10	73	34	50	11	42	8	2753	965	115	43	385	122	768	96
mod25	110	26	53	11	82	41	49	9	34	6	2516	1100	99	42	269	124	782	120
mod26	180	31	40	14	73	31	52	15	40	10	2634	976	124	48	424	126	906	93
mod27	126	33	52	12	88	38	40	15	34	9	2516	1041	100	40	337	141	881	113
mod28	167	31	44	13	78	50	43	17	37	10	2342	1415	103	50	334	120	812	50
mod29	103	37	37	13	79	26	40	13	32	7	2205	996	115	44	308	130	693	45
mod30	123	24	67	14	84	37	48	14	36	6	2349	1054	128	34	494	121	1070	54
mod31	102	27	49	13	87	40	49	16	31	10	2487	1173	111	49	394	134	794	49

Models	Frequency Indices (Days)										Intensity Indices (mm)							
	CDD		CWD		R10		R20		R25		PRCPTOT		RX1		R95		R95P	
	mk	rm	mk	rm	mk	rm	mk	rm	mk	rm	mk	rm	mk	rm	mk	rm	mk	rm
mod42	107	20	62	15	38	12	10	1	4	0	1046	549	42	21	134	49	378	43
mod43	76	21	32	10	41	20	17	5	12	1	1219	753	65	26	136	65	451	92
mod44	85	19	132	43	47	19	17	0	13	0	1725	872	127	20	325	64	780	67
mod45	104	15	156	30	51	16	16	0	9	0	1512	815	117	19	398	60	564	21
mod46	107	23	124	25	86	31	24	2	9	0	1969	889	128	25	288	91	646	50
mod48	27	6	110	22	73	26	26	3	12	0	1801	783	114	23	248	65	655	44
mod50	28	8	49	11	54	14	16	3	11	0	1529	712	61	23	181	65	543	69
mod51	135	29	49	11	54	8	15	0	6	0	1594	643	45	16	135	52	470	55
mod52	131	35	74	16	61	19	26	4	15	1	1598	735	88	26	302	94	707	60
mod54	34	10	67	5	47	2	19	1	13	0	1351	151	76	24	192	49	484	55
mod55	201	61	122	25	93	21	30	1	8	0	2212	1097	43	21	184	58	730	24
mod56	249	69	61	15	46	5	15	0	11	0	1209	431	121	15	295	47	588	19
mod57	236	46	70	13	34	9	14	0	10	0	1154	455	108	19	365	51	540	21
mod58	227	61	51	11	33	12	9	0	7	0	1139	496	117	17	384	71	473	43
mod60	94	26	103	9	46	5	15	0	10	0	1335	328	121	15	295	47	715	23
mod61	179	46	64	19	51	23	14	0	9	0	1474	686	167	17	328	60	600	23
mod63	185	26	57	15	44	12	28	1	23	1	2138	574	214	30	547	65	524	38
mod64	111	29	52	12	54	8	27	3	14	0	1389	335	56	24	177	61	452	29
mod66	149	19	33	8	48	3	17	1	9	0	1319	186	49	20	181	36	330	25
mod68	59	12	53	12	67	28	34	12	27	7	2038	983	117	40	306	117	773	40
mod69	70	16	59	14	87	39	45	13	35	8	2658	1191	93	43	308	131	761	124
mod72	203	41	73	16	78	27	46	14	34	5	2422	1158	93	43	308	131	808	111
mod73	209	55	21	5	51	15	18	3	9	1	1200	462	55	25	169	69	290	28
mod74	91	22	23	5	50	21	19	4	13	1	1167	551	59	32	174	67	326	32
mod75	76	16	32	10	53	23	23	3	16	2	1659	701	159	28	322	78	758	55
mod77	32	10	32	10	65	4	15	0	11	0	1626	404	59	17	192	51	515	71

Table 6: Summary of acceptable models for each indicator

Frequency Indices (Days)

CDD	CWD	R10	R20	R25
mod4 bcc-csm1-1_rcp60_r1i1p1	mod1 ACCESS1-3_rcp45_r1i1p1	mod44 GFDL-CM3_rcp45_r3i1p1	mod43 FGOALS-g2_rcp45_r1i1p1	mod5 BNU-ESM_rcp45_r1i1p1
mod46 GFDL-ESM2G_rcp45_r1i1p1	mod25 CSIRO-Mk3-6-0_rcp45_r3i1p1	mod54 inmcm4_rcp45_r1i1p1	mod44 GFDL-CM3_rcp45_r3i1p1	mod7 CanESM2_rcp45_r2i1p1
mod1 ACCESS1-3_rcp45_r1i1p1	mod23 CSIRO-Mk3-6-0_rcp45_r1i1p1	mod66 MIROC-ESM_rcp45_r1i1p1	mod66 MIROC-ESM_rcp45_r1i1p1	mod50 GISS-E2-R_rcp45_r6i1p1
mod60 IPSL-CM5A-LR_rcp60_r1i1p1	mod30 CSIRO-Mk3-6-0_rcp45_r8i1p1	mod74 MPI-ESM-MR_rcp45_r1i1p1	mod73 MPI-ESM-LR_rcp45_r1i1p1	mod56 IPSL-CM5A-LR_rcp45_r1i1p1
mod43 FGOALS-g2_rcp45_r1i1p1	mod31 CSIRO-Mk3-6-0_rcp45_r9i1p1	mod45 GFDL-CM3_rcp60_r1i1p1	mod13 CCSM4_rcp45_r6i1p1	mod77 NorESM1-M_rcp45_r1i1p1
		mod61 IPSL-CM5A-MR_rcp45_r1i1p1	mod54 inmcm4_rcp45_r1i1p1	
		mod73 MPI-ESM-LR_rcp45_r1i1p1	mod74 MPI-ESM-MR_rcp45_r1i1p1	

Intensity Indices (mm)

PTOT	RX1	R95	R95P
mod7 CanESM2_rcp45_r2i1p1	mod1 ACCESS1-3_rcp45_r1i1p1	mod50 GISS-E2-R_rcp45_r6i1p1	mod1 ACCESS1-3_rcp45_r1i1p1
mod10 CanESM2_rcp45_r5i1p1	mod19 CMCC-CM_rcp45_r1i1p1	mod66 MIROC-ESM_rcp45_r1i1p1	mod5 BNU-ESM_rcp45_r1i1p1
mod21 CNRM-CM5_rcp45_r1i1p1	mod69 MIROC5_rcp45_r3i1p1	mod64 MIROC-ESM-CHEM_rcp45_r1i1p1	mod21 CNRM-CM5_rcp45_r1i1p1
mod54 inmcm4_rcp45_r1i1p1	mod25 CSIRO-Mk3-6-0_rcp45_r3i1p1	mod55 inmcm4_rcp45_r1i1p1	mod57 IPSL-CM5A-LR_rcp45_r2i1p1
mod66 MIROC-ESM_rcp45_r1i1p1	mod27 CSIRO-Mk3-6-0_rcp45_r5i1p1	mod74 MPI-ESM-MR_rcp45_r1i1p1	mod63 IPSL-CM5B-LR_rcp45_r1i1p1

RMSE	Correlation	Frequency Distribution
mod75 MRI-CGCM3_rcp45_r1i1p1	mod17 CESM1-CAM5_rcp45_r1i1p1	mod1 ACCESS1-3_rcp45_r1i1p1
mod25 CSIRO-Mk3-6-0_rcp45_r3i1p1	mod56 IPSL-CM5A-LR_rcp45_r1i1p1	mod5 BNU-ESM_rcp45_r1i1p1
mod30 CSIRO-Mk3-6-0_rcp45_r8i1p1	mod1 ACCESS1-3_rcp45_r1i1p1	mod12 CCSM4_rcp45_r2i1p1
mod52 HadGEM2-AO_rcp45_r1i1p1	mod12 CCSM4_rcp45_r2i1p1	mod31 CSIRO-Mk3-6-0_rcp45_r9i1p1
mod74 MPI-ESM-MR_rcp45_r1i1p1	mod59 IPSL-CM5A-LR_rcp45_r4i1p1	mod44 GFDL-CM3_rcp45_r3i1p1
mod5 BNU-ESM_rcp45_r1i1p1	mod30 CSIRO-Mk3-6-0_rcp45_r8i1p1	mod62 IPSL-CM5A-MR_rcp45_r1i1p1
	mod27 CSIRO-Mk3-6-0_rcp45_r5i1p1	

Figures

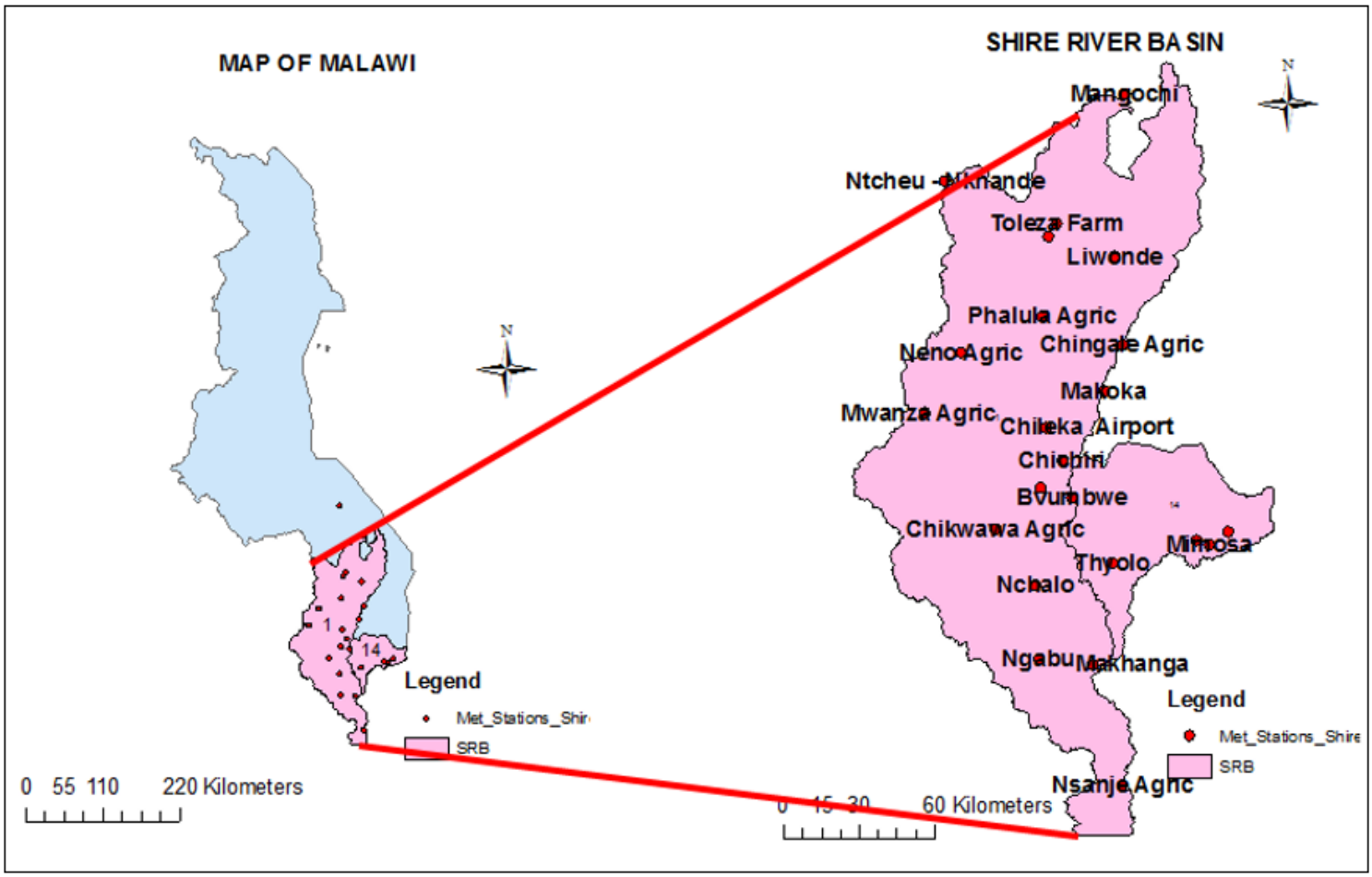

Figure 1

The Shire River Basin in Malawi

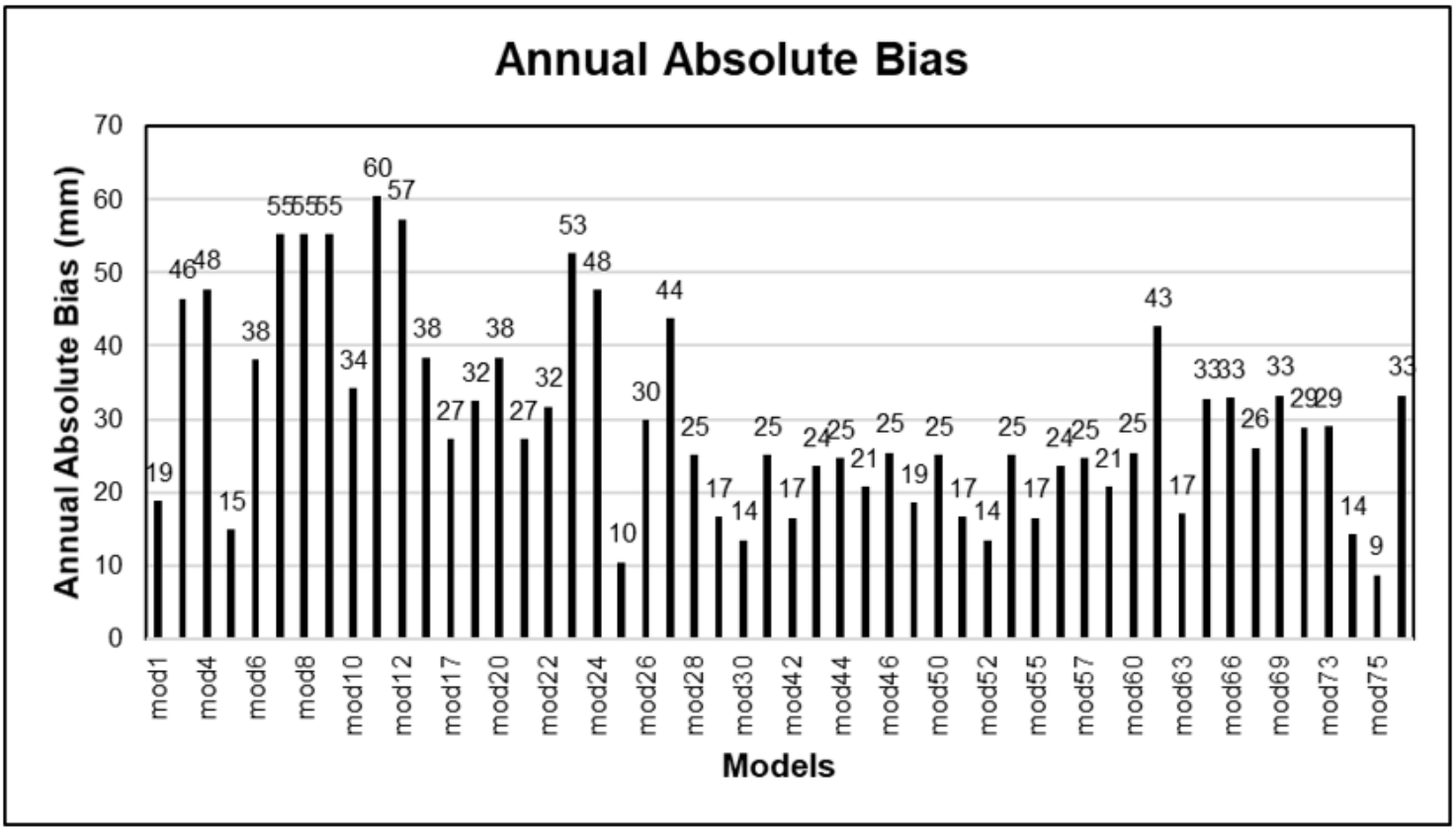

Figure 2

Annual bias of the GCMs for precipitation

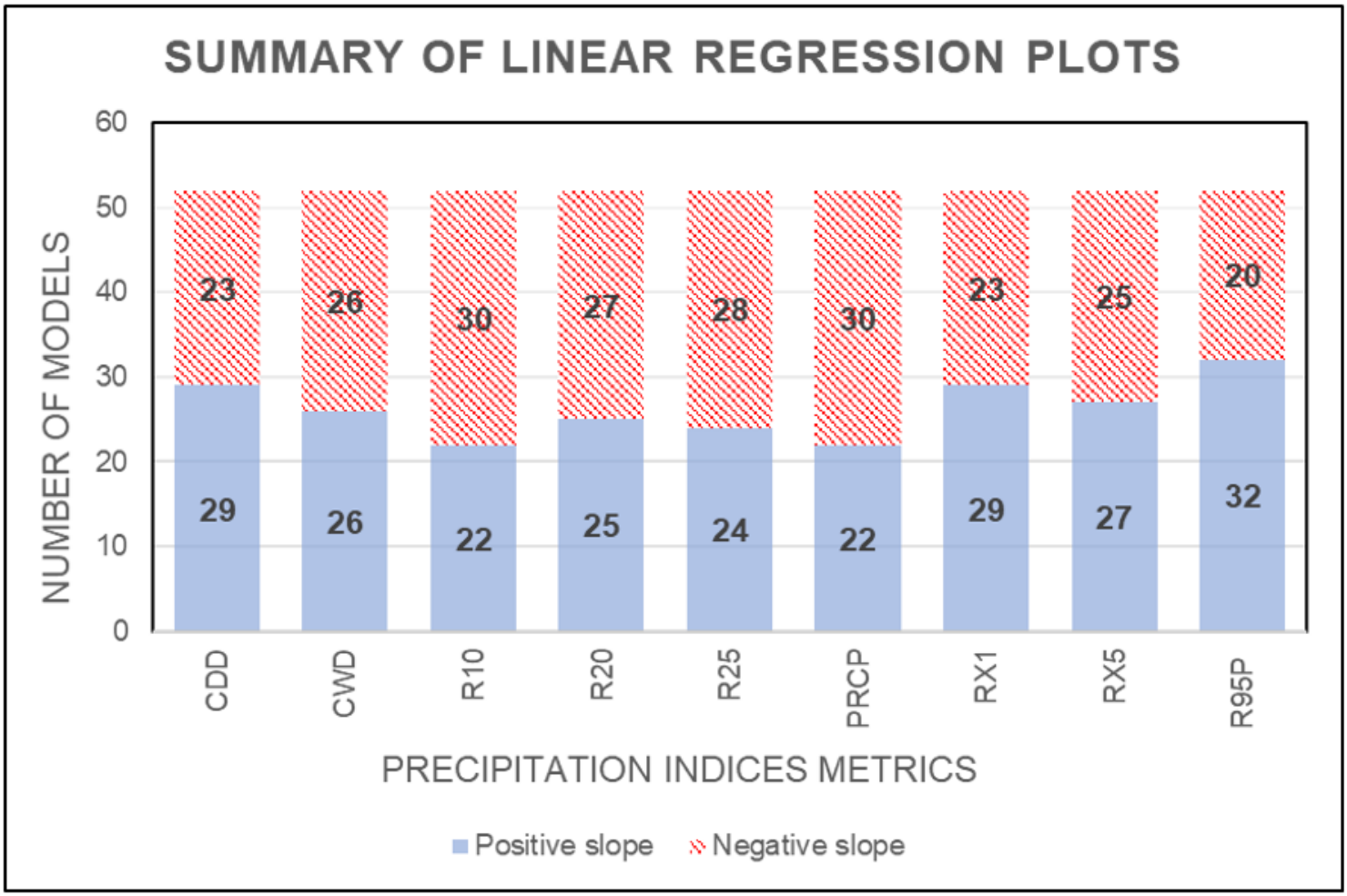

Figure 3

Summary of Linear Regression plots

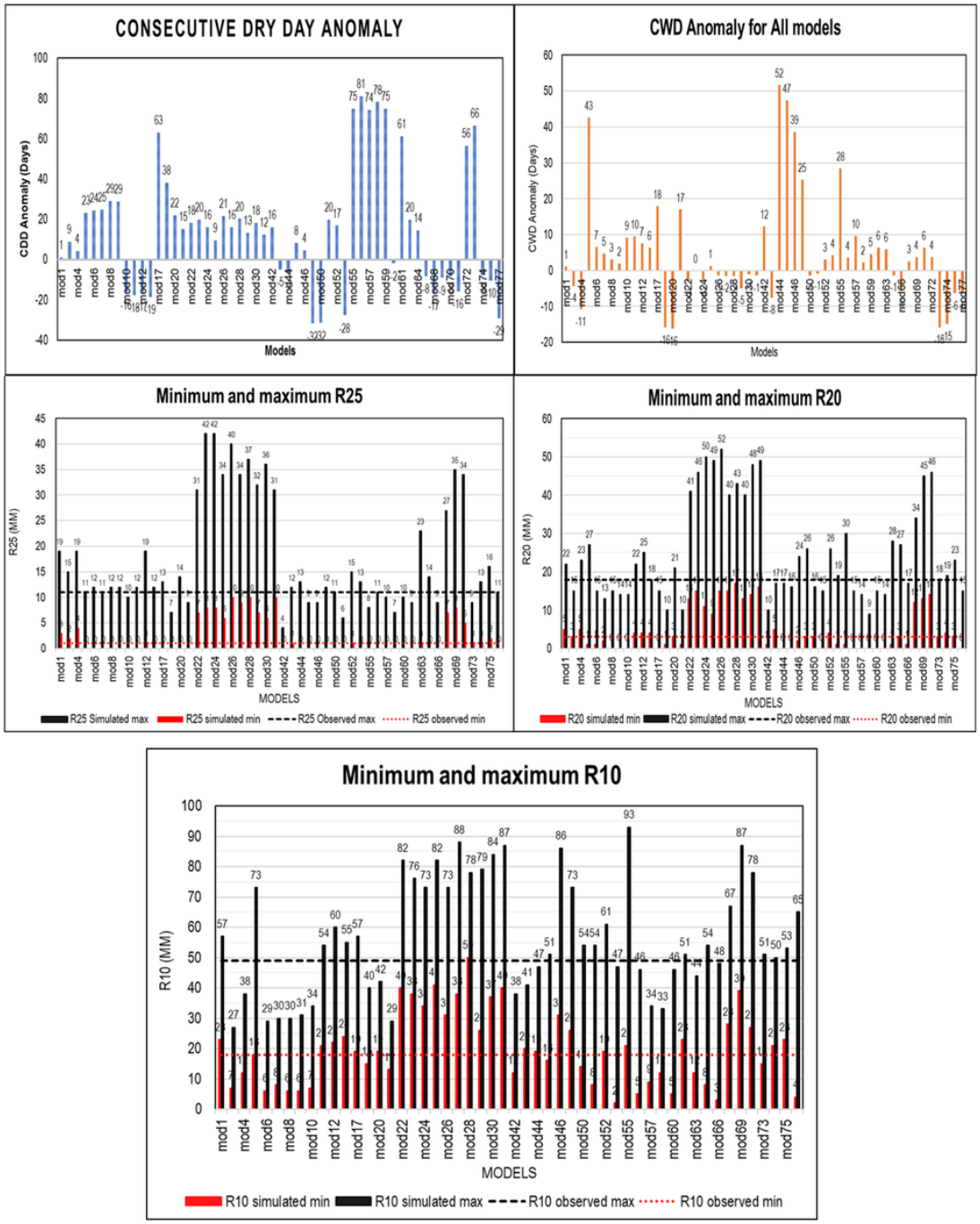

Figure 4

Frequency indices for all models

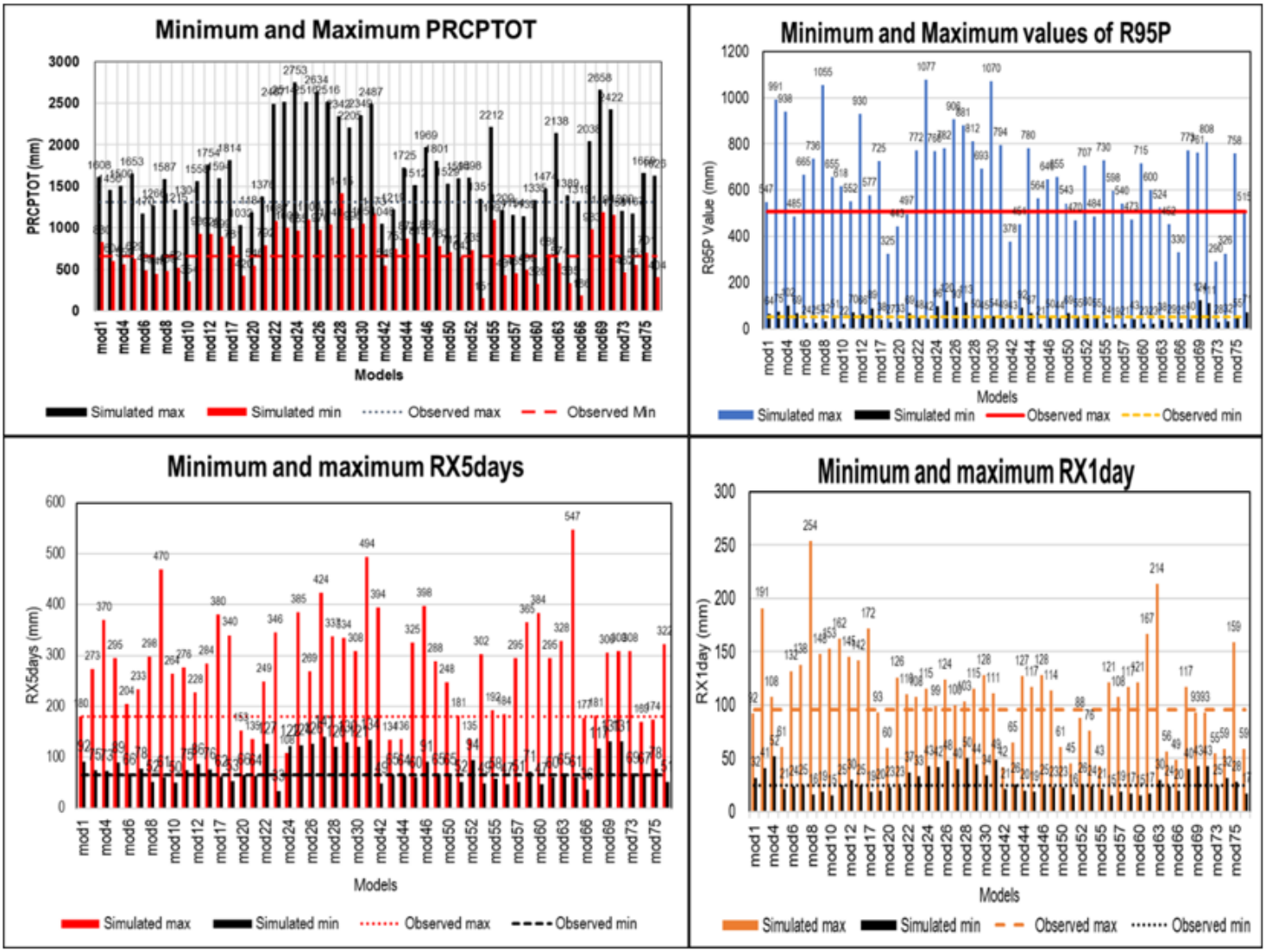

Figure 5

Intensity indices

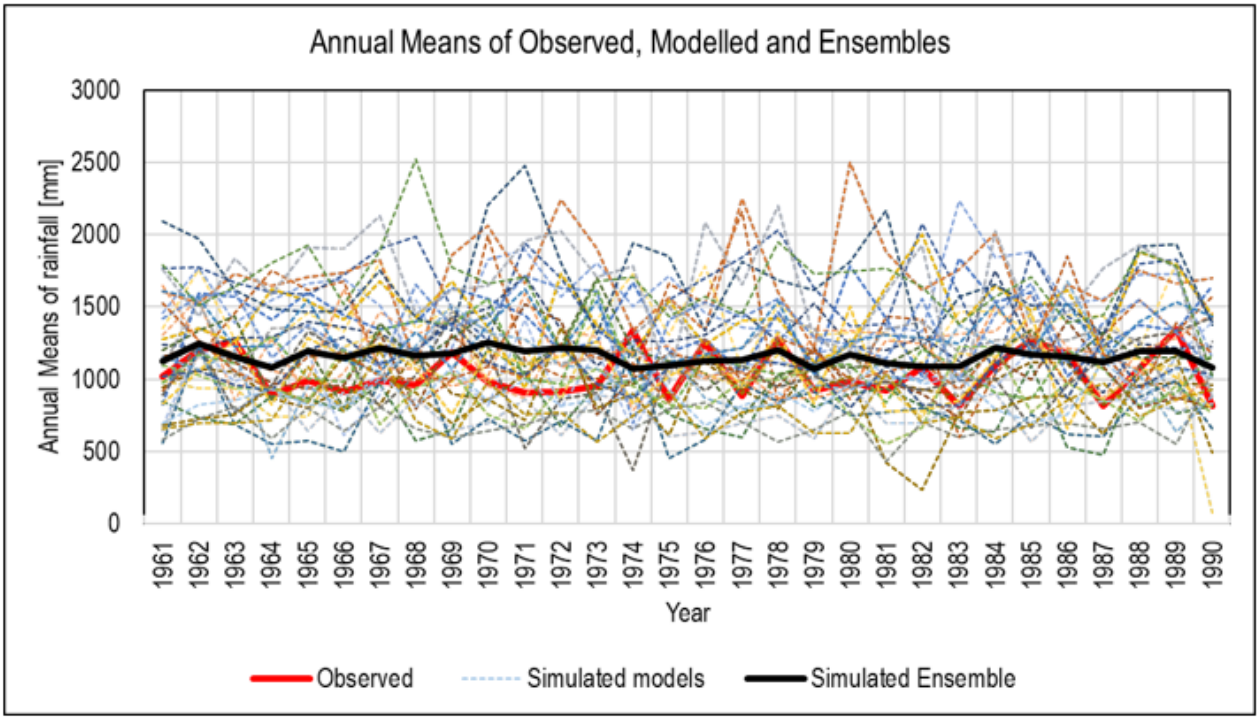

Figure 6

Means of observed, simulated and ensembles means of the GCM runs

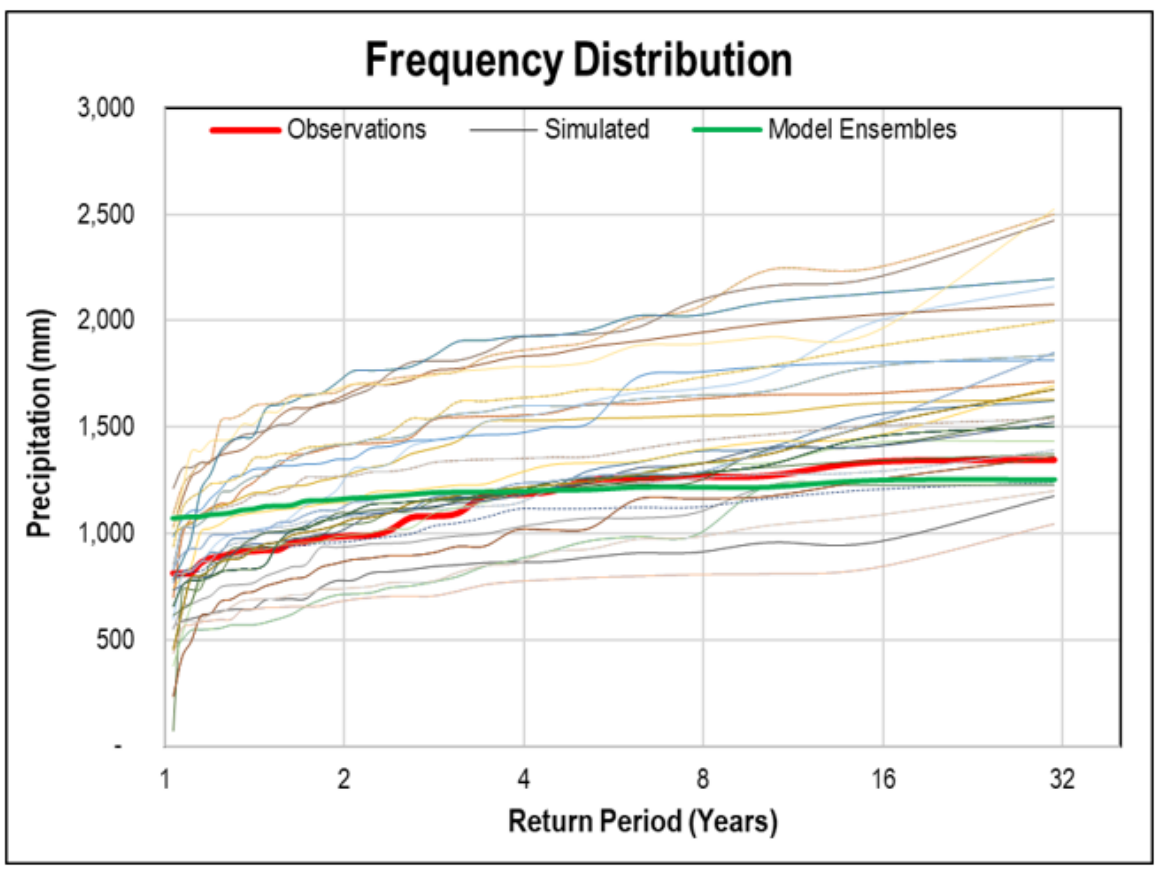

Figure 7

Frequency distribution of precipitation