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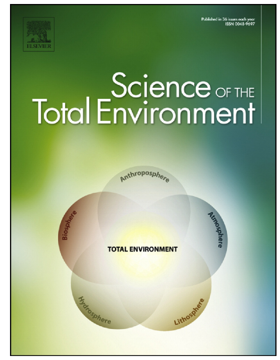

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Temperature and Precipitation Change in Malawi: Evaluation of CORDEX-Africa Climate Simulations for Climate Change Impact Assessments and Adaptation Planning

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Useful Abbreviations:
CORDEX: Coordinated Regional Climate Downscaling Experiment
ERAINT: ERA-interim
GCMs: General Circulation Models
Pr: precipitation rate
RCMs: Regional Climate Models
RCPs: Representative Concentration Pathways
Seasons:
- DJF: summer (December, January, February)
- MAM: autumn (March, April, May)
- JJA: winter (June, July, August)
- SON: spring (September, October, November)

SSA: Sub-Saharan Africa
Tas: monthly mean surface air temperature
TasMax: maximum surface air temperature
TasMin: minimum surface air temperature

Abstract

Malawi is highlighted as one of the most vulnerable countries in the world to the effects of climate change. The large uncertainty around future climate change in the region remains a barrier to adaptation planning. Despite this high potential vulnerability, relatively little research has gone into determining how well available models represent this country's climate. This work therefore evaluates the ability of existing General Circulation Models (GCMs) and Regional Climate Models (RCMs) to hindcast climatic variables in Malawi at a resolution appropriate for climate change impact assessment and adaptation planning. We focus on monthly precipitation rate, and mean, maximum and minimum surface air temperature. This assessment compares available observed datasets against the outputs of six ERA-interim driven RCMs and 21 GCM-driven RCMs from the Coordinated Regional Climate Downscaling Experiment (CORDEX) initiative, and the 11 GCMs which form their boundary conditions. It was found that the performance of the RCMs is highly influenced by their boundary conditions. None of the individual or ensemble RCMs or GCMs assessed in this paper correlate well with the observed datasets for any of the assessed climatic variables. While, they do simulate the trending change in temperature variables well, the simulated outputs for precipitation are highly divergent. Based on these findings we suggest that either the ensemble RCMs or ensemble GCMs would be suitable for understanding projected temperature trends, with the RCMs providing better spatial resolution. However, none of the assessed models provide certainty over future precipitation trends in Malawi. As such we suggest that impact assessments and adaptation plans in Malawi will need to be designed and tested against a range of future precipitation scenarios. To improve modelling for Malawi it is recommended that regional climate models be improved for higher spatial resolution and inclusion of the impacts from large water bodies, including Lake Malawi.

Keywords

Regional Climate Models, General Circulation Models, Sub-Saharan Africa

1. Introduction

Sub-Saharan Africa (SSA) has been identified as being particularly vulnerable to future climate change due to its high exposure and low adaptive capacity (Davies et al., 2010, Niang et al., 2014). Climate change is expected to exacerbate existing challenges with food security, health, poverty and development in the region (Niang et al., 2014). The complexity and uncertainty surrounding the impacts of climate change in SSA is one of the main challenges hindering effective adaptation planning (Thornton et al., 2016). While understanding the impacts of future climate change has a level of uncertainty in every region of the world, the levels of confidence are amongst the lowest over SSA due to a lower resolution of available climate models and a lower level of research being conducted (Niang et al., 2014). Therefore, increasing the level of confidence in the projections for this region, or at least quantifying the scale of the uncertainty will be a big step towards providing the certainty required for effective adaptation planning.

Within SSA, Malawi has been highlighted as being especially vulnerable to climatic changes due to high levels of poverty, and heavy reliance on a predominantly rain-fed agricultural sector for its economy, employment and food security (Minot, 2010, FAO, 2017, Giertz et al., 2015). Malawi is one of the poorest economies in the world, with a fifth of the population classified as undernourished, and while progress is being made with treatment, there are still high levels of communicable diseases such as HIV/AIDS, tuberculosis and malaria making the population particularly vulnerable (IMF, 2017, FAO et al., 2015, The Global Fund, 2018). Most of the calorific intake of Malawi's population comes from agricultural production within the country's borders (Minot, 2010) and in 2015, 78 percent of Malawi's population was employed in the agricultural sector making it a main source of income (FAO, 2017). The agricultural sector is also a significant contributor to the overall Malawian economy, responsible for 32 percent of the total Gross Domestic Product (GDP) and over 78 percent of the country's total exports in 2016 (CIA, 2017). With much of the agricultural production coming from smallholder rain-fed production, climatic shocks such as floods and droughts have a significant impact on the country's economy and frequently affect its agricultural exports, and food security (Giertz et al., 2015, Ministry of Agriculture and Food Security, 2011, FAO, 2010, Pauw et al., 2010). For example, the 2005 drought led to 40 percent of the population requiring immediate food aid (Giertz et al., 2015).

Climate change is expected to exacerbate existing issues with water availability, adding to the vulnerability of wetland and aquatic habitats, and the human systems which rely on them (USAID, 2013). With 96 percent of the country's energy produced through hydropower, water scarcity is already causing energy shortages, and this is expected to worsen (ibid.). While little research exists to prove an explicit link in Malawi, it is also expected that climate change will have negative human health impacts through increased incidence of malaria, cholera and diarrhoea (Irish Aid, 2015). As such climate change is likely to be an additional challenge for achieving various sustainable development goals in Malawi, including the goals for no poverty, zero hunger, good health and well-being, affordable and clean energy, and decent work and economic growth.

To adequately quantify the impact that climate change will have on Malawi, and how the population can best adapt to these changes, a clear understanding of the projected changes is required. While some regional climate modelling has taken place, relatively little research has gone into evaluating how well the available climate models represent this small but heterogeneous country. Multiple studies looking at Malawi's climate vulnerability have highlighted the need for better short-term and mid-term climate projections in Malawi to allow for effective decision making, policy planning, and implementation of adaptation projects and climate services to take place (Nyamwanza et al., 2017, Vincent et al., 2015). While updating the weather and climate observation network would be a large investment for Malawi, research into the impact for Africa as a whole indicates that this money would be more than balanced through avoided losses of infrastructure, productivity, and human life (World Bank, 2017). Some countries have created nation-specific tools which can help estimate more local-scale impacts and appropriate adaptation responses (UKCIP, 2017, Natural Resources Canada, 2017). While no such tool yet exists for Malawi a recently approved United Nations Development Programme (UNDP) project, funded by the Green Climate Fund, will provide the opportunity to improve Malawi's climate-information and early warning systems (Green Climate Fund, 2015).

Thus far, General Circulation Models (GCMs) have been used for climate change projections at the regional level for SSA and Malawi more specifically (Mittal et al., 2017, Osborn et al., 2015, Serdeczny, 2017). Regional analysis has shown GCMs to be relatively good at reproducing temperature trends, but they tend to overestimate precipitation in all seasons for Southern Africa (Flato et al., 2013, Buontempo et al., 2015). Furthermore, climate projections using GCMs represent changes over a relatively large area, however to carry out context-specific impact and adaptation assessments, a more detailed local understanding is required (Kim et al., 2014).

To achieve a greater level of detail, and improve the accuracy of projections, many studies have started to use regional downscaling methods (Nolan et al., 2017, Jeong et al., 2016, Stratton et al., 2018). With a high level of confidence, Flato et al. (2013) found that Regional Climate Models (RCMs) add value to climate projections particularly in areas with variable topography, and extreme or small-scale climatic processes. Studies by

Kalognomou et al. (2013) and Endris et al. (2013) also found that an ensemble of 10 RCMs was able to adequately simulate precipitation the distribution and scale of rainfall patterns in Southern and Eastern Africa respectively. Stratton et al. (2018) similarly found that downscaling the Met Office's global-scale Unified Model to the Africa-wide domain allowed for additional detail to be included to the model, particularly higher resolution and convection parametrization. They concluded that the downscaling and improved continent-scale information, particularly the inclusion of convection, allows for improved precipitation simulation during the June-August period.

While RCMs naturally inherit the biases of the GCMs which form their boundary conditions, Buontempo et al. (2015) showed that local climate forcings and the RCM formulation have a larger influence over the results and decrease the impact of these biases in the African region. Some analysis has shown that RCMs are better able to represent annual cycles in Southern Africa and provide finer details to the projections (Nikulin et al., 2012, Buontempo et al., 2015, Dosio et al., 2015). However, it has also been found that the way the RCMs inherit the biases from the GCMs varies for different regions and variables within Africa, therefore it is important for impact assessment studies to re-evaluate the models for suitability before use (Kim et al., 2014).

Our study focusses on evaluating the ability of existing GCMs and RCMs to hindcast climatic variables in Malawi at a resolution appropriate for climate change impact assessment. We focus on the main climatic variables relevant to Malawi's largest exporting and employment sector, agriculture – surface temperature (mean, maximum and minimum) and precipitation rate. We also assess the models' ability to hindcast the frequency and timing of drought events, which are listed as the major environmental risk factor for Malawi's agricultural and hydro-based electricity sector (Giertz et al., 2015, Conway et al., 2017). This analysis provides a basis for future impact and adaptation analysis and an understanding of the limitations and error margins on the use of RCMs and GCMs for this purpose.

2. Data and Methods

The most straightforward method to assess the accuracy of climate models is to compare observed climate data with simulated climate outputs (Flato et al., 2013). However, the vast number of variables and timescales which can be considered means there is no standard set of tests which can be applied to a climate model to carry out this comparison (Gleckler et al., 2008). There are many ways in which this comparison can be undertaken, each having its own limitations. Our study is limited to comparing observational data for mean (Tas), maximum (TasMax) and minimum (TasMin) surface air temperature and precipitation rate (Pr) with reanalysed and simulated climate model datasets for Malawi.

2.1. Description of Observations

There are few high-quality observational datasets for Malawi's climate at sufficient spatial resolution, and where data does exist there can be discrepancies (Dosio et al., 2015, Nikulin et al., 2012). This limitation is predominantly due to insufficient gauge stations and varied data management techniques; however, it is slightly improved by the introduction of data from satellite measurements (ibid.). While uncertainty exists, studies by Diallo et al. (2014) and Zhang et al. (2013) have shown that there is a good level of agreement between the main datasets over the African region. Therefore, where more than one observed dataset was available, an average was used for comparison purposes and the range of observed data is shown in all temporal assessments. It is acknowledged that the accuracy of the observed data will have an impact on the results of this study and as such is a potential source of error. All the observed data sets used in this study are listed in Table 1.

2.2. Description of Reanalysed and Simulated Regional Climate Models

Here, we make use of the RCMs produced by many different groups within the Coordinated Regional Climate Downscaling Experiment (CORDEX) initiative. The CORDEX initiative sets a standard grid, domain size, experiment protocols, and data format allowing for direct comparison of the model outputs (Giorgi et al., 2009, Nikulin et al., 2012). Within this framework, only models which were publicly available and provided projections for Representative Concentration Pathways (RCPs) 4.5 and 8.5 were selected as these are deemed the most useful for further research on future climate change vulnerability and responses. All the RCMs are atmospheric models produced within the defined CORDEX-Africa domain, they provide data on a monthly time scale, and have a 0.44-degree (approximately 50km2) resolution. All of the models other than CanRCM4_r2 were accessed through The Earth System Grid Federation (ESGF) data index (ESGF, 2017). The CanRCM4_r2 model was accessed through the Canadian Centre for Climate Modelling and Analysis website (CCCma, 2017a).

To better understand the source of any biases within the models, comparisons are made with both RCMs, which use GCMs to set their lateral boundary conditions (GCM-driven RCMs), and ERA-interim driven RCMs (ERAINT) which are reanalysed to use observed data for lateral boundary conditions. All the simulated and reanalysed models used in this study are listed in Table 2 along with the institutions which built them, the conditions which set the lateral boundaries, and the source reference.

2.3. Description of Reanalysed and Simulated Global Climate Models

To allow for a fair comparison, we make use of the eleven GCMs which are used to form the lateral boundary conditions in the CORDEX RCM models listed in Table 2. These models are part of the Fifth Phase of the Coupled Model Intercomparison Project (CMIP5) and the details of these models are found in Table 3. All the GCMs are coupled atmospheric-ocean models running historical projections with all forcings being time variable. All the GCM models have monthly data for the atmospheric realm. The resolution of each model is different and listed in Table 3 as the distance between adjacent grid points in degrees. The longitudinal resolution is consistent over the whole globe, however the latitudinal resolution listed is that for the equator, and some deviation will exist for high latitudes (ENES, 2016).

The CanESM2 model was accessed through the Canadian Centre for Climate Modelling and Analysis website (CCCma, 2017a). CNRM-CM5, HadGEM2-ES, IPSL-CM5A-MR, MIROC5 and MPI-ESM-LR were all accessed through The Earth System Grid Federation (ESGF) data index (ESGF, 2017). CSIRO-MK3, EC-EARTH r12i1p1 and NORESM1-M were accessed via the Centre for Environmental Data Analysis (CEDA) data catalogue (CEDA, 2017). EC-EARTH r3i1p1 was downloaded directly from the Danmarks Meteorologiske Insitut (DMI) servers upon request (DMI, 2016).

2.4. Description of Experimental Design

Analysis of the results was performed using a Python interface. Within the interface, the numerical mathematics and graphical plotting were produced using a variety of open source Python libraries and packages. The code used for each assessment can be found in the author's GitHub repository[1].

The analysis is limited to the time-period in which all the observed data and models overlap. Therefore, the GCM-driven RCMs and GCMs are assessed against observed data over the period of 1961-2005 and the ERA-interim driven RCMs are assessed against observed data over the period of 1990-2008. For the purposes of comparison of relative performance, where all three of the model groups are assessed together and the data are compressed temporally, all data are assessed against observed data over the largest overlapping time-period, 1990-2005.

As the data are associated with 3 dimensions (latitude, longitude and time), it was necessary to compress them on at least one variable for assessment. Therefore, the assessment has been carried out with the same data over both

[1] Erika Warnatzsch GitHub directory: https://github.com/ErikaWarnatzsch/Malawi-Historical-Climate-Modelling-Assessment

spatial and temporal scales, where the temporal or spatial variable(s) have been compressed respectively. The model outputs were assessed for annual and seasonal changes and compared with the available observed data sets. The seasons are summer (December, January, February – DJF), autumn (March, April, May – MAM), winter (June, July, August – JJA), and spring (September, October, November – SON). Where more than one observed dataset was available an average of the data was taken. The models were assessed individually, and multimodel average or ensembles of the ERA-interim driven RCM outputs, the GCM-driven RCM outputs, and GCM outputs were also assessed.

While the ERA-interim and GCM-driven RCMs are all in the same resolution, the observed data and GCMs have differing resolutions. To accommodate the differing resolutions, the data in all the models needed to be regridded to match the lowest resolution dataset. For spatial assessment, the models were regridded based on their group, therefore for the ERA-interim driven and GCM-driven RCM spatial assessments, the observed data were regridded to match the ERA-interim and GCM-driven RCM models respectively, which all have the same resolution. For the GCM spatial assessments, all the models and the observed data were regridded to match the GCM model will the lowest resolution (CanESM2). For temporal assessments, all the models and data were regridded to match the model with the lowest resolution (GCM CanESM2). Due to this low resolution, and the limitation of using a rectangular boundary, the temporal assessment includes spatial data that are larger than the actual country boundary, as shown in Figure 1. Figure 1b also shows the elevation in Malawi, which is useful for understanding some of the results of this research. The elevation map was created using data from the Joint Institute for the Study of the Atmosphere and Ocean (JISAO, 2014).

Spatial assessment was carried out by compressing the data over the previously stated timeframes and plotting both the absolute values and the bias compared to the observed data on a map. Maps were created for each variable in every season and over time. This analysis highlighted the geographical differences in the climatic variables and which areas of the country had higher or lower levels of bias in the model simulations.

The temporal assessment was carried out by compressing the data over the previously stated latitude and longitude and plotting it over the relevant time period (e.g. the line graphs showing the model outputs over the 1961-2005 period). This was done by month for all years in the stated time-period, and by year for each season and overall. To assess the data statistically, the spatially-averaged data were assessed using Taylor Diagrams (Taylor, 2001). These provide a succinct statistical analysis of the degree of pattern correspondence between the modelled data and observed data in terms of their Pearson's correlation, root-mean-square error, and ratio of their variances.

Since its creation, the Taylor Diagram has become a popular and useful tool in the evaluation of climate models (Kim et al., 2014, Gleckler et al., 2008, Loikith et al., 2015).

To determine how well the models were able to replicate droughts, monthly outputs for 1961-2005 were analysed to determine how many months showed precipitation levels that were 1.5 and 2 standard deviations away from the model's own 1971-2000 mean for the same month. This exercise was also carried out for the observed data sets for comparison. The results were then compared with known droughts years from literature (Masih et al., 2014, Pauw et al., 2010) and the number of false positives, false negatives and matches were determined. This methodology is in line with the Standardized Precipitation Index (SPI) (Keyantash, 2018), which is a commonly used to assess drought occurrence (Shah et al., 2015, Okpara et al., 2017, Meroni et al., 2017).

3. Results

3.1. Precipitation

As summarized in Table 4, the observed data for the period 1961-2005 indicate that Malawi had higher levels of precipitation in the summer months (November – March) with an average of over 225mm in January. In the winter months, precipitation rates dropped drastically, to less than 12mm per month in June – September. The Northern Region, and the western most districts of the Southern Region of the country, received higher levels of precipitation than other areas. Between 1961 and 2005 the country has seen a slight decrease in precipitation levels every decade, from an average of 1140.8mm in 1961-1970 to 1042.4mm in 1991-2000. The annual precipitation varies greatly from year to year (standard deviation 110.9), for example 1989 saw 1317.8mm of precipitation while the next year only received 939.1mm, a drop of almost a third.

Figure 2 shows that the ensemble GCM simulation slightly overestimated precipitation overall (average of +7 percent between 1961 and 2005) and in all seasons except autumn (MAM) which showed an underestimation. Alternatively, the ensemble GCM-driven RCM simulation underestimated precipitation in all seasons (average of -10 percent between 1961 and 2005) except spring (SON), which showed an overestimation. The ensemble ERA-interim driven RCM output underestimated precipitation in all seasons by an average of -34 percent between 1990 and 2005. All the ensembles preformed best in the dry season (May-September).

While most of the model outputs were clustered together, one GCM-driven RCM (HIRHAM5_NorESM1-M) was an outlier, greatly underestimating the precipitation in most seasons, particularly the wet season (October-April) (see blue dotted line in Figure 3). With this outlier removed the annual ensemble GCM-driven RCM simulation for 1961-2005 comes to within 6 percent of the average observed data trend over the same period, however the correlation is still low.

All of the models are able to replicate the seasonal trend in precipitation (i.e. wetter winters and drier summers), however neither the GCM or the GCM-driven RCM simulations replicate the scale of the downward trend in precipitation levels that the observed data show over this period; the trendline associated with the observed data over the period of 1961-2005 has a slope of -2.74mm y^{-1} while the ensemble GCM-driven RCM simulation's trend shows a less steep slope of -0.19mm y^{-1}, and the ensemble GCM shows an increasing trend with a slope of +0.47mm y^{-1}over the same period. Table 5 and Table 6 show the regression slopes for the observed and individual modelled precipitation rates.

The scale of precipitation is not well represented by the ensemble ERA-interim driven RCM, but these models do better at representing variations in extremes from year to year. Both the simulated GCMs and GCM-driven RCMs show much less inter-annual fluctuation, although are on average within the normal range of precipitation for Malawi. The lower inter-annual fluctuations found in the models compared to the observed data, and the lack of correlation between the datasets is supported by the relatively lower standard deviations and low Pearson's Correlation Coefficients shown in Figure 4 for the GCM-driven RCM and GCM simulations. None of the individual GCM-driven RCMs or GCMs have a correlation with the observed data greater than +/- 0.57. While the correlations for the ERA-interim driven RCMs are higher, they are still, on average, low overall, and for the summer and winter months in particular. Correlation of the precipitation output of the ERA-interim driven RCMs is relatively good for spring and autumn.

The bias of the models is not equally distributed spatially across the country. The maps shown in Figure 5 demonstrate this bias for the average simulations in each group annually and by season. Areas of higher bias can be seen particularly in the ensemble ERA-interim driven RCM and the ensemble GCM-driven RCM simulations in areas of higher altitude (see elevation map Figure 1b), particularly around the Shire Highlands in the south (approximately 15.5°S, 35°E); Kasungu National Park and Nyaka National Park, and the area in between in the north (approximately 10.5-12.5°S, 33-34°E); and the area between Dedza-Salima Forest Reserve and the Mozambique border in the centre (approximately 14.5°S, 34°E). The amount of precipitation tends to be overestimated in these areas of higher altitude, while a bias towards underestimating the precipitation is seen around the boundary of Lake Malawi. Getting detail on the spatial distribution of these biases is difficult with the

GCMs owing to the relatively low resolution. Further maps can be found in the author's GitHub repository (see Footnote 1).

3.2 Droughts

According to the literature, within our assessment period of 1961-2005, severe droughts occurred in Malawi in five calendar years: 1987, 1990, 1992, 2002 and 2005, and five maize crop seasons (November – April): 1986/7, 1991/2, 1993/4. 2003/4 and 2004/5 (Masih et al., 2014, Pauw et al., 2010). Using the SPI method with a standard deviation of 1.5 from the 1971-2000 mean led to far more drought signals occurring in calendar years within the observed datasets (17) as well as most of the RCMs (3-23, average of 13.62l ensemble RCM: 26), and all of the GCMs (8-21, average of 15.36; ensemble GCM: 21). This drought bias was also seen when assessing the same data over the maize crop season using a 1.5 standard deviation definition, with 12 drought signals in the observed data, the RCMs showing 2-17 drought signals (average: 10.48; ensemble RCM: 15), and the GCMs showing 8-16 drought signals (average 12.09; ensemble GCM: 12). Using the SPI method with a standard deviation of 2 from the 1971-2000 mean brought the results closer to reality with the observed data sets over a calendar year showing 3 droughts, the RCMs showing 0-7 (average of 2.7l; ensemble RCM: 6) and the GCMs showing 1-6 (average of 3.18; ensemble GCM: 2). Similarly, over the maize crop season, the observed datasets again showed 3 drought signals, the RCMs show 0-6 (average 2.38; ensemble RCM: 4), and the GCMs show 1-4 (average 2.27; GCM ensemble: 2). While the 2 standard deviation definition did not pick up all droughts in the observed dataset, the three which it did signal corresponded to crop seasons where droughts actually occurred (1991/2, 1993/4, 2004/5), and two of the three signalled calendar years with droughts (1992, 2005). The annual precipitation levels in 1987, 1990 and 2002 were 1.7, 1.2 and 0.3 standard deviations below the 1971-2000 mean. The majority of the RCMs and GCMs were not able to show any matches with the actual drought years. For the RCMs, seven and of the 21 individual models were able to correctly predict one or more drought years in the correct year, using the 2 standard deviation definition. Likewise, four of the individual RCM models were able to correctly predict the one or more years of crop season drought using this definition. For GCMs, correct prediction was observed in six and seven of the 11 individual models for calendar year and crop season drought respectively.

3.3 Temperature

Table 7 summarizes the observed data sets over the period of 1961 to 2005 for mean, maximum and minimum surface temperature. Temperatures were highest in November and lowest in July. The largest difference between the daily maximum and daily minimum temperature was seen in September. Spatially, the temperature was relatively consistent across the country, with temperatures slightly higher in the Southern Region and on the boundary of Lake Malawi. Over the period of 1961 to 2005 a warming trend is seen in Malawi with the mean temperature increasing from an average of 22.0^{o}C in 1961-1970 to 22.6 ^{o}C in 1991-2000.

The ensemble GCM-driven RCM and GCM simulations show a cool bias underestimating mean and maximum temperature in all seasons, sometimes by over 2^{o}C, as seen in sections i and ii of Figure 6. While the ensemble GCM-driven RCM and GCM simulations also underestimate minimum temperature, the simulations are better, usually within 0.5 degrees of the observed data (see section iii of Figure 6). The ensemble ERA-interim driven RCM outputs for mean, maximum and minimum temperature are relatively good at recreating both the scale and the variability of temperature in all seasons, predominantly varying within less than 0.5^{o}C of the observed data.

Most of the model outputs were quite closely grouped together, however, like the precipitation simulations, one GCM-driven RCM simulation was an outlier for the temperature datasets; HIRHAM5_NorESM1-M greatly overestimated the mean, maximum and minimum temperature in all seasons. As the ensemble GCM-driven RCM simulation is already underestimating temperature, removing this outlier makes the bias even greater.

While the scale of the temperature output from the ensemble GCM-driven RCM and GCM simulations was underestimated, they were both able to replicate the rate of change seen in the observed datasets for mean and minimum temperature of approximately +0.02^{o}C y^{-1} over the 1961-2005 period. The ensemble GCM-driven RCM and GCM simulations also replicated an upward trend in maximum temperature, however the models only showed an average increase of +0.02 ^{o}C y^{-1}over the 1961-2005 period, while the observed data indicate that this increase is occurring faster, at an average rate of +0.03 ^{o}C y^{-1}over the same period.

Similar to the precipitation results, the ERA-interim driven RCMs have a relatively high correlation with the observed datasets, while the GCM-driven RCMs and GCMs do not. Unlike the precipitation analysis. The standard deviations for the observed, reanalysed and simulated datasets are similar. These statistics are shown graphically in Figure 7.

Like the bias seen in the precipitation models, the largest biases in the models were seen in areas of higher altitudes and around the boundary of Lake Malawi (see elevation map Figure 1b). Overall the direction of the bias (either cooler or warmer than the observed) was fairly consistent spatially in all seasons for the ensemble GCM-driven RCM simulations. The ensemble ERA-interim driven RCM outputs showed some spatial variation in the direction of the bias, particularly in summer. Again, getting detail on the spatial distribution of these biases is difficult with the GCM models owing to the relatively low resolution.

4. Discussion and Conclusions

Understanding the impact of climate change on Malawi's agricultural sector requires robust projections of a variety of factors, including precipitation and temperature, to design appropriate adaptation plans (Reddy, 2015). Domestically-grown rainfed maize is the main source of calories for the Malawian population (FAOSTAT, 2018), and those studies which have assessed maize crop models around the world for sensitivity to precipitation and temperature change have highlighted the importance of these climatic variables in determining future productivity and yield (Bassu et al., 2014, Knox et al., 2012, Zhang et al., 2015, Stevens and Madani, 2016). Notably, Challinor et al. (2016) found that a warming climate could lead to reduced crop durations for maize in SSA, with implications both for yields of current maize varieties and the traits likely to be required in new, more climate-resilient varieties.

Similarly, studies assessing the impact of climate change on Malawi's hydrological cycle, and in particular hydropower generation in the region, have also found temperature and precipitation to be key determinants (Hamududu and Killingtveit, 2016, Kumambala and Ervine, 2010). Changes in the timing and intensity of precipitation, together with enhanced evapotranspiration rates at higher temperatures, pose a potential risk to the commercial viability of current and planned hydropower installations, especially the run-of-river schemes common to Malawi (Kaunda and Mtalo, 2013, Kachaje et al., 2016). For example, the late rainy season and prolonged dry spells of 2015 reportedly reduced energy generation by two-thirds for hydroelectric plants on Malawi's Shire river (Sanje, 2015).

With the vast majority of the domestic energy in Malawi produced through hydropower (USAID, 2013) and the majority of the food supply, employment, and income depending on rain for irrigation (Minot, 2010, FAO, 2017, Giertz et al., 2015), it is important to understand the uncertainties around Malawi's climate modelling if these projections are to be successfully used in impact and adaptation planning.

Our analysis indicates that the boundary conditions greatly influence the performance of the RCMs. While the ERA-interim driven RCMs provide a reasonable correlation with the observed data for both precipitation and surface temperature (mean, maximum and minimum), the GCM-driven RCMs and GCMs do not. Furthermore, while the RCMs and GCMs do reasonably well at determining the frequency of drought events, particularly when assessing the data for the maize crop season only (roughly corresponds to wet season) rather than the whole calendar year, they do not do well at determining which years those droughts occur in. Therefore, these models, using the SPI method for drought, would have been less useful for predicting specific annual events or informing short-term adaptation responses over this historical period. For example, the 2005 drought is clearly visible in the observed data, with only 849.7mm of precipitation falling over the country (21% percent less than, and 2 standard deviations below the 1971-2000 average). While most of the ERA-interim driven RCM outputs, and the ensemble of these, do indicate a downturn in precipitation in that year, neither the ensemble GCM-driven RCM or ensemble GCM predict the severe drought that was experienced. It is worth noting that the observed precipitation datasets and inferred droughts (using the SPI method with a sensitivity of 2 standard deviations from the 1971-2000 baseline) did not match with all reported droughts in the study period. As such, it is possible that either the drought definition (2 standard deviations below the mean) or the chosen baseline for the SPI assessment are not always appropriate for defining a drought in Malawi. This also highlights the limitations of using the SPI method for drought impact assessment as droughts are not only caused by the absolute amounts of precipitation but also evapotranspiration rates and runoff (Trenberth et al., 2013).

In the last few decades, Malawi has experienced multiple severe droughts and flash flooding events which have had a significant impact on the country's overall development, including energy provision, infrastructure, and food security (Pauw et al., 2010, MRCS and IFRC, 2015). Over the last half century both the number and extent of floods and droughts have increased sharply (ActionAid, 2006). It will be important for Malawi to create adaptation plans to minimise the impact of future climatic shocks, but it is also important for planners to understand the limitations that climate models have for predicting the timing and frequency of these events, and the scale of the uncertainty around precipitation patterns more generally.

A lack of correlation between the models and the observed data is not a barrier to use in itself; climate models are not used to predict a specific weather event which may occur in any one year, but rather the trend in climatic change. Both the GCM-driven RCMs and GCMs recreate the trending change in the temperature variables with reasonable accuracy, however this is not true for precipitation where a clear signal is not seen. The projections for precipitation are highly divergent across the models assessed here. Furthermore, the scale of the simulation outputs shows a bias for all variables, to a lesser or greater degree. While this analysis can only state that this uncertainty exists for the simulations of the past, we suggest that this would also be true for future projections. As such, we find that these models, as they are, cannot easily be used to understand future changes in precipitation, but may have more utility for temperature projections, particularly if used for understanding the scale of change in temperature rather than absolute values.

Further improvements may come from better representation of topography and large climate-relevant features, such as Lake Malawi. Lake Malawi makes up over three-quarters of the eastern border and about one fifth of the country's total area (Eccles, 1974). The Great Rift Valley passes through the country from north to south causing elevations to rise from 37 meters above sea level where the Shire River meets the border of Mozambique, to 3003 meters above seas level at the peak of Mulanje Massif in the Shire Highlands (WorldAtlas, 2018). This diversity in Malawi's geography makes climate modelling difficult. When this heterogeneity is coupled with the relatively low resolution of the GCMs (used as is, or as boundary conditions in the RCMs), providing spatial analysis which would be useful on the scale of a local (e.g. <25km^2, UKCIP09) climate change impact assessments is not possible.

Impact assessments, including those using crop models, generally require higher spatial resolution inputs than those provided by GCMs (Niang et al., 2014). Kim and Yoo (2015) looked specifically at crop yield modelling in Korea and the impact that different spatial resolutions had on uncertainty levels of the meteorological inputs. It was found that the higher the spatial resolution the smaller the uncertainty, however the degree of uncertainty varied depending on the climatic variable in question (ibid.). Kim and Yoo (2015) also highlighted that the impact of this uncertainty would be more problematic for drawing conclusions from the models associated with those crops most sensitive to small changes. Their study compared climate models with 1km^2 and 12.5km^2 spatial resolution. Based on this, we suggest that the climate models currently available for Malawi would have even higher levels of uncertainty due to their lower spatial resolution (approximately 50km^2 and 124km^2 to 310km^2 for the RCMs and GCMs respectively).

Kim and Yoo (2015) also reported that there were higher levels of uncertainty in climatic variables in the area near the ocean. While Malawi is landlocked, Lake Malawi, the ninth largest lake in the world (Makwinja et al, 2007), is likely to have a significant impact on the local climate. Studies from many regions of the world have shown large lakes to have a significant impact on the local water and energy cycles (Long et al., 2007, Samuelsson et al., 2010, Wen et al., 2015). As such, the inclusion of large bodies of water, including lakes, creates a significant improvement in the outputs of simulations for local temperature, evaporation and precipitation, compared to models which do not consider the lake effect (Long et al., 2007). The likely influence of Lake Malawi on the local climate is supported by our spatial analysis of the degree of bias in both the precipitation and temperature variables, with high levels of bias seen in areas closest to the lake boundary. As the RCMs assessed here are atmospheric models they will not include the full complexity of the climatic interaction with Lake Malawi. Expanding the RCMs into coupled atmospheric-lake models would likely improve the accuracy of the outputs. This suggestion is supported by the findings of studies that found that coupling a freshwater lake model to a RCM improved the performance of the model for simulating precipitation and temperature over the African Great Lakes area and Malawi more specifically (Thiery et al., 2015, Diallo et al., 2017a, Diallo et al., 2017b).

In line with other studies which have assessed the performance of African CORDEX models (Kalognomou et al., 2013, Endris et al., 2013, Kim et al., 2014, Nikulin et al., 2012), this study shows that the multimodel average, or ensemble simulation, generally outperforms individual model simulations for both precipitation and temperature variables. We suggest that future studies can use either the ensemble RCMs or ensemble GCMs analysed in this paper to understand the trends and degree of change seen in Malawi's future temperature, however the RCMs do allow for greater spatial understanding and should therefore be preferentially used. It should be noted that the absolute temperature that these models predict is likely to be less accurate, particularly for mean and maximum temperatures. With respect to precipitation and frequency of meteorological droughts, the authors suggest that any current impact and adaptation plans consider a range of potential outcomes, including the maximum, minimum and average projections from the models, as well as a business as usual projection. This uncertainty highlights the need for further development in climate modelling for Malawi and suggests that impact assessment and adaptation planning would benefit from being designed and tested against a range of future scenarios.

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Figure 1: Map a) shows the data boundary used in this assessment. Black lines show national borders and the shaded grey-blue area is Lake Malawi. Letters on the map represent different countries; A – Malawi, B – Tanzania, C – Mozambique, and D – Zambia. Map b) shows elevation data for Malawi in meters above sea-level at a 0.25-degree (approximately 27km^2) resolution.

Figure 2: Average observed and simulated a) annual and b) monthly precipitation in Malawi for 1961-2005 and 1990-2005 respectively. The grey area represents the range of observed data.

Figure 3: Individual and average ensemble GCM-driven RCMs run for annual, monthly and seasonal precipitation in Malawi from 1961-2005. The grey area represents the range of the observed data.

Figure 4: Taylor diagrams showing annual and seasonal precipitation for Malawi from 1990-2005. The red star denotes the observed data for the relevant period, and the individual ERA-interim driven RCMs, GCM-driven RCMs, and GCMs are denoted by black, cyan, and magenta numbers respectively. The ensemble of each group is shown by a circle in the same colour.

Figure 5: Average group simulated bias in Malawi's precipitation annually and by season relative to observed data. The graphs in the left-hand column are for the time period of 1990-2005 while those in the central and right column are for 1961-2005. Please note that the colour bar is different for each season and annually.

Figure 6: Average observed and simulated i) mean, ii) maximum and iii) minimum temperature in Malawi. The graphs in column a) represent annual data and those in column b) monthly data for 1961-2005 and 1990-2005 respectively. The grey area represents the range of observed data.

Figure 7: Taylor diagrams showing annual (i) and seasonal (ii=SON, iii=DJF, iv=MAM, v=JJA) a) mean, b) maximum, and c) minimum temperature for Malawi from 1990-2005. The red star denotes the observed data for the relevant period, and the individual ERA-interim driven RCMs, GCM-driven RCMs, and GCMs are denoted by black, cyan, and magenta numbers respectively. The ensemble of each group is shown by a circle in the same colour.

Table 1: Observed Data

Dataset	Variable Used	Resolution	Time-Period Available	Source	Reference
Climate Research Unit (CRU) version 4.0	Tas, TasMax and TasMin	0.5° Monthly Land Only	1901-2015	Gridded Station Data	(Harris et al., 2014)
	Pr				
University of Delaware (UDel) version 4.01	Tas	0.5° Monthly Land Only	1901-2010	Gridded Station Data	(Willmott and Matsuura, 2001)
	Pr				
Global Precipitation Climatology Centre (GPCC) version 7	Pr	1.0° Monthly	1901-2010	Satellite and Station Data	(Schneider et al., 2015)

Table 2: Reanalysed (ERA-interim driven) and Simulated (GCM-driven) Regional Climate Models (RCMs)

RCM	Institution	Lateral Boundary Conditions	Reference
CCLM4-8-17_v1	Climate Limited-area Modelling Community (CLMcom)	ERA-interim	(COSMO, 2017)
		CNRM-CM5 r1i1p1	
		HadGEM2-ES r1i1p1	
		EC-EARTH r12i1p1	
		MPI-ESM-LR r1i1p1	
HIRHAM5_v2	Danmarks Meteorologiske Insitut (DMI)	ERA-interim	(Christensen et al., 2007)
		EC-EARTH r3i1p1	
		NORESM1-M r1i1p1	
RACMO22T_v1	Koninklijk Nederlands Meteorologisch Instituut (KNMI)	ERA-interim	(van Meijgaard et al., 2008)
		HadGEM2-ES r1i1p1	
		EC-EARTH r12i1p1	
RCA4_v1	Sveriges Meteorologiska och Hydrologiska Institut (SMHI)	ERA-interim	(Samuelsson et al., 2015)
		CanESM2 r1i1p1	
		CNRM-CM5 r1i1p1	
		CSIRO-MK3-6-0 r1i1p1	
		GFDL-ESM2M r1i1p1	
		IPSL-CM5A-MR r1i1p1	
		HadGEM2-ES r1i1p1	
		EC-EARTH r12i1p1	
		MIROC5 r1i1p1	
		MPI-ESM-LR r1i1p1	
		NORESM1-M r1i1p1	
REMO2009_v1	Climate Service Centre Germany (CSC) and Max Planck Institut (MPI)	ERA-interim	(Jacob et al., 2012)
		EC-EARTH r12i1p1	
		MPI-ESM-LR r1i1p1	
CanRCM4_r2	Canadian Centre for Climate Modelling and Analysis (CCCma)	ERA-interim	(Scinocca et al., 2016)
		CanESM2 r1i1p1	

Table 3: Simulated General Circulation Models (GCMs)

GCM	Institution	Ensemble	Resolution		Reference
			Latitude	Longitude	
CanESM2	Canadian Centre for Climate Modelling and Analysis (CCCma)	r1i1p1	2.7906	2.8125	(CCCma, 2017b)
CNRM-CM5	Centre Européen de Recherche et de Formation Avancée en Calcul Scientifique (CERFACS)	r1i1p1	1.40008	1.40625	(Voldoire et al., 2013)
CSIRO-MK3-6-0	Commonwealth Scientific and Industrial Research Organisation (CSIRO)	r1i1p1	1.8653	1.875	(Jeffrey et al., 2013)
EC-EARTH	Sveriges Meteorologiska och Hydrologiska Institut (SMHI)	r12i1p1	1.1215	1.125	(Hazeleger et al., 2010)
	Danmarks Meteorologiske Insitut (DMI)	r3i1p1			
GFDL-ESM2M	National Oceanic and Atmospheric Administration (NOAA)	r1i1p1	2.0225	2.5	(Dunne et al., 2012, Dunne et al., 2013)
HadGEM2-ES	Met Office Hadley Centre	r1i1p1	1.25	1.875	(Collins et al., 2011)
IPSL-CM5A-MR	Institut Pierre Simon Laplace (IPSL)	r1i1p1	1.2676	2.5	(Dufresne et al., 2013)
MIROC5	Atmospheric and Ocean Research Institute (AORI)	r1i1p1	1.4008	1.40625	(Watanabe et al., 2010)
MPI-ESM-LR	Max Planck Institute for Meteorology (MPI)	r1i1p1	1.8653	1.875	(Giorgetta et al., 2013)
NORESM1-M	EarthClim	r1i1p1	1.8947	2.5	(Bentsen et al., 2013, Iversen et al., 2013)

Table 4: Observed average monthly precipitation in Malawi from 1961 to 2005 (mm per month)

	J	F	M	A	M	J	J	A	S	O	N	D
Precipitation	229.3	191.1	186.6	98.2	26.0	11.0	10.3	6.7	6.1	17.7	75.8	178.1

Table 5: Regression slope of Precipitation Rate for observed and ERA-interim driven RCMs in Malawi between 1990 and 2008

Dataset	Year	DJF	MAM	JJA	SON
Observed	5.13	13.83	3.47	0.31	2.80
CCLM4-8-17_v1 ERA-interim	4.12	12.24	4.47	0.14	-0.37
HIRHAM5_v2 ERA-interim	-3.37	-8.14	0.39	-0.38	-5.37
RACMO22T_v1 ERA-interim	-0.50	-1.19	3.91	0.66	-5.36
RCA4_v1 ERA-interim	1.25	-0.51	6.80	-0.66	-0.64
REMO2009_v1 ERA-interim	-1.82	-4.53	-7.55	-0.55	5.34
CanRCM4_r2 ERA-interim	-2.77	-26.66	15.58	0.62	-0.60
Average ERA-Interim	-0.52	-4.80	3.93	-0.03	-1.16

Table 6: Regression slope of Precipitation Rate for observed data, GCM-driven RCMs and simulated GCMs in Malawi between 1961 and 2005

Dataset		**Year**	**DJF**	**MAM**	**JJA**	**SON**
Observed		-2.74	-3.83	-3.95	-0.13	-3.36
GCM-driven RCM	CCLM4-8-17_v1 CNRM-CM5 r1i1p1	0.92	2.16	1.03	0.35	0.16
	CCLM4-8-17_v1 HadGEM2-ES r1i1p1	-0.26	-1.34	1.62	0.40	-1.70
	CCLM4-8-17_v1 EC-EARTH r12i1p1	1.27	3.91	0.87	-0.02	0.33
	CCLM4-8-17_v1 MPI-ESM-LR r1i1p1	-0.55	1.45	-1.53	-0.13	-1.99
	HIRHAM5_v2 EC-EARTH r3i1p1	-0.72	-2.09	-0.46	0.12	-0.47
	HIRHAM5_v2 NORESM1-M r1i1p1	0.02	1.36	-0.41	0.36	-1.21
	RACMO22T_v1 HadGEM2-ES r1i1p1	-0.05	2.57	-1.34	0.31	-1.72
	RACMO22T_v1 EC-EARTH r12i1p1	0.96	2.35	1.37	0.23	-0.12
	RCA4_v1 CanESM2 r1i1p1	-1.19	0.44	-2.93	0.24	-2.49
	RCA4_v1 CNRM-CM5 r1i1p1	1.05	3.68	-0.50	0.49	0.54
	RCA4_v1 CSIRO-MK3-6-0 r1i1p1	0.22	-0.64	0.67	-0.26	1.10
	RCA4_v1 GFDL-ESM2M r1i1p1	-0.96	-1.87	-0.81	-0.26	-0.89
	RCA4_v1 IPSL-CM5A-MR r1i1p1	0.21	2.49	-0.40	-0.25	-1.01
	RCA4_v1 HadGEM2-ES r1i1p1	0.49	1.73	0.06	-0.18	0.33
	RCA4_v1 EC-EARTH r12i1p1	0.89	3.03	-2.06	0.59	2.00
	RCA4_v1 MIROC5 r1i1p1	-2.92	-5.77	-1.01	-0.54	-4.37
	RCA4_v1 MPI-ESM-LR r1i1p1	-3.12	-2.07	-4.59	-0.44	-5.37
	RCA4_v1 NORESM1-M r1i1p1	-0.47	-1.77	1.99	0.43	-2.52
	REMO2009_v1 EC-EARTH r12i1p1	-0.38	-0.49	-0.79	0.03	-0.26
	REMO2009_v1 MPI-ESM-LR r1i1p1	1.37	0.74	3.73	0.05	0.96
	CanRCM4_r2 CanESM2 r1i1p1	-0.84	-1.23	-1.23	-0.38	-0.53
	Average RCM	-0.19	0.41	-0.32	0.06	-0.92
GCM	CanESM2 r1i1p1	0.67	1.87	1.88	-0.24	-0.81
	CNRM-CM5 r1i1p1	3.36	2.52	6.35	0.49	4.10
	CSIRO-MK3-6-0 r1i1p1	-0.58	-4.19	2.20	-0.27	-0.04
	EC-EARTH r12i1p1	0.47	1.89	0.82	0.21	-1.05
	EC-EARTH r3i1p1	2.26	6.69	0.28	-0.06	2.12
	GFDL-ESM2M r1i1p1	1.85	7.17	0.89	-1.23	0.57
	HadGEM2-ES r1i1p1	-0.83	-0.47	-2.32	-0.48	2.17
	IPSL-CM5A-MR r1i1p1	-1.28	-2.90	-2.95	0.19	0.56
	MIROC5 r1i1p1	-3.39	-4.63	-4.87	-1.12	-2.94
	MPI-ESM-LR r1i1p1	-0.33	-0.80	1.22	-0.23	-1.49
	NORESM1-M r1i1p1	2.91	6.62	5.69	0.25	-0.91
	Average GCM	0.47	1.25	0.83	-0.23	0.21

Table 7: Observed monthly mean (Tas), maximum (TasMax) and minimum (TasMin) surface temperatures in Malawi from 1961 to 2005 (^oC)

	J	F	M	A	M	J	J	A	S	O	N	D
Tas	23.7	23.7	23.5	22.6	20.9	19.1	18.7	20.1	22.4	24.4	24.7	24.0
TasMax	28.8	28.8	29.1	28.2	27.5	26.2	25.6	27.4	29.7	31.2	31.3	29.6
TasMin	19.4	19.4	19.1	17.7	15.5	13.2	12.4	13.8	15.9	18.1	19.5	19.5

Highlights

- The performance of the RCMs is highly influenced by their boundary conditions
- RCMs and GCMs performed similarly well, but RCMs allow for better spatial analysis
- Current models are suitable for projecting temperature trends but not precipitation
- Future plans will need to consider a range of future precipitation scenarios
- Model improvements would allow for better impact assessment and adaptation planning

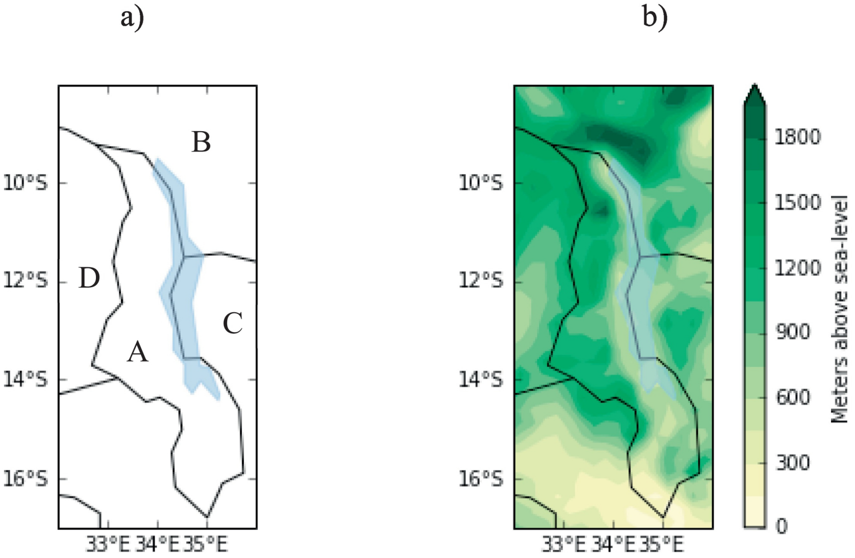
a)
b)
B
D
C
A
10°S
12°S
14°S
16°S
33°E 34°E 35°E
1800
1500
1200
900
600
300
0
Meters above sea-level

Figure 1

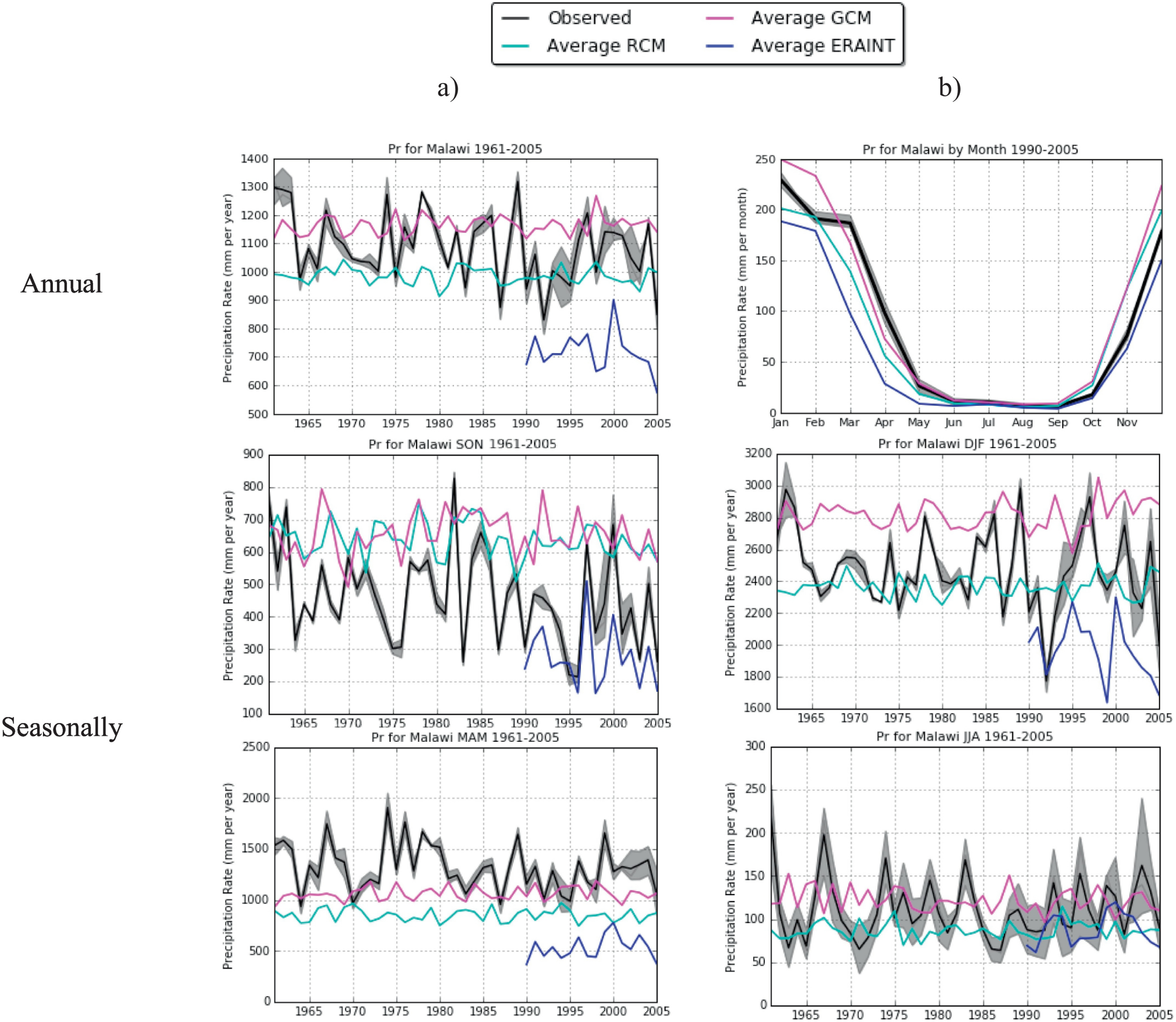
Observed
Average RCM
Average GCM
Average ERAINT
a)
b)
Annual
Seasonally
Pr for Malawi 1961-2005
Pr for Malawi by Month 1990-2005
Pr for Malawi SON 1961-2005
Pr for Malawi DJF 1961-2005
Pr for Malawi MAM 1961-2005
Pr for Malawi JJA 1961-2005
Precipitation Rate (mm per year)
Precipitation Rate (mm per month)
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov

Figure 2

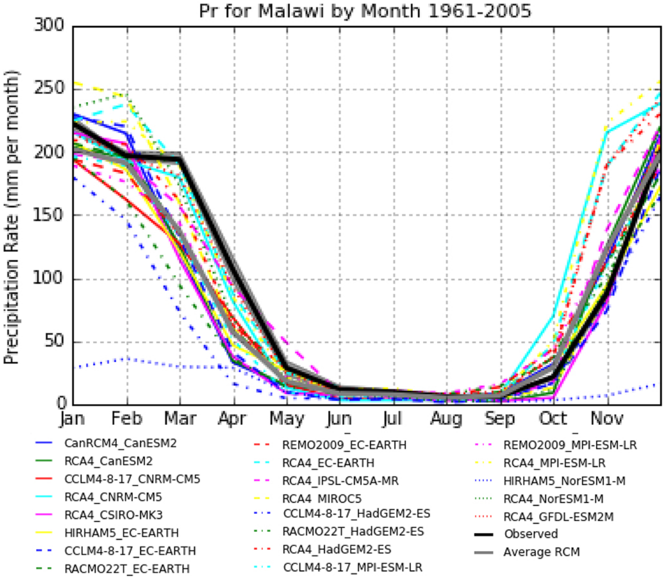
Pr for Malawi by Month 1961-2005
Precipitation Rate (mm per month)
300
250
200
150
100
50
0
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
CanRCM4_CanESM2
RCA4_CanESM2
CCLM4-8-17_CNRM-CM5
RCA4_CNRM-CM5
RCA4_CSIRO-MK3
HIRHAM5_EC-EARTH
CCLM4-8-17_EC-EARTH
RACMO22T_EC-EARTH
REMO2009_EC-EARTH
RCA4_EC-EARTH
RCA4_IPSL-CM5A-MR
RCA4_MIROC5
CCLM4-8-17_HadGEM2-ES
RACMO22T_HadGEM2-ES
RCA4_HadGEM2-ES
CCLM4-8-17_MPI-ESM-LR
REMO2009_MPI-ESM-LR
RCA4_MPI-ESM-LR
HIRHAM5_NorESM1-M
RCA4_NorESM1-M
RCA4_GFDL-ESM2M
Observed
Average RCM

Figure 3

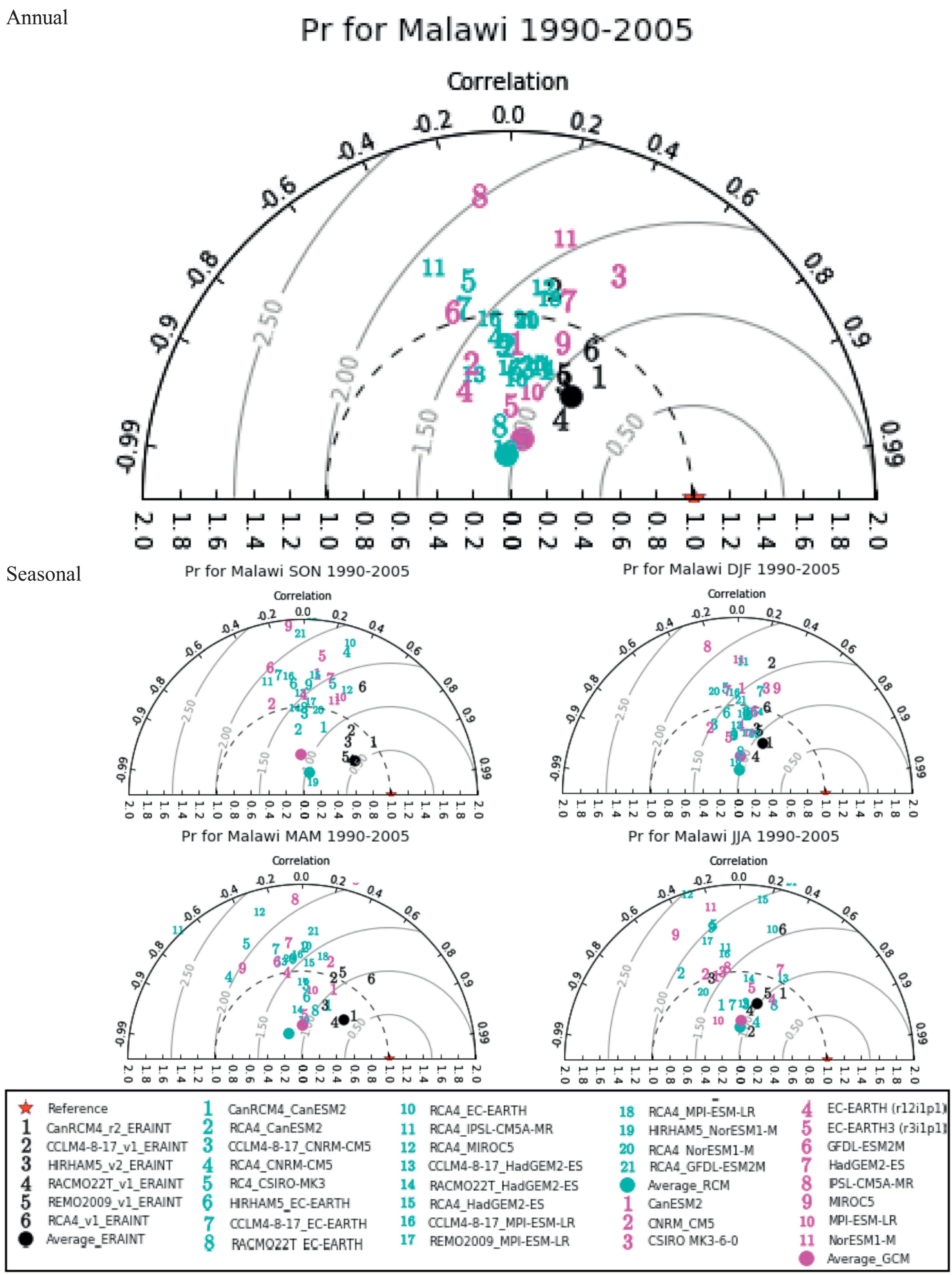
Annual
Pr for Malawi 1990-2005
Correlation
Seasonal
Pr for Malawi SON 1990-2005
Pr for Malawi DJF 1990-2005
Pr for Malawi MAM 1990-2005
Pr for Malawi JJA 1990-2005
Reference
1 CanRCM4_r2_ERAINT
2 CCLM4-8-17_v1_ERAINT
3 HIRHAM5_v2_ERAINT
4 RACMO22T_v1_ERAINT
5 REMO2009_v1_ERAINT
6 RCA4_v1_ERAINT
Average_ERAINT
1 CanRCM4_CanESM2
2 RCA4_CanESM2
3 CCLM4-8-17_CNRM-CM5
4 RCA4_CNRM-CM5
5 RC4_CSIRO-MK3
6 HIRHAM5_EC-EARTH
7 CCLM4-8-17_EC-EARTH
8 RACMO22T_EC-EARTH
10 RCA4_EC-EARTH
11 RCA4_IPSL-CM5A-MR
12 RCA4_MIROC5
13 CCLM4-8-17_HadGEM2-ES
14 RACMO22T_HadGEM2-ES
15 RCA4_HadGEM2-ES
16 CCLM4-8-17_MPI-ESM-LR
17 REMO2009_MPI-ESM-LR
18 RCA4_MPI-ESM-LR
19 HIRHAM5_NorESM1-M
20 RCA4_NorESM1-M
21 RCA4_GFDL-ESM2M
Average_RCM
1 CanESM2
2 CNRM_CM5
3 CSIRO MK3-6-0
4 EC-EARTH (r12i1p1)
5 EC-EARTH3 (r3i1p1)
6 GFDL-ESM2M
7 HadGEM2-ES
8 IPSL-CM5A-MR
9 MIROC5
10 MPI-ESM-LR
11 NorESM1-M
Average_GCM

Figure 4

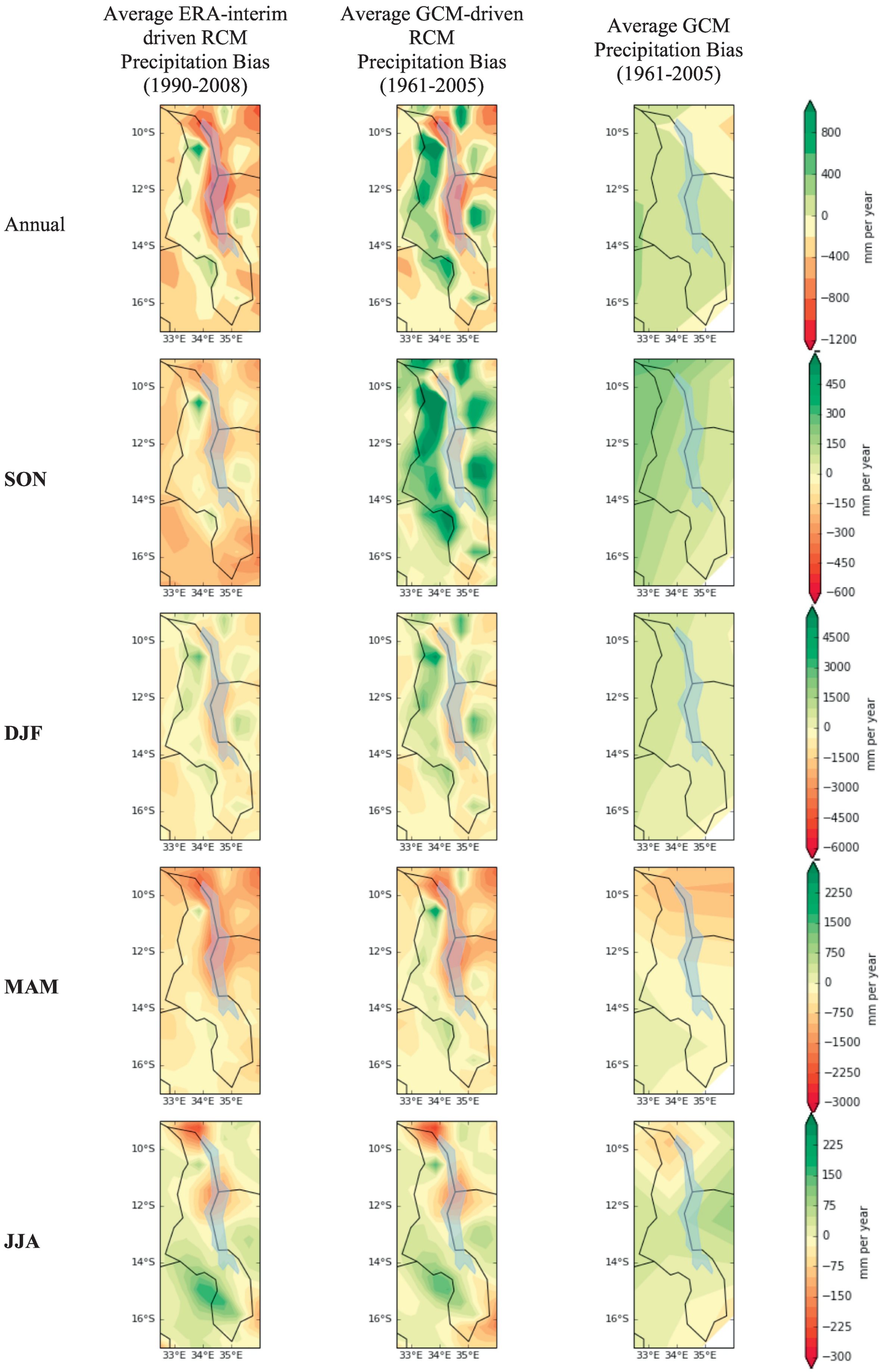
Average ERA-interim driven RCM Precipitation Bias (1990-2008)
Average GCM-driven RCM Precipitation Bias (1961-2005)
Average GCM Precipitation Bias (1961-2005)
Annual
SON
DJF
MAM
JJA
10°S
12°S
14°S
16°S
33°E 34°E 35°E
800
400
0
−400
−800
−1200
450
300
150
0
−150
−300
−450
−600
4500
3000
1500
0
−1500
−3000
−4500
−6000
2250
1500
750
0
−750
−1500
−2250
−3000
225
150
75
0
−75
−150
−225
−300
mm per year

Figure 5

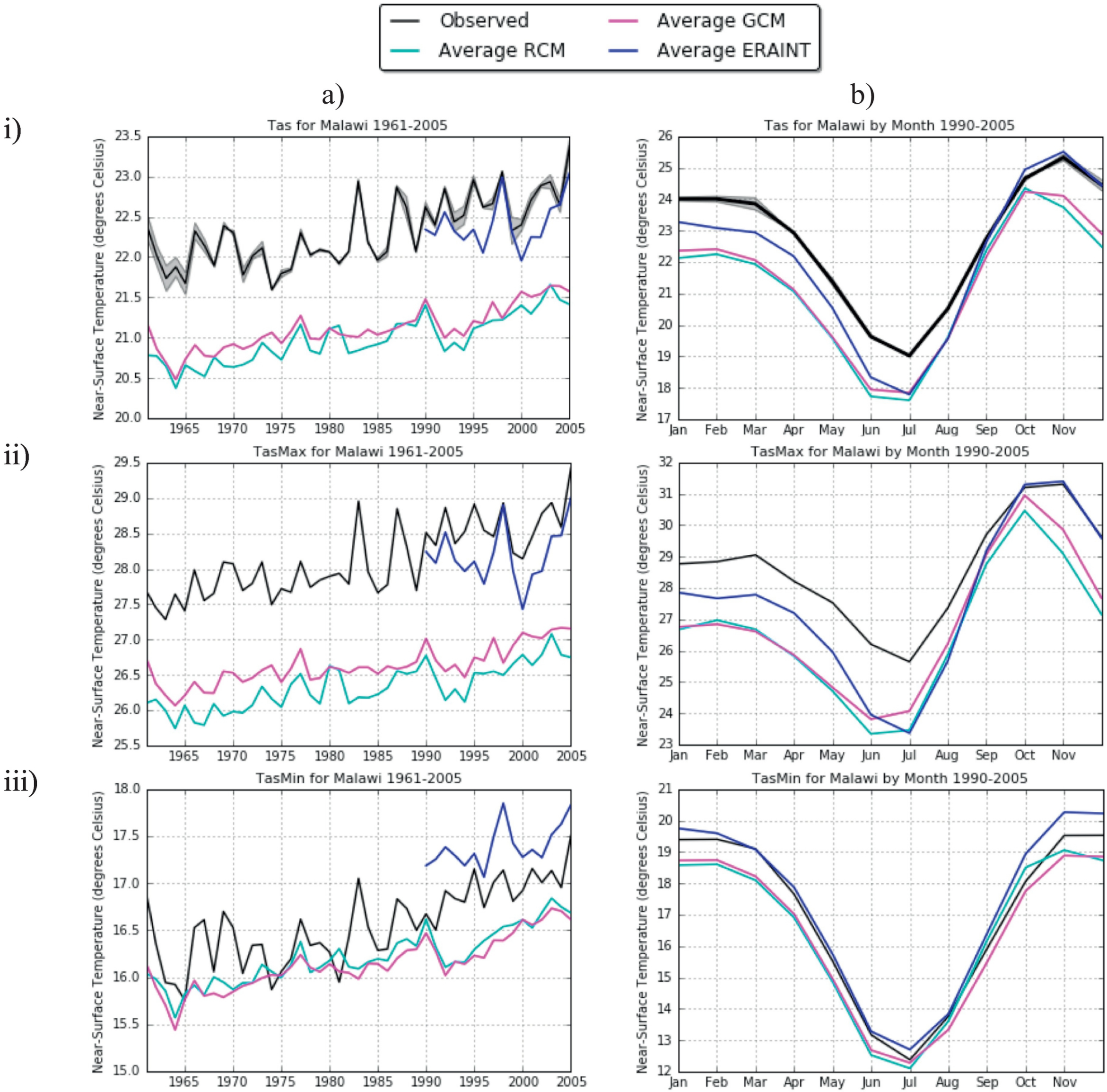
Observed
Average GCM
Average RCM
Average ERAINT
a)
b)
i)
ii)
iii)
Tas for Malawi 1961-2005
Tas for Malawi by Month 1990-2005
TasMax for Malawi 1961-2005
TasMax for Malawi by Month 1990-2005
TasMin for Malawi 1961-2005
TasMin for Malawi by Month 1990-2005
Near-Surface Temperature (degrees Celsius)
1965
1970
1975
1980
1985
1990
1995
2000
2005
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov

Figure 6

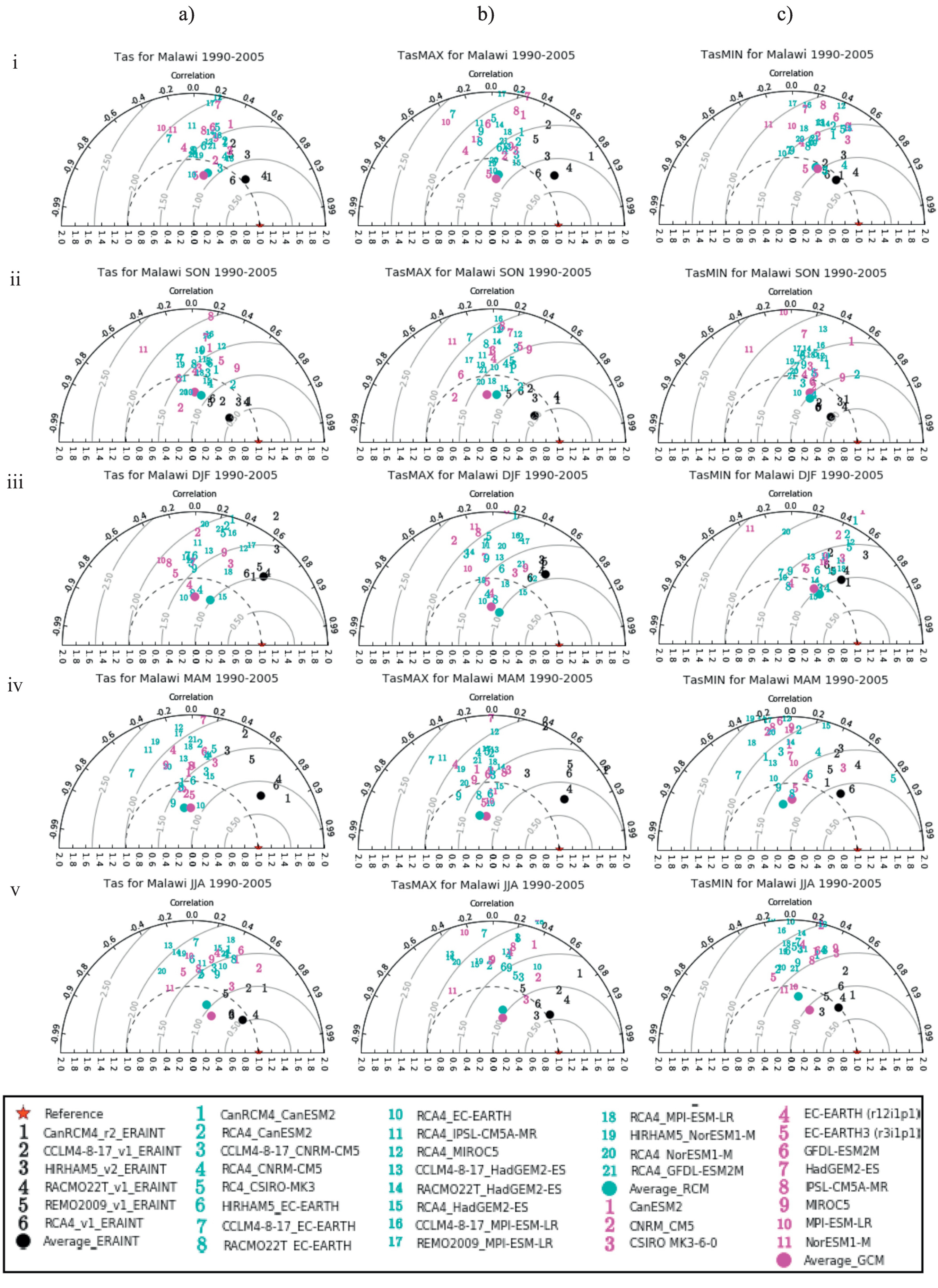
a)
b)
c)
i
ii
iii
iv
v
Tas for Malawi 1990-2005
TasMAX for Malawi 1990-2005
TasMIN for Malawi 1990-2005
Tas for Malawi SON 1990-2005
TasMAX for Malawi SON 1990-2005
TasMIN for Malawi SON 1990-2005
Tas for Malawi DJF 1990-2005
TasMAX for Malawi DJF 1990-2005
TasMIN for Malawi DJF 1990-2005
Tas for Malawi MAM 1990-2005
TasMAX for Malawi MAM 1990-2005
TasMIN for Malawi MAM 1990-2005
Tas for Malawi JJA 1990-2005
TasMAX for Malawi JJA 1990-2005
TasMIN for Malawi JJA 1990-2005
Correlation
Reference
1 CanRCM4_r2_ERAINT
2 CCLM4-8-17_v1_ERAINT
3 HIRHAM5_v2_ERAINT
4 RACMO22T_v1_ERAINT
5 REMO2009_v1_ERAINT
6 RCA4_v1_ERAINT
Average_ERAINT
1 CanRCM4_CanESM2
2 RCA4_CanESM2
3 CCLM4-8-17_CNRM-CM5
4 RCA4_CNRM-CM5
5 RC4_CSIRO-MK3
6 HIRHAM5_EC-EARTH
7 CCLM4-8-17_EC-EARTH
8 RACMO22T EC-EARTH
10 RCA4_EC-EARTH
11 RCA4_IPSL-CM5A-MR
12 RCA4_MIROC5
13 CCLM4-8-17_HadGEM2-ES
14 RACMO22T_HadGEM2-ES
15 RCA4_HadGEM2-ES
16 CCLM4-8-17_MPI-ESM-LR
17 REMO2009_MPI-ESM-LR
18 RCA4_MPI-ESM-LR
19 HIRHAM5_NorESM1-M
20 RCA4 NorESM1-M
21 RCA4_GFDL-ESM2M
Average_RCM
1 CanESM2
2 CNRM_CM5
3 CSIRO MK3-6-0
4 EC-EARTH (r12i1p1)
5 EC-EARTH3 (r3i1p1)
6 GFDL-ESM2M
7 HadGEM2-ES
8 IPSL-CM5A-MR
9 MIROC5
10 MPI-ESM-LR
11 NorESM1-M
Average_GCM

Figure 7