Analysis of precipitation based on ensembles of regional climate model simulations and observational databases over Ethiopia for the period 1989–2008

Daniel T. Reda,a* Agizew N. Engida,b Dereje H. Asfawb and Rafiq Hamdic

a Department of Physics, College of Natural Science, Addis Ababa University, Ethiopia
b School of Civil and Environmental Engineering, Addis Ababa Institute of Technology, Addis Ababa University, Ethiopia
c Royal Meteorological Institute, Brussels, Belgium

ABSTRACT: This study examines the performance of multimodel numerical simulations and multiobservational databases focusing on seasonal cycles and spatial variations of precipitation over Ethiopia. Seven regional climate models (RCMs) driven by the European Center for Medium Range Weather Forecasting (ECMWF) Interim reanalysis (ERA-Interim) and generated in the framework of COordinated Regional climate Downscaling EXperiment (CORDEX) project, and four observational databases computed using different interpolation techniques and blending strategies were evaluated against typical observational database produced by Climate Research Unit (CRU) over Ethiopia on monthly basis. All were produced at 48.8 km grid resolution for the period 1989–2008. The preliminary results showed that ensembles [multimodel ensemble (MME) + multiobservational ensemble (MOE)] were as good as CRU in reproducing the temporal variability and the geographical distribution of precipitation. Comparison of seasonal means and temporal correlation results revealed that there were good agreements between ensembles and CRU at each grid point and in close proximity to each other. Results of rotated principal components (RPCs), rotated empirical orthogonal functions (REOFs), and the associated power spectra showed that every ensemble’s element was able to simulate the seasonal cycles and homogeneous precipitation zones of CRU reasonably well. Excessive and deficient rainfall periods, which were seen in every ensemble’s RPCs, matched CRU historical records.

KEY WORDS CORDEX; precipitation; regional climate model

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1. Background

Climate models are perpetually ameliorated and upgraded to higher and higher grid resolution with the intention of reproducing climate variables at finer scale. However, as climate model resolution tends to be finer, the noise on grid cells is likely to happen. Uncertainty in climate model is becoming much of the present interest as poor performance in present climate conditions is linked with outliers in the future projection (Knutti et al., 2010; Brands et al., 2011). Despite the fact that RCMs are downscaling tools aspired to upgrade the modelling of local physical processes, they are highly sensitive to model formulation, grid resolution, numerical schemes, and other physical parameterizations and result, therefore, in differences in downscaling skills (Fowler and Ekström, 2009; Maraun et al., 2010). There is growing evidence that regions and seasons showing the greatest model biases in the simulation of climate variables are often those with the greatest intermodel differences (Frei et al., 2006; Fowler et al., 2007; Maraun et al., 2010). Before using RCMs for future studies, it is believed that they should pass through some evaluation mechanisms. To address this issue, several climate modelling groups from around the world have been downscaling global climate models (GCMs) to regional scale using their own model setup. The aim is to offer qualified downscaled model outputs for recent historical and 21st century projections. This will not only let one to have rigorous climate features and can utilize the information as input into further climate impact and adaptation studies but also allow us to investigate the applicability of models to our region, Ethiopia. On top of that, it enables us to know which models are more liable to resolve local forcing and capture certain climate features than others as different models have different strengths and weaknesses, and there is usually not one obviously best model to be used for all climate variables and all impact and adaptation studies (Christensen and Christensen, 2007; Jacob et al., 2007; Maraun et al., 2010).

An improved approach for cross checking a set of regional climate models is the COordinated Regional Climate Downscaling Experiment (CORDEX) project (http://wcrp-cordex.ipsl.jussieu.fr/). It is an initiative of the World Climate Research Program (WCRP) performed with the intention of producing an ensemble of high-resolution climate change projections by downscaling GCM
simulations from Coupled Model Intercomparison Project Phase 5 (CMIP5) data archive (Jones et al., 2011). The major aims of the CORDEX initiative are to provide a quality controlled dataset of downscaled information, coordinated model evaluation framework, and an interface to the applicants of the climate simulations for further climate change impact, adaptation, and mitigation studies (Giorgi et al., 2009).

Recent analyses in relation to CORDEX simulations over Africa can be found in Nikulin et al. (2012), Hernández-Díaz et al. (2013), and Jacob et al. (2012). Nikulin et al. (2012) evaluate the ability of ten RCMs over Africa and conclude that all RCMs simulate the seasonal mean and annual cycle quite accurately. Likewise, it is verified that the mean of multimodel outputs do better than individual simulation. Hernández-Díaz et al. (2013) strengthen the achievement of Nikulin et al. (2012). They successfully reproduce the overall features of geographical and seasonal distribution over most Africa. In their report, CORDEX simulations succeed in reproducing the average distribution of precipitation and its large geographical differences. Jacob et al. (2012) have integrated REGional MOdelf (REMO) over six CORDEX continents and found that REMO is well suited to examine projected future changes in all these domains in spite of wet and dry biases appear over the mountainous regions and East Africa, respectively. On the other hand, the African Monsoon Multidisciplinary Analysis-Model Intercomparison Project (AMMA-MIP) provides contribution relevant to CORDEX and achieves good correlation between the accumulated rainfall over the Sahel and the latitude of the African Easterly Jet (Ruti et al., 2011). Ensemble outputs from CORDEX experiment are not only a compulsory for climate studies, and a roadmap to adaptation and mitigation strategies but also good source of data for us to apply them to our region, Ethiopia, where climate change is already observed (Philander, 2008). Ethiopia (Figure 1) is located in eastern Africa along the continent’s Great Rift Valley. It is situated between 3°–15°N and 33°–48°E. The country has an area of 1,221,900 km² with physiographic features of: massive highland complex of mountains, dissected plateaus divided by the Great Rift Valley, and lowlands, steppes, or semi-desert surrounding the plateaus. The great variety of terrain determines wide variations in climate. Forty per cent of the country’s land area is categorized as highland over 1500 m above sea level. The Great East African Rift Valley that runs from southwest to northeast bisects the Ethiopian Plateau into the northwestern highlands and the southeastern highlands. The northwestern highlands are considerably more extensive and rugged. Topography ranges from several very high mountain ranges (the Semien Mountains and the Mendeblo Mountains) to one of the lowest area (Danakil Depression so-called Dalol) of land in Africa. All of Ethiopia’s rivers originate from the highlands and flow outward in many directions through deep gorges. Most prominent is the Blue Nile, the country’s biggest river, whose tributaries supply two-thirds of the Nile River’s flow. The Blue Nile, the Tekezé, and the Baro rivers account for about half of the country’s water outflow. In the northern half of the Great Rift Valley flows the Awash River. The Awash flows east and vanishes in the saline lakes near the border with Djibouti. The south-east is drained by the Ganale and Shebelle Rivers into Somalia, and the Omo River in southwest drains into Lake Rudolf in Kenya. The terrain diversity is fundamental to the regional variations in Ethiopia climate. This complex terrain together with geographical locations cause high spatial variability in precipitation, with the seasonal cycle, the factors governing interannual variability and the annual total all exhibiting large variability within the country (Diro et al., 2011a).

Climate of Ethiopia is typical of equatorial regions but topography complicates its pattern and character. It induces diverse microclimates ranging from hot desert over the lowlands to cool, very wet over highlands (Nicholson, 1996; Slengo et al., 2005; Dinku et al., 2007; Segele et al., 2009). Ethiopia’s rainfall is highly variable both in amount and distribution across regions and seasons. Haile (1988) and Bekele (1997) report that the seasonal and annual precipitation variation over Ethiopia is the result of large-scale changes in macroscale pressure systems and monsoon flows. The broad scale spatial variation of precipitation is highly influenced by the changes in intensity, position and direction of the rain-producing systems (Camberlin, 1995, 1997; Grist and Nicholson, 2001; Segele and Lamb, 2005; Segele et al., 2009). However, the fine-scale spatial distribution of precipitation in East Africa is significantly influenced by topography (NMSA, 1996; Slengo et al., 2005). So far, three well-known seasons are identified in Ethiopia. The first is the main rainy season from June to September; the second is the dry season from November to January, and the third is the small rainy season from February/March to May known locally as Kiremt/Summer, Bega, and Belg, respectively (NMSA, 1996). The northern and central western part of the country has a single rainy season June–September (Kiremt). Central and eastern Ethiopia has two rainy periods March–May (Belg) and Kiremt. Southern Ethiopia has two rainy seasons, the long rain (March–May) and the short rain (September/October–November).

Precipitation is a crucial resource in various socioeconomic activities, particularly for those African countries, which are predominantly relying on rain-fed agriculture (Philander, 2008). Farming in Ethiopia, practiced under the condition of inadequate and variable rainfall (Degefa and Berhanu, 2000; Dinku et al., 2007), is highly susceptible to climate variability and small rain perturbation. The Ethiopian economy has been affected by precipitation variability and long-term changes in both rainfall amount and distribution in recent years (Philander, 2008). Hastenrath et al. (2007) and Zeleke et al. (2013) prove that the region has recently witnessed frequent incidents of both excessive and deficient rainfall.

On the other hand, RCMs can simulate the trends of climate variability, identify extreme climate events, give precise temporal and spatial patterns of projected future climate, decompose superimposed microclimate air
masses, and ultimately serve us to alleviate problems associated with climate driven hazards. However, earlier works related to climate studies are very scarce over this region and can be summarized as follows: Segele et al. (2008) and Zeleke et al. (2013) achieve some successes in reproducing fine climate features using the International Centre for Theoretical Physics-REGiOnal Climate Model (ICTP-RegCM) over Ethiopia. Segele et al. (2008) customize and evaluate the performance of ICTP-RegCM in reproducing the Ethiopian summer rainfall variability. It is concluded that the ICTP-RegCM not only reproduces the spatial variability of dry and wet years but also correlates well with gauge data. Zeleke et al. (2013) confirm that ICTP-RegCM model simulates in satisfactory way most aspects of observed precipitation climatology including seasonal cycle and interannual variability. However, these researches have not assessed climate output variables in an integrated way based on set of numerical simulations. Therefore, careful examination on climate variability using ensembles of RCM outputs and observational databases has yet to be done over the least studied region, Ethiopia (IPCC, 2007).

This paper examines the ability of multiple model outputs and multiple observational databases in reproducing seasonal cycles, homogeneous zones, and most extreme years of precipitation over Ethiopia. Outcomes from this research will serve as a basis for future projection studies.

We integrated and evaluated two sets of precipitation products, namely multiobservational ensemble (MOE) and multimodel ensemble (MME). In this paper, the word ‘ensembles’ is utilized to represent both ensembles (MME and MOE) throughout the analyses. MME corresponds to coordinated high-resolution models (seven RCMs) simulated in the framework of CORDEX project whereas MOE represents a set of observational databases from different global sources. Multiple databases were included because all differed slightly as the consequence of lack of uniformity in station density, data availability and interpolation techniques. This allows us not only to visualize observation-to-observation, observation-to-model, and model-to-model similarities and differences, but also to provide inclusive assessment of ensembles in reproducing the present climate conditions. We put emphasis on the precipitation climate parameter because it has straight link to severe Africa droughts and humanitarian crisis as it was seen in recent years (Adikari and Yoshitani, 2009).

The paper is organized as follows. Section 2 presents the data used in the study. Section 3 gives a brief description of statistical techniques. Results and discussions are included in Section 4. Lastly, Section 5 summarizes the main points of the work.

2. Data

This work incorporated monthly mean precipitation from seven model outputs and four observational databases. Precipitation data matrix, \( Pr = (240 \times 980) \), was used as input for the analyses. It had 240 months covering

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Figure 1. Ethiopia-map (Source: www.freeworldmaps.net).
the period 1989–2008 and 980 grid points bounded by 3°–15°N, 33°–48°E at horizontal resolution of 0.44°.

2.1. Observational data

Observational precipitation datasets from Climate Research Unit (CRU), Global Precipitation Climatology Project (GPCP), gridded precipitation dataset based on rain gauges records (GAUGE), and Air Temperature and Precipitation data product from University of Delaware (ATP-UDEL) were used.

CRU database from the East Anglia (UK) University has produced 0.5° resolution dataset of monthly surface-based climate parameters covering the period 1901–2010 (New et al., 2002; Mitchell and Jones, 2005). Among these parameters, monthly mean precipitation was generated from available gauge datasets. As reference for ensembles validation, CRU rainfall was adopted for diagnosing the spatial and temporal precipitation variability, whereas GPCP, GAUGE, and UDEL together with the model outputs were cross-validated against CRU. GPCP is a global precipitation product found from multiple sources of observations. It is a blended dataset produced by optimally merging estimates computed from microwave, infrared, and sounder data observed by the international constellation of precipitation-related satellites and precipitation gauge analyses ( Huffman et al., 1997, Adler et al., 2003). Such merged observational product is essential for data poor region and where rainfall is highly variable (e.g. Ethiopia). CRU and GPCP had been originally computed at resolution of 0.5°. Later, we interpolated them from their earlier resolution, 0.5°, to grid spacing equals to that of the models resolution (0.44°). Interpolation of precipitation at unknown locations was based on Ordinary Kriging. As inputs to the Ordinary Kriging, the nearest four grid points surrounding the required value were used. A detail of the procedure followed by Ordinary Kriging is discussed in Section 3.3. UDEL precipitation dataset was produced by the University of Delaware, USA. It was created from a large number of stations, global historical climate network, and archive of Willmott and Matsuura (1995). The result consists of monthly global gridded high-resolution land data for precipitation.

The rain-gauge data in Ethiopia have numerous gaps in space and time and needs to be brought to the required model grid resolution (0.44°) under investigation. To handle the problem, spatial interpolation of observed data was performed by Ordinary Kriging accompanied by linear and spherical semi-variogram fittings over the region ( Davis, 1986). As an input to Ordinary Kriging, monthly rainfall at 300 rain gauge stations covering the period 1989–2008 was utilized. Interpolation at a point of interest was determined based on observed values using nearest data points enclosed by a circular domain centered at the required point. It was convenient to select domains bounded by concentric circles circumscribed around concentric squares, whose center (the required point) was the barycenter of the circles, and which had sides (latitude–longitude values) that were integral and half-integral multiple of the model’s grid resolution (0.44°). The inscribed squares, whose sides (latitude–longitude values) previously set to $/\times 0.22^\circ$ (where $l$ is non-zero positive integer), have diagonal lengths $0.22\sqrt{2}l$ which are always equal to twice of the circles radii $(0.11\sqrt{2}l)$ according to the Pythagorean theorem.

Interpolation was started by counting number of data points (number of stations with non-missed records) inside a circular domain centered at the point of interest. Initial radius of the circular area was assigned to $0.11\sqrt{2}$°. When the number of known values was below six, the common length of the latitude–longitude was increased simultaneously to $0.22\sqrt{2}$ then iteration continued till six or more points were found. We selected increment 0.11° and minimum sample size six (as stopping criterion to exit the iteration) considering the data gaps and the dynamic nature of the rainfall in the region.

The major part of Ethiopia was filled with interpolated values onto $0.44^\circ \times 0.44^\circ$ grid using this method. However, Kriging underestimated extrapolated values for unknown point of interest not bounded by the neighborhood data points. Moreover, it had no value for the periods where the number of data was below six. To minimize this error, spatial and temporal interpolation using Levenberg–Marquards fitting method was implemented. The interpolation was performed following the procedure described in Daniel and Alem (2009). Extrapolated and missed values were replaced by the results found from linear regression functions fitted to CRU data. Both temporal and spatial curve fittings were carried out supposing gauge as dependent variable and CRU (interpolated to 0.44°) as independent variable.

The temporal approach was used to fill rainfall data gaps in time for a given station. At a fixed location (at a given gauge-station), we considered temporal monthly rainfall records as predictands and CRU (i.e. CRU at geographical location closest to the station) monthly precipitations as predictors. Then, linear regression function was fitted to a graph constructed by predictand versus predictor, and linear regression coefficients were computed. Missed value of the station was filled by the result found from the fitted linear equation. Finally, this process was repeated for the remaining 299 gauge stations.

Spatial fitting was applied as an alternative to replace the extrapolated and underestimated data by Ordinary Kriging. Keeping time variable constant (at a given month), we supposed non-missed records of gauge stations as predictands and CRU data at geographical locations closest to the stations as predictors. Next, rainfall records versus CRU graph was fitted with linear regression function, and coefficients of the function were determined. The linear regression function was employed to compute precipitation at missed stations or underestimated locations at the given month. Finally, the procedure was repeated for the remaining 239 months.

2.2. Model data

WCRP has been organizing an international coordinated framework to produce an improved generation of regional
climate change projections around the world (Jones et al., 2011). In the framework of CORDEX project (http://cordex.dmi.dk), ensembles of regional climate simulations have been established for the entire African continent at a horizontal resolution of 0.44° × 0.44°. This is a good source of recent data with common resolution, output variables, domains, time, and format. The products were obtained from CORDEX experiment with kind permission from the project group. Seven model outputs were integrated from the experiment, namely University of Quebec At Montreal-Canadian Regional Climate Model (UQAM-CRCM5), Centre National de Recherche Méteorologique-Aire Limitée Adaptation dynamique Développement InterNational (CNRM-ALADIN52), Royal Netherlands Meteorological Institute-Regional Atmospheric Climate Model (KNMI-RACMO22T), International Centre for Theoretical Physics-REgional Climate Model version 3 (ICTP-RegCM3), Sweden’s Meteorological and Hydrological Institute-the Rossby Centre Regional Atmospheric Climate Model (SMHI-RCA4), Max Planck Institute for Meteorology-REgional Model (MPI-REMO), and Danish Meteorological Institute-the High Resolution Limited Area Model (DMI-HIRHAM5). The large-scale forcing of all RCMs was taken from ERA-Interim reanalysis at a horizontal resolution of 0.75° × 0.75° (Simmons et al., 2007; Uppala et al., 2008) followed by a downscaling to a resolution of 0.44° × 0.44° (48.8 × 48.8 km²) for the time period from January 1989 to December 2008.

3. Methods of analysis

Basic and advanced statistical techniques were applied to evaluate the ensembles performances. Mean, mean difference, Pearson correlation, and Spearman rank correlation analyses were incorporated in the basic statistical tools. Advanced statistical methods were Ordinary Kriging, rotated principal component analysis (RPCA), and power spectral analysis.

3.1. Mean and mean difference

Comparison of interseasonal precipitation variabilities were performed using seasonal means and mean differences. Averages of three rainy seasons, namely June–September (JJAS/Summer/Kiremt), March–May (MAM/Spring/Belg), and October–November (ON), were examined. Selection of seasons is in line with classifications by Gissila et al. (2004) and Korecha and Barnston (2007). These seasons were also chosen subjectively by visually classifying homogeneous precipitation regions. Uncertainties in seasonal means were explicitly computed by subtracting seasonal means of CRU from the corresponding seasonal means of each ensemble member at every grid point.

3.2. Correlations

Dependencies between the reference, CRU, and ensembles were analysed by employing Pearson and Spearman time correlations of monthly means at each grid point. Linear relationships between CRU and ensembles were determined using Pearson correlation. Monthly precipitations from CRU and each ensemble’s element were entered to the Pearson correlation formula at every grid point. However, Pearson values are only linear relations between two variables. Weak correlation indices do not necessarily mean that two variables are unrelated to each other. For this reason, Spearman correlation calculations were repeated for all data. Different procedure was followed to determine the nonlinear dependencies between the two precipitations. At a given grid point, the monthly precipitation data from CRU and ensemble member were separately positioned in ascending order of their values. Next, tied values were assigned ranks equal to the averages of their positions to give new ranked variables. Then, Spearman correlation was computed from these ranked variables using Pearson formula.

3.3. Ordinary Kriging

Ordinary Kriging was used to interpolate CRU, GAUGE, and GPCP precipitation products over Ethiopia. It was implemented to find precipitation value at unknown locations using a weighted average of known precipitation data (Davis, 1986). First, Euclidian distance matrix at constant month from geographical positions of known precipitation values was obtained. Afterward, experimental semi-variogram, which is defined as the sum of the squared differences between precipitation pairs separated by equal distance divided by two times the number of equal distances, was plotted against distance in a graph. Then both spherical and linear models were fitted to the experimental semi-variogram graph, and coefficients of either of the models were obtained. The model together with its coefficients which better fitted the experimental semi-variogram pattern was taken as gamma function.

The fitting process was performed based on Levenberg–Marquards approach. It is self-adjustable algorithm between two minimizing strategies: Gradient descent and Hessian methods. It enables us to find coefficients of any regression function fitted with observations after few iterations. See Daniel and Alem (2009) for more details. The previous distances found from Euclidian distance matrix were reinserted to the chosen model/gamma function. Subsequently, values of the weights, those that minimize the difference between estimated precipitation value and actual value, and Lagrange multiplier, parameter added to assure minimum possible estimation error, were found by solving simultaneous equations constructed from the values of the gamma function. Finally, the sum of the products of the weights and the input precipitation values were used to fill the unknown precipitation value.

3.4. Rotated principal component analysis

Principal component analysis (PCA) is a widely used method in atmospheric science (Fukuoka, 1951; Lorenz,
Here, it is used to determine dominant modes of seasonal and interannual precipitation variabilities, and to identify homogeneous rainfall regions. Before applying the PCA technique, the size of the input time-space precipitation matrix was reduced from \((240 \times 582)\) to \((240 \times 582)\). Out of 980 grid points, grids only inside political boundary were selected. This minimizes the influence of precipitation variabilities from neighbouring countries on the statistical results over Ethiopia. As input for the PCA, we used the standardized anomaly of the precipitation matrix. Principal components (PCs), eigenvectors (EOFs), and eigenvalues in PCA were computed using singular value decomposition (SVD) (Preisendorfer, 1988; Von Storch and Zwieters, 1999; Wilks, 2006). However, the PCs found from SVD are orthogonal to each other. These cause problem in interpretation if data compression by PCA is not the primary goal. Therefore, the orthogonality constraints on the PCs and EOFs were resolved using the most common approach in the orthogonal rotation called the varimax rotation method (Kaiser, 1958) to produce the desired REOFs and RPCs.

3.5. Spectral density

Spectral density associated with autoregressive model at lag of different months was used to identify pseudoperiodicities of the leading RPCs. We chose value of lag lying within the acceptable range between 240/3 and 240/2 (Wilks, 2006). Firstly, autocorrelations were computed by inserting each RPC and its time-lagged data into serial correlation formula. Secondly, values of autoregressive parameters were calculated from the autocorrelations using Yule–Walker equations. Then, the spectral values for every RPC were computed using Box and Jenkins (1994) by varying frequency from zero to Nyquist. Finally, the reciprocals of the frequencies at spectra peaks were taken as pseudoperiodicities of the RPCs. See Wilks (2006) for more details about spectral density.

4. Results and discussion

4.1. Inteseasonal precipitation variability

4.1.1. Mean precipitation from June to September

Figure 2 shows spatial distribution of both MOE and MME mean JJAS precipitation over Ethiopia averaged between 1989 and 2008. Panels are ordered beginning with observational databases and the model results repro-duced the geographical patterns of CRU JJAS mean precipitation on the statistical results over Ethiopia. As input for the PCA, we used the standardized anomaly of the precipitation matrix. Principal components (PCs), eigenvectors (EOFs), and eigenvalues in PCA were computed using singular value decomposition (SVD) (Preisendorfer, 1988; Von Storch and Zwieters, 1999; Wilks, 2006). However, the PCs found from SVD are orthogonal to each other. These cause problem in interpretation if data compression by PCA is not the primary goal. Therefore, the orthogonality constraints on the PCs and EOFs were resolved using the most common approach in the orthogonal rotation called the varimax rotation method (Kaiser, 1958) to produce the desired REOFs and RPCs.

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4. Results and discussion

4.1. Interseasonal precipitation variability

4.1.1. Mean precipitation from June to September

Figure 2 shows spatial distribution of both MOE and MME mean JJAS precipitation over Ethiopia averaged between 1989 and 2008. Panels are ordered beginning with observational databases followed by model outputs then sorted according to their similarities. At first glance, JJAS mean precipitation pattern of every ensemble’s member was similar to the CRU. In the northwestern plateau, they had relatively higher rainfall above 3 mm day\(^{-1}\). The eastern (Afar lowlands), southeastern (Ogaden lowlands), and southern Ethiopia received less rain below 3 mm day\(^{-1}\). According to NMSA (1996) and Korecha and Barnston (2007), kiremt rainfall covers most of the country with the exception of the south and southeast of Ethiopia. The east and northeast part experience total rainfall <300 mm (<2.5 mm day\(^{-1}\)) despite JJAS being the main rainy season. NMSA (1996) points out that during Kiremt the air flow is dominated by a zone of convergence in low-pressure systems accompanied by the oscillatory Inter Tropical Convergence Zone (ITCZ) extending from West Africa through the north of Ethiopia towards India. The ITCZ drags winds carrying moisture fluxes from various continental and oceanic sources, forced up to higher ground, depleting moisture in orographically induced precipitation (Ellen and Asgeir, 2011) but brings little rain to the east and northeast coastal areas of Ethiopia (Segele and Lamb, 2005; Korecha and Barnston, 2007).

Figure 3 represents differences between ensembles and CRU. As mentioned in Section 2.1., out of the four observational products produced by different interpolation techniques and blending strategies, CRU data were chosen as reference for comparison of model results and the remaining observational databases. By a visual inspection of Figure 3, GPCP, GAUGE, UDEL, and RACMO22T are not too different from CRU. Noticeable differences were seen in the Blue Nile basin, above Mendebo Mountains, in the westernmost outskirts, and aligned to the Awash River Basin. Precipitation was overestimated in relation to CRU in the Blue Nile basin (by CRCM5, ALADIN52, RegCM3, and RCA4), along Ethiopian Escarpment (by RCA4 and HIRHAM5), on Mendebo Highlands (by CRCM5, ALADIN52, RegCM3, RCA4, HIRHAM5, and REMO), and above Ahmar Moorlands (by RegCM3). In the Blue Nile basin, differences were as big as 5 mm day\(^{-1}\) in the majority of the model outputs except for RACMO22T. These higher magnitude positive biases in the upper catchment of the Blue Nile River, area that has about 60% contribution to the main Nile River flow (Sutcliffe and Parks, 1999; Engida and Esteves, 2011), cannot be solely due to model errors, it is rather the sum of the biases originated from both models and CRU. GAUGE and UDEL showed better patterns of mean precipitation and could be taken as evidences of our thoughts. They increased rainfall in the upper Nile basin, and approached plausibly towards model results than that of CRU and GPCP. GAUGE and UDEL are most likely interpolated from denser gauge stations because the higher the gauge density we use for interpolation, the closer the results between model outputs and observational databases. These results indicate that rainfall over the highlands was reasonably presented and explained by models. Contrary to the earlier, HIRHAM5 and REMO showed negative uncertainties greater than −3 mm day\(^{-1}\) in the western and northwestern peripheral lowlands oriented with Ethio-Sudan boundary. Particularly, REMO had negative bias about −2 mm day\(^{-1}\) aligned to the Awash Valley. It was most likely induced while adapting the stream courses during the simulations. In general, majority of the observational databases and the model results reproduce the geographical patterns of CRU JJAS mean precipitation for the period 1989–2008. However, model results show enhanced rainfall over Ethiopian Highlands while HIRHAM5 and REMO underestimate precipitation in areas coinciding with the western and northwestern side-lines and the Awash Basin.
4.1.2. Mean precipitation from March to May

MAM season, known locally as Belg, is the long rainy season in southern Ethiopia but short rainy period in eastern Ethiopia (NMSA, 1996; Camberlin and Philippon, 2002; Diro et al., 2011b). The Belg rain emerges when the ITCZ starts to arrive at southern Ethiopia in its south–north movement. Figure 4 presents distribution of mean rainfall for MAM season. By visually inspecting the panels, several ensemble’s members showed good resemblance with CRU and across themselves despite few weaknesses appeared in some members of the ensembles. Rainfall amounts were in the range of 0–7 mm day$^{-1}$. The heaviest rain for every ensemble member was positioned south and southwest of Ethiopia but weakened on the way towards northern and southeastern Ethiopia (Ogaden lowlands).

In MAM season, the Sun was obviously overhead at southern Ethiopia; however, the Ogaden lowlands, part of the southern Ethiopia, experienced less precipitation due to the generation of the low level Somali Jet. Camberlin and Philippon (2002) reports that wind (with relatively higher moisture) from south Indian Ocean crossing the flat lands of eastern Kenya starts to dominate the easterly/southeasterly wind associated with the Arabian High in May. During the journey to Ethiopia, the wind is split as it crosses the northern Kenya Mountains towards low pressure landmasses located over Sudan and India (Nicholson,
1996). The first air stream brings rainfall to the mountains of southern and western Ethiopia. In contrast, the second wind is deflected further eastward by Ahmar Mountain barriers while making transition from southeast monsoon (ascending wind) to southwest trade (descending wind). It persists as Somali Jet, and consequently weakening of rainfall activity in the Ogaden lowlands (Flohn, 1987).

GPCP, GAUGE, UDEL, CRCM5, and ALADIN52 were close to CRU. For CRU and ensembles, the intense rainfall was near the eastside of Lake Abaya although RCA4, HIRHAM5, and REMO repositioned it a little towards the neighbouring Mountains of Mendebo where rain could be enhanced by orography effects. GPCP’s, GAUGE’s, UDEL’s, CRCM5’s, and ALADIN52’s rainfalls were more strengthened in the southwestern Ethiopia. CRCM5, RACMO22T, RegCM3, and RCA4 extended the position of the intense MAM rain towards western Ethiopia. As stated by Kassahun (1987) and Diro et al. (2011b), the southwestern region receives plentiful rainfall in early March (sometimes even before March) induced by the difference in the heat capacity of the land surface and Indian Ocean even though the main
ITCZ is slightly south of it. Of all, extra ample rain was identified by UDEL in the Tir-Shet Basin located in the northern side of Goba. RACMO22T, RegCM3, and RCA4 overestimated rainfall (as compared to CRU) in the western part, increased it a little on Mendebo Hilltops but underestimated it in the Ogaden Desert. HIRHAM5 and REMO were somewhat distinct from CRU and the rest. They showed slightly enhanced rainfall at the slopes of the Ethiopian Escarpment, but underestimated it over the areas oriented with west, south, and south-east lowlands surrounding the Ethiopian Plateau. Of all, HIRHAM5’s MAM precipitation increase more and more on Mendebo mountain slopes in response to the rise in elevation.

According to NMSA (1996) and Camberlin and Philippon (2002), the MAM season coincides with the domination of the Arabian High as it moves towards the north Arabian Sea, and the development of thermal Low (cyclone) in southern Sudan. Winds from the Gulf of Aden and the Indian Ocean High that are drawn towards this centre blow across central and southern Ethiopia. These easterly and southeasterly moist winds produce the main rain in southern and southeastern Ethiopia and short rain in the central part of the northwestern highlands.
The differences between ensembles and CRU are displayed in Figure 5. GPCP did not show significant difference with CRU. Small positive differences were observed in UDEL, GAUGE, and CRCM5 near south Omo. GAUGE and CRCM5 extended the imperfections towards western Gambella whereas CRCM5 stretched it northwards tracking the Ethiopian sidelines beyond Gambella. GAUGE and CRCM5 showed little tendency to overestimate rainfall over the Red Sea and in the southern Somalia where gauge stations were absent and sparse, respectively. ALADIN52, RACMO22T, RegCM3, and RCA4 exhibited significant positive biases about 2.5 mm day$^{-1}$ in the upper part of Baro-Akobo Basin (western Ethiopia). On the other hand, regardless of Mendebo Summits, four of them showed negative uncertainties around $-2$ mm day$^{-1}$ on the slopes of the southeastern highlands. This negative bias was extended towards Ogaden lowlands by RegCM3. Little positive partialities on Choke Mountains (south of Lake Tana) were observed in ALADIN52 and RegCM3. Omitting Mendebo Tops and Ogaden lowlands, HIRHAM5 and REMO revealed relatively similar negative uncertainties in the western peripheries and in the southern part of Ethiopia. Above Mendebo Hilltops, orographic influenced precipitation bias ($>2.5$ mm day$^{-1}$)
was described by HIRHAM5 model. These limitations (uncertainties) seen in HIRHAM5 and REMO might need further investigations although they are reasonably amended by the rest of the ensembles.

4.1.3. Mean precipitation from October to November

ON season is another bimodal rainy term for western and southern Ethiopia. This rainfall is lower in amount and short in period than MAM season. Ensemble’s geographical distribution of mean precipitation in ON season had generally comparable patterns as CRU (Figure 6). Several members of the ensembles tracked CRU spatial indices. Except RCA4, HIRHAM5, and REMO, ensemble’s rainfall became more intense towards the southwestern Ethiopia. For RCA4, HIRHAM5, and REMO, rainfall intensity increased towards the Mendebo Mountains. Ensembles rainfall for ON season varied from below 1 to roughly 7 mm day$^{-1}$. With the exception of CRCM5, RACMO22T, RegCM3, and HIRHAM5, rainfall distributions for the remaining ensembles spreaded between 0 and $3.5 \pm 1$ mm day$^{-1}$ (or CRU $\pm 1$ mm day$^{-1}$). CRCM5 and RCA4 had peaks around 5 and 5.5 mm day$^{-1}$.
respectively, whereas RegCM3 and HIRHAM5 possessed heavy rainfall close to 6.5 and 7 mm day\(^{-1}\) correspondingly. Intense rain of RCA4, HIRHAM5, and REMO were located on the Hilltops of Mendeb but the rest were positioned them in the southwestern Ethiopia. CRU revealed ample ON rains in the vicinity of Kebbi-Dehar (southeastern Ogaden) and in the Tir-Shet Basin. These were also correctly generated by UDEL. GAUGE succeeded in reproducing the Tir-Shet’s rain but missed out the Kebbi-Dehar’s ON rain.

Spatial rain bias distributions during ON season had similar patterns with MAM (Figure 7). GAUGE was unbiased with respect to CRU. For GPCP, UDEL, CRCM5, ALADIN52, RACMO22T, and RegCM3, the differences from CRU were positive near south Omo and in the fringes of southwestern Ethiopia. These positive partialities were stretched to Gambella and western Wellega by CRCM5, RACMO22T, and RegCM3. ALADIN52 and RegCM3 to some extent overestimated it over the Red Sea. CRCM5 and ALADIN52 showed little tendency to overrate it in central Somalia. In contrast, RCA4, HIRHAM5, and REMO revealed negative biases about 2 mm day\(^{-1}\) in the southern, southwestern, and western parts. Additionally, in the southwestern and southernmost Ethiopia, signs of underestimation were shown by RACMO22T and RegCM3, respectively. Partially negative and positive minor spots were also seen near Lake Tana and on Mendeb summits in most of the model outputs.

These few localized but significant biases could arise from model uncertainty and natural climate fluctuations. Actually significant biases do not mean models are weak to reproduce the seasonal variability. This point of view was witnessed by Pearson and Spearman rank correlation analyses as discussed in Section 4.2. They successfully reproduced the region’s intraseasonal variability at monthly basis. In the next subsection, the results of both methods are presented.

4.2. Correlations analyses

4.2.1. Pearson correlation analysis

The linear dependencies between CRU and ensembles were analysed using Pearson correlation analysis. The correlations were calculated for the time series of monthly precipitation. They are shown in Figure 8. Correlation coefficient \((r)\) varied in accordance with seasons and topography. Correlation between every ensemble’s member and CRU was strong in the northwestern plateau (monomodal rainfall region), moderate in the southern Ethiopia (bimodal rainfall region), but low along Main Ethiopia Rift (MER) (largely quasi-bimodal rainfall region). Top three panels in Figure 8 depict correlation between CRU and the remaining MOE (GPCP, GAUGE, and UDEL). Each of them was well correlated with CRU for the entire region. Value of \(r\) ranged between 0.5 and 1.0. As \(r\) exceeds 0.5 for MOE, subsequent discussion only focuses on MME.

The \(r\) calculated from model simulations was similar in pattern, with lower value, and more delimited by the influence of MER as compared to MOE. CRU and MME were highly correlated over northwestern plateau (above the Rift Valley) exhibiting \(r > 0.7\). This suggests that CRU monomodal rain is well retrieved by every model output as it is the case for all MOE. Below MER, the correlation between MME and CRU becomes different. Correlation of CRU with both CRCM5 and ALADIN52 was quite strong \((r > 0.7)\). \(r\) related to RACMO22T and RCA4 exceeded 0.6. Correlation of CRU with HIRHAM5 surpassed 0.5. In connection with RegCM3 and REMO, \(r\) minimum threshold dropped to 0.4 yet it was statistically significant.

Aligned to the MER and its escarpments, spatial pattern of \(r\) was more governed by the topography. Dinku et al. (2007), Nicholson (1996), and Slingo et al. (2005) articulate that topography induces micro-precipitation that leads to dynamic \(r\) along the Rift Valley. In the Valley, CRCM5 and ALADIN52 correlated better with CRU than other numerical simulations. Correlation went beyond 0.5 with the exception of: Danakil Block of the northeastern coastal areas \((r > 0.3)\), Omo lower valley situated southwest of Ethiopia \((r > 0.2)\), the vicinity of Lake Abaya, and Lake Rudolf \((r > 0.4)\). In relation to RACMO22T, RegCM3, and RCA4, poor \(r\) below 0.5 was rarely seen notably in the Danakil Depression, Lake Rudolf, Omo basin, and Ahmar Mountains. \(r\) connected to HIRHAM5 fell down below 0.5 throughout MER and its escarpments. Likewise, Omo lower valley and northern portion of Lake Rudolf showed reduced \(r\) in all model outputs.

In general, excluding the following areas and the associated model outputs (1) Danakil Block of CRCM5, (2) Danakil Depression of RACMO22T, RegCM3, and RCA4, (3) Ahmar ridges of RACMO22T, RegCM3, RCA4, and REMO, (4) Omo lower valley of all, and (5) south of Lake Abaya and Afar Rift of HIRHAM5, the rest of the ensembles had good correlation with CRU \((r > 0.5)\). Hence ensembles sufficiently reproduce CRU temporal variability at each grid point at monthly basis in the period 1989–2008.

4.2.2. Spearman rank correlation analysis

Spearman rank correlation analysis was applied to examine the nonlinear dependencies between CRU and ensembles. The same array size \((240 \times 980)\) but different input data were used to compute \(r\). Instead of the raw data, we used ranks computed from averages of precipitation positions already arranged in ascending order of their values. Correlation contour maps are displayed in Figure 9. Spearman correlation analysis outperformed in terms of values and caught better the micro-precipitations of Ethiopia than that of Pearson correlation. From the results shown in the panels, each ensemble’s element and CRU were significantly correlated at every grid point in the entire region in spite of the existence of low value of \(r\) in few locations. Locations connected to relatively low \(r\) were southeastern Ethiopia, Danakil Block, Ethiopian Escarpment, and east central Afar. Apart from these locations appearing in some models, the remaining region had \(r > 0.8\) in all ensembles. These better results are good...
Fig. 7. ON mean precipitation differences (unit: mm day$^{-1}$) between ensembles and CRU for the period 1989–2008.

evidences to reason out the efficiencies of models in capturing the trends of CRU.

In the northern Lake Rudolf, $r$ between CRU and RegCM3/HIRHAM5 exceeded 0.5. The rest were strongly correlated with CRU ($r > 0.8$). In Danakil Block, with the exception of UDEL, CRCM5, RCA4, and HIRHAM5, the remaining was better correlated with CRU ($r > 0.7$). For CRCM5 and HIRHAM5, it was above 0.5. UDEL like CRU had missed values over the Red Sea and along its shorelines (Danakil Block) where gauge data are absent and scarce, respectively. Therefore, it was characterized by weak $r$ values. With regard to RCA4 and HIRHAM5, lower values were obtained ($r > 0.3$) due to the influence of topography in the Danakil Depression and along Ethiopian Escarpment. The remaining areas were characterized by $r > 0.6$. Over east central Afar, HIRHAM5 had relatively lower $r$ value but still higher than 0.5. There was no good correlation over north of Lake Rudolf for HIRHAM5 and REMO. In addition, RegCM3 underestimated $r$ outside Ethiopia in the central Somalia. In general, omitting these insignificant values of $r$ seen rarely in the models, each ensemble’s element and CRU had strong relationship.

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As conclusion, the following statement holds true for most of the country and majority of the precipitation products. Each ensemble’s member and CRU are significantly linearly correlated (Figure 8), and admirably nonlinearly correlated in the monomodal rainfall receiving region and in the entire region, respectively.

4.3. REOFs, RPCs, and spectral densities
RPCA was computed to distinguish regions with homogeneous precipitation climatology and to compare dominant modes of rainfall variability. It was applied to monthly averaged precipitation field. As mentioned in Section 3.5., the size of the original time–space precipitation matrix was reduced from $240 \times 980$ to $240 \times 582$. There are 582 fractions of precipitation variability inside Ethiopia’s political boundary at 0.44° resolution. We did it in order to avoid the impact of precipitation variability from neighbouring countries on the results of RPCA over Ethiopia. Standardized anomaly of the precipitation data was decomposed using SVD into spatial (EOFs) and temporal (PCs) indices. To avoid orthogonality constrains among eigenvectors, varimax method (Kaiser, 1958) was applied to EOFs and PCs to yield REOFs and RPCs. Each one of the few selected leading RPCs (in our case four) was then entered to power spectral density. We chose lags lying between $240/3$ and $240/2$. The reciprocals of the
Figure 9. Spearman time correlations between CRU’s and ensembles’ monthly precipitations at every grid point.

frequencies at the spectral peaks gave pseudoperiodicities of the RPCs.

The temporal patterns of leading four RPCs, the corresponding spatial patterns of REOFs, and major spectral peaks possessed by RPCs are displayed in Figures 10–12, respectively. Figure 10 shows time series of four dominant RPCs. The corresponding REOFs are in Figure 11. They describe dominant homogeneous precipitation zones of the associated RPCs. Spectral densities (Figure 12) reveal pseudoperiodicities of the RPCs. For the sake of visibility, we have rescaled GAUGE’s RPC3, GPCP’s RPC4, and RegCM3’s RPC4 to 0.5, 0.5, and 0.33 of their original lengths respectively.

RPCs’ trend profiles, contour patterns of REOFs, and spectral peaks of RPCs for ensembles were equivalent to CRU results. Moreover, they were closer to each other. Cumulative and separate RPCs’ percentages of variances were near CRU values. As shown in Table 1, ensembles’ cumulative percentages were in the range of 70.37–81.18%. CRU’s total percentage of variance, 77.43%, was close to the median of the percentages’ spread, 75.77%. RPC1s’ percentages of variances for
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ensembles and for CRU explained large fraction of their corresponding joint variances. Except for GAUGE, all RPC1s’ percentages of variances were in the interval 30.18–42%. CRU’s value, 36.80%, was almost at the middle of the range (≈36.09%). GAUGE’s RPC1 had 27.00%. It went beyond the range by approximately −3%. All RPC1s oscillated once per year (Figure 10(a)). They had positive anomaly in JJAS. That is obviously the long rainy season (Kiremt season) in Ethiopia. Figure 11(a) illustrates zones (REOF1s) that are characterized by RPC1s’ rain patterns. Except for RegCM3, every ensemble’s REOF1s resembled CRU’s REOF1. They explained strong correlation results over the northwestern plateau. These spatial patterns of REOF1s are also consistence with JJAS mean precipitation in Figure 2, and that of Pearson top scores in Figure 8. Spectra of RPC1s are displayed in Figure 12(a). Counting out RegCM3’s RPC1 spectrum, ensembles’ and CRU’s RPC1s spectra possessed strong signal at frequency, $f = 0.83 \text{ month}^{-1}$ (or period, $T = 12 \text{ months}$). They stand for unimodal rainfall type (JJAS/Kiremt season). In RegCM3, RPC1 had mixed character. It slightly merged unimodal and quasi-bimodal rainfalls originated from the northern, central, and the eastern parts of Ethiopia, respectively, because its spectrum possessed extra small peak/pseudoperiodicity/serial correlation at $f = 0.166 \text{ month}^{-1}$ ($T = 6 \text{ months}$). Such merging by PCA is likely to happen if MAM rain in eastern Ethiopia is less as compared to JJAS, and the northern or central parts experience even a single rain in March or April. While choosing extreme events, we looked at communal RPCs’ patterns and the composite of RPCs. Both normalized and non-normalized RPCs were taken into account when RPCs were composited. The three wettest JJAS precipitation years, which were identified by

Figure 10. Leading four RPCs for the period 1989–2008.
Figure 10. Continued.

RPC1s and ranked according to their strengths, were 1998, 1999, and 2001. Deficient rainfalls rated by their intensities of the severities were observed in 1993, 1997, and 2002. The abundant Kiremt rains were in consistent with the incidences of negative equatorial eastern Pacific sea surface temperature anomalies (La Niña events) though the 2001’s JJAS seasonal rainfall was connected with weak La Niña development. Deficient Kiremt rainfalls that happened in 1997 and 2002 were in harmony with positive equatorial eastern Pacific sea surface temperature anomalies (El Niño events). The inadequate JJAS rain, which was recorded in 1993, matched the occurrence of weak El Niño. In 1997, the majority of northern Ethiopia received unusual rain (RPC1s in Figure 10(a)) above average in April and October months. The April precipitation was possibly an extension of excessive MAM seasonal rain associated with El Niño development whereas October rain emerged doubtless as a consequence of the development of the strongest (of the time range) positive tropical western Indian Ocean sea surface temperature anomalies [positive Indian Ocean Dipole (IOD) event]. Nevertheless, it experienced reduced rain in June and July attributable to El Niño event. These results are also in line with the CRU historical rainfall events (Saji and Yamagata, 2003; Yilma and Zanke, 2004; Korecha and Barnton, 2007; Meyers et al., 2007; Zeleke et al., 2013).

RPC2s of ensembles and CRU in Figure 10(b) accounted for 25–31% of the total variance except for RegCM3 (=17.35%). Percentages of variances for GAUGE, UDEL, RACMO22T, RCA4, HIRHAM5, and REMO were bounded by 26.39 ± 1% or CRU ± 1.0. Every ensemble’s REOF2s (shown in Figure 11(b)), as that of CRU’s REOF2, had good spatial coverage in southern and southeastern Ethiopia. The southeastern region’s correlation scores were better than southern correlation scores. RPC2s spectra (in Figure 12(b)) had strong signals at
rainfall pattern. Excessive rainfall seasons recognized by southward movement of ITCZ gave rise to a bimodal pattern. The results are periods. The ON rain looked somewhat unstable in time seasons (MAM and ON) separated by well-marked dry per year. Therefore, they equivalent to two distinct rainy RPC2 were: (1) MAM of 1997 (intense flood) and (2) ON of 1997 (intense rainstorm), 2008 and 2006. Deficient rainfalls rated by their severities were observed in: (1) MAM 1999, 1998, and 2001 and (2) ON 1991, 1996, and 2003. The intense MAM seasonal rainfall occurred in 1997 coincided with strong El Niño development while the excessive ON rainy periods matched the 1997s, 2006s, and 2008s positive IOD events (Saji and Yamagata, 2003; Meyers et al., 2007). In 1997, IOD ceiling caused flood in southern Ethiopia (Goddard and Graham, 1999).

Figure 11. Correlation-based leading four REOFs.

\( f = 0.167 \text{ month}^{-1} \) \((T = 6 \text{ months})\). They oscillated twice per year. Therefore, they equivalent to two distinct rainy seasons (MAM and ON) separated by well-marked dry periods. The ON rain looked somewhat unstable in time and reduced in amount than MAM rain. Sometimes it also possessed September rain intermittently. The results are as close as rains in MAM in Figure 4 and rains in ON in Figure 5. Forward (northward movement) and retreat (southward movement) of ITCZ gave rise to a bimodal rainfall pattern. Excessive rainfall seasons recognized by
Deficient MAM rainfalls coincided with La Niña events in 1998, 1999, and 2001. Insufficient ON rain happened in 1996 was in good agreement with the incidence of negative IOD. Nevertheless, it is unclear how deficient rain happened in ON 1991 and 2003. This shortfall might be connected to other large scale tele-episodes.

Ensemble’s RPC3s’ percentages of variances were spread between 4 and 12% except for GAUGE and RegCM3. CRU’s RPC3 represented 9.84% of its total variance. Several ensemble members had percentages a little lower than CRU. As far as their corresponding REOF3s (in Figure 11) had spatial patterns similar to CRU, it was reasonable for us to accept the amount of percentages they already had. GAUGE and RegCM3 exaggerated and understated percentages of RPC3s. They had 21.58 and 1.82%, respectively. In CRU and all ensembles, the double rainy seasons of Afar were well explained by RPC3s. The first rain (JJAS rain) was better in intensity, longer in time, and more uniform than the second rain (MAM rain). For GAUGE, the net deficit in percentage observed in RPC1 brought surplus to RPC3. In RegCM3, the contribution from Afar was partly explained by RPC1 and partly by RPC3 as shown in Figure 11(a) and (c). Ensembles’ REOF3s captured the Afar precipitation patterns although REOF3s of CRCM5, HIRHAM5, and REGCM3 were more localized. CRCM5’s REOF3 referred to upper parts of Danakil whereas HIRHAM5’s and REGCM3’s REOF3 pointed to the southern Afar. In relation to spectra of RPC3s (Figure 12(c)), all except CRCM5 possessed two unbalanced rainy terms that stand for quasi-bimodal rainfall type. The unequal peaks represented occurrence of long and short rain seasons (e.g. Kiremt and Belg) separated by either 6 months (as RACMO22T, RegCM3, and RCA4) or 4 months (as GAUGE, UDEL, ALADIN52, and REMO) or both (as CRU, GPCP, and HIRHAM5). Earlier or late Kiremt and/or Belg onset/cessation can yield lead/lag pseudoperiodicities. CRCM5’s RPC3 had strong serial correlation.

Figure 11. Continued.
with itself at 6-month lag. It connoted bimodal rainfall type. Rain at the northern Danakil (see CRCM5’s REOF3) could be the source of its bimodalness as offshore wind originated from the Red Sea brings humidity to the area (Tucker and Pedgley, 1977). With regard to abundant Kiremt seasonal rainfalls, RPC3s’ extreme positive scores share RPC1s’ results. The wettest Kiremt years were 1998, 2001, and 1999. Likewise, the wettest Belg years were 1993 and 1989. As RPC3s were characterized by several deficits, we skipped the driest years.

RPC4s is drawn in two panels. The first panel exhibits similar pattern with CRU (Figure 10(d-1)). They are eight in number and labelled as group 1. The rest three (UDEL, ALADIN52, and RegCM3) which differ from CRU are
collected in Figure 10(d-2) and named as group 2. RPC4s displayed in group 2 showed fall short of RPCA in tracking CRU trends. Actually it is a matter of reordering of REOFs. We have selected only four dominant variabilities out of many RPCs taking into account only the dominant modes of variabilities without considering their geographical similarities.

CRU spatial and temporal patterns were reproduced reasonably by group 1. RPC4s in group 1 and in CRU accounted for 2.18–7.51% of the total variance. They had area coverages, precipitation patterns, and extreme events similar to the CRU’s and ensembles’ RPC2s (Figures 10–12(b)). However, RPC4s were more correlated with the rains of southwestern than that of southeastern Ethiopia. Spectra of RPC4s (except for RegCM3 that was unimodal, and HIRHAM5 and REMO that were quasi-bimodal) were comparable to CRU’s RPC4 spectrum (in Figure 12(d)). They showed dominant
Table 1. Percentage of variances for the leading four RPCs.

|     | RPC1 | RPC2 | RPC3 | RPC4 | Total |
|-----|------|------|------|------|-------|
| CRU | 35.80| 26.39| 9.84 | 5.40 | 77.43 |
| GPCP| 35.58| 30.04| 4.57 | 7.51 | 77.70 |
| GAUGE| 27.00| 25.29| 21.58| 3.40 | 77.17 |
| ATP-UDEL| 38.97| 25.96| 6.69 | 2.58 | 74.19 |
| UQAM-CRCM5| 33.96| 31.29| 5.99 | 2.18 | 73.42 |
| CNRM-ALADIN52| 42.00| 30.43| 6.08 | 2.63 | 81.18 |
| KNMI-RegCM022T| 37.55| 26.84| 10.3 | 3.16 | 77.85 |
| ICTP-RegCM3| 31.13| 17.35| 1.82 | 15.24| 75.08 |
| SMHI-RCA4| 40.21| 27.21| 6.77 | 4.62 | 78.81 |
| DMI-HIRHAM5| 36.37| 25.74| 5.47 | 3.13 | 70.71 |
| MPI-REMO| 30.18| 25.36| 11.89| 2.94 | 70.37 |

peaks at 6 months. In spite of the existence of another peak at 12 months, strong peak at 6 months explains bimodal type-2 rainfall type. REOF4s of HIRHAM5 and REMO stretched from Omo lower valley, through Mendeb to Ahmar Mountain ranges. They were relatively oriented with the slopes of the southeastern plateau. For ALADIN52, REOF4 covered southern and southwestern Ethiopia’s periphery. UDEL and ALADIN had bimodal pattern. But they had temporally unstable rainfall months. RegCM3’s RPC4 represented the longest rainfall already existed in western Ethiopia. Its rain strengthened either in May/June or September with little dip in June caused by the double passage of the (nearby overhead) Sun.

The other unmentioned principal components captured the rest random variations departing from overall regional values. On the basis of the spectra peaks, rainfall can be divided into unimodal (one season) and bimodal (two seasons) types. Bimodal can be further split up to bimodal type-1 and bimodal type-2. These methods reaffirmed the classification made by NMSA (1996). Monomodal rainfall pattern in the northern, quasi-bimodal in the eastern, and bimodal rainfall pattern in southern and southeastern Ethiopia.

5. Conclusion

We demonstrated the ability of multiobservational databases and multimodel numerical simulations in reproducing intraseasonal, seasonal, and interannual precipitation variability over Ethiopia. Seven model outputs generated in the frame work of CORDEX project and four observational databases from different sources were integrated. We chose CRU historical rainfall records as reference for the evaluation of the ensembles. For analysis, the monthly averaged precipitation data at resolution of 48.8 km and its anomalies were used for the period 1989–2008.

Evaluation of seasonal means and seasonal differences shows that majority of ensembles produce more or less correctly the spatial patterns of CRU precipitation in spite of few significant uncertainties that can arise from various sources of errors. In JJAS season, every ensemble’s member and CRU reveal plentiful rain in the northwestern plateau and on the Mendebo Mountains whereas the Afar lowlands, Oganen lowlands, and southern Ethiopia experience less rain. In relation to MAM season, several ensembles’ members exhibit good similarity with CRU. Their MAM rainfall distributions are in the south and southwest of Ethiopia but decrease towards northern and southeastern of Ethiopia. In ON season, ensembles tracked CRU spatial patterns. Rainfall indices for the majority of the ensemble members spread around CRU values.

The results obtained from Pearson correlation analysis indicate that every ensemble’s member and CRU significantly agree in amplitude and phase at each grid point in the northwestern plateau (monomodal rainfall region), but moderately correlate in the southern and the eastern Ethiopia (bimodal and quasi-bimodal rainfall regions respectively). Whereas Spearman correlation analysis outperform in terms of values and better caught the micro-precipitations throughout Ethiopia.

The leading four RPCs, REOFs, and the associated power spectra demonstrate that ensembles are as good as CRU in explaining seasonal cycle, classifying homogeneous precipitation zones, and identifying extreme rainfall events. They differentiate rainfall into unimodal, quasi-bimodal, and bimodal rainfall types occur in the northwestern plateau, the eastern, and the southern Ethiopia, respectively. Extreme positive scores rated by their intensities are observed in JJAS 1998, 1999, and 2001, in MAM 1997, 1993, and 1989, and in ON 1997, 2008, and 2006. Deficient rainfall periods ranked according to their severity are JJAS in 1993, 1997, and 2002, MAM in 1999, 1998, and 2001, and ON in 1991, 1996, and 2003. Abundant/deficient JJAS seasonal rainfalls are in consistent with La Niña/El Niño events; on the other hand, excessive/deficient MAM seasonal rains coincide with El Niño/La Niña developments. Excessive/deficient ON rainfalls are in harmony with positive/negative IOD incidences except 1991 and 2003.

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References

Adikari Y, Yoshitani J. 2009. Global trends in water-related disasters: an insight for policy makers. United Nations World Water Development Report 3: Water in a Changing World, UNESCO, Paris.

Adler RF, Huffman GJ, Chang A, Ferraro R, Xie P, Janowiak J, Rudolf B, Schneider U, Curtis S, Bolvin D, Gruber A, Susskind J, Arkin P. 2003. The version-2 global precipitation climatology project (GPCP) monthly precipitation analysis (1979—present). J. Hydrometeorol. 4(6): 1147–1167.
Bekele F. 1997. Ethiopian use of ENSO information in its seasonal forecasts. *Internet J. Afr. Stud.* 1(2): 1–5.

Box GEP, Jenkins GM, Reinsel GC. 1994. *Time Series Analysis Forecasting and Control*, 3rd edn. Prentice Hall:Englewood Cliffs, NJ.

Brands S, Taboada JJ, Cono AS, Sauter T, Schneider C. 2011. Statistical downscaling of daily temperatures in the NW Iberian Peninsula from global climate models: validation and future scenarios. *Clim. Res.* 48(2–3): 163–176.

Camberlin P. 1995. June–September rainfall in northeastern Africa and atmospheric signals over the tropics: a zonal perspective. *Int. J. Climatol.* 15: 773–783.

Camberlin P. 1997. Rainfall anomalies in the source region of the Nile and their connection with the Indian summer monsoon. *J. Clim.* 10: 1380–1392.

Camberlin P, Philippon N. 2002. The East African March–May rainy season: associated atmospheric dynamics and predictability over the 1968–1997 periods. *J. Clim.* 15: 1002–1019.

Christensen JH, Christensen OB. 2007. A summary of the PRUDENCE model projections of changes in European climate by the end of this century. *Clim. Change* 81: 7–30.

Daniel TR, Alem M. 2009. Multidimensional and multi-parameter Fortran-based curve fitting tools. *MEJS* 1(1): 95–112.

Davis JC. 1986. *Statistical Data Analysis in Geology*. John Wiley & Sons: New York, NY.

Degoeq B, Berhanu N (eds). 2000. Annual Report on the Ethiopian Economy, 1999/2000. Ethiopian Economic Association: Addis Ababa.

Dinku T, Ceccato P, Grover-Kocpe E, Lemma M, Connor SJ, Ropelewski CF. 2007. Validation of satellite rainfall products over East Africa’s complex topography. *Int. J. Remote Sens.* 28: 1503–1526.

Diro G, Grimes D, Black E. 2011a. Teleconnections between Ethiopian summer precipitation and sea surface temperature: part II seasonal forecasting. *Clim. Dyn.* 37: 121–131.

Diro G, Grimes D, Black E. 2011b. Large scale features affecting Ethiopian precipitation. *Clim. Dyn.* 37: 13–50.

Ellen V, Asgeir S. 2011. Moisture transport into the Ethiopian highlands. *Int. J. Climatol.* 10: 1002–1009.

Engida AN, Esteves M. 2011. Characterization and disaggregation of daily rainfall in the Upper Blue Nile Basin in Ethiopia. *J. Hydrol.* 399: 226–234.

Flinn H. 1987. Rainfall teleconnections in northern and northeastern Africa. *Theor. Appl. Climatol.* 38: 191–197.

Fowler HJ, Ekström M. 2009. Multi model ensemble estimates of climate change impacts on UK seasonal precipitation extremes. *Int. J. Climatol.* 29(3): 385–416.

Fowler HJ, Ekström M, Blenkinsop S, Smith AP. 2007. Estimating change in extreme European precipitation using a multimodel ensemble. *J. Geophys. Res.* 112: D18104. DOI: 10.1029/2007JD008619.

Frei C, Scholl R, Fukutome S, Hagemann S, Sushama L, Martynov A, Winger R, Kjellström E, Lenderink G, Rockel B, Sánchez E, Schär C, Seneviratne S, Somot S, Ulden AV, den Hurk BV. 2007. An inter-comparison of regional climate models for europe: model performance in present-day climate. *Clim. Change* 80: 71–92.

Jacob D, Elizalde A, Haensler S, Hagemann S, Kumar P, Podzun R, Rechid D, Remedio AR, Sæset F, Sieck K, Teichmann C, Willehlm C. 2012. Assessing the transferability of the Regional Climate Model REMO to different Coordinated Regional Climate Downscaling Experiment (CORDEX) regions. *Atmosphere* 3(4): 185–199.

Jones C, Giorgi F, Asrar G. 2011. The Coordinated Regional Downscaling Experiment: CORDEX An international downscaling link to CMIP5. *CLIVAR Exchanges* 16: 34–40.

Kaiser HF. 1958. The Twenty-Nine algorithm for analytic rotation in factor analysis. *Psychometrika* 23: 187–200.

Kassahun B. 1987. Weather systems over Ethiopia. In *Proceedings of First Technical Conference on Meteorological Research in Eastern and Southern Africa*, Kenya Meteorological Department, Nairobi, 53–57.

Knutti R, Furrer R, Tebaldi C, Cermak J, Meehl GA. 2010. Challenges in combining projections from multiple models. *J. Clim.* 23: 2739–2756.

Korecha D, Barnston AG. 2007. Predictability of June–September rainfall in Ethiopia. *Mon. Weather Rev.* 135: 628–650.

Lorenz EN. 1956. Empirical orthogonal functions and statistical weather prediction. Scientific Report No. 1, Statistical Forecast Project Report 1, Dept. of Meteor, MIT, Cambridge, 49 pp. http://www.o3d.org/abracco/Atlantic/Lorenz1956.pdf.

Maraun D, Wetterhall F, Ireson AM, Chandler RE, Kondj EJ, Widmann M, Brienzen S, Rust HW, Sauter T, Themell M, Venema V, Chun KP, Goodess CM, Jones RG, Onof C, Vrac M, Thiele-Eich I. 2010. Precipitation downscaling under climate change. Recent developments to bridge the gap between dynamical models and the end user. *Rev. Geophys.* 48: RG0003.

Meyers G, McIntosh P, Pigot L, Pook M. 2007. The years of El Niño, La Niña, and interactions with the Tropical Indian Ocean. *J. Clim.* 20: 2872–2880.

Mitchell TD, Jones PD. 2005. An improved method of constructing a database of monthly climatology observations and associated high-resolution grids. *Int. J. Climatol.* 23: 693–712.

New M, Listner D, Hulme M, Markin I. 2002. A high-resolution data set of surface climate over land areas. *Clim. Res.* 21: 1–25.

Nicholson SE. 1996. *A Review of Climate Dynamics and Climate Variability in Eastern Africa*. The Limnology, Climatology and Paleoecology of the Eastern Africa Lakes. London and Breach: New York, NY.

Nikulin G, Jones C, Giorgi F, Asrar G, Büchner M, Cerezo-Mota R, Christensen OB, Déqué M, Fernandez J, Hansl E, van Meijgaard E, Samuelsson P, Sylva MB, Sushama L. 2012. Precipitation climatology in an ensemble of CORDEX-Africa regional climate simulations. *J. Clim.* 25: 6057–6078, DOI: 10.1175/JCLI-D-11-00375.1.

NMSA (National Meteorological Service Agency). 1996. Climatic and agroclimatic resources of Ethiopia. Meteorological Research Report Series I(1): 1–137, Addis Ababa, Ethiopia.

Philander SG. 2008. *Encyclopedia of Global Warming and Climate Change*. Sage: London, 395.

Preissendorfer RW. 1988. *Principal Component Analysis in Meteorology and Oceanography*, Elsevier: Amsterdam.

Ruti PM, Williams JE, Haurin FD, Guichard F, Boone A, Van Velthoven P, Favor F, Musat I, Rummukainen M, Domínguez M, Gaertner MA, Lafpre JP, Losada T, Rodrigo de Fonseca MB, Polcher J, Giorgi F, Xue Y, Bourar A, Law K, Josse B, Barret B, Yang X, Mari C, Traore MA, Rockel B, Sánchez E, Seneviratne S, Somot S, Ulden AV, den Hurk BV. 2010. Precipitation downscaling under climate change. Recent developments to bridge the gap between dynamical models and the end user. *Rev. Geophys.* 48: RG0003.

Segele ZT, Lamb PJ. 2005. Characterization and variability of Kiremt rainy season over Ethiopia. *Meteorol. Atmos. Phys.* 89: 153–180.

Segele ZT, Leslie LM, Lamb PJ. 2008. Evaluation and adaptation of a regional climate model for the Horn of Africa: rainfall climatology
and interannual variability. *Int. J. Climatol.* **29**: 47–65, DOI: 10.1002/joc.1681.

Segele ZT, Lamb PJ, Leslie LM. 2009. Large-scale atmospheric circulation and global sea surface temperature associations with Horn of Africa June–September rainfall. *Int. J. Climatol.* **29**: 1075–1100.

Simmons AS, Uppala DD, Kobayashi S. 2007. ERA-interim: new ECMWF reanalysis products from 1989 onwards. *ECMWF Newsl.* **110**: 29–35.

Slingo J, Spencer H, Hoskins B, Berrisford P, Black E. 2005. The meteorology of the western Indian Ocean and the influence of the East African Highlands. *Philos. Trans. R. Soc.* **A363**: 25–42.

Sutcliffe JV, Parks YP. 1999. The Hydrology of the Nile. IAHS Special Publication No. 5. IAHS Press: Wallingford, England, 179 pp.

Tucker MR, Pedgley DE. 1977. Summer winds around the southern Red Sea. *Arch. Meteorol. Geophys. Bioklimatol.* **B25**: 221–231.

Uppala S, Dee D, Kobayashi S, Berrisford P, Simmons A. 2008. Towards a climate data assimilation system: status update of ERA-interim. *ECMWF Newsl.* **115**: 12–18.

Von Storch H, Zwiers FW. 1999. *Statistical Analysis in Climate Research*. Cambridge University Press: Cambridge, UK.

Wilks DS. 2006. *Statistical Methods in the Atmospheric Sciences*, 2nd edn. Amsterdam: Academic Press.

Willmott CJ, Matsuura K. 1995. Smart interpolation of annually averaged air temperature in the United States. *J. Appl. Meteorol.* **34**: 2577–2586.

Yilma S, Zanke U. 2004. Recent changes in rainfall and rainy days in Ethiopia. *Int. J. Climatol.* **24**: 973–983.

Zeleke T, Giorgi F, Mengistu TG, Diro GT. 2013. Spatial and temporal variability of summer rainfall over Ethiopia from observations and a regional climate model experiment. *Theor. Appl. Climatol.* **111**: 665–681, DOI: 10.1007/s00704-012-0700-4.