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Research Article

Comparative study of seven bias correction methods applied to three Regional Climate Models in Mekrou catchment (Benin, West Africa)

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Abstract

An international awareness against climate change and its consequences is observed in recent decades. To predict adaptation to these climate changes, simulations of past and future climate were made using the Regional Climate Models (RCMs). These simulations are subject to bias; and many methods are developed to reduce these bias. In this study, seven (07) different methods (Delta change, Scaling, EQM, AQM, GQM, GPQM and ISIMIP) were applied to correct the precipitation of three (03) RCMs (REMO, DMI-HIRHAM5 and RCA4). Three (03) correction methods (Scaling, EQM and AQM) gave the most satisfactory results at different time scales (daily, monthly and yearly). The analysis of the future evolution of annual rainfall amounts for REMO model showed a downward trend for RCP4.5 and RCP8.5 scenarios with an emphasis on RCP8.5 scenario. As against the HIRHAM5 and RCA4 models, there was a tendency to increase on the evolution of annual rainfall amounts. The combination of the three models revealed a rising trend of future annual rainfall amounts for RCP8.5 scenario while the trend was almost constant for RCP4.5 scenario.

Keywords: *climate change, bias correction, RCM and future rainfall*

1. Introduction

An international awareness against climate change and its consequences has been observed in recent decades. If opinions are somewhat divided regarding the causes (natural, anthropogenic) of climate changes, as for their impacts, all communities seem to agree on the fact that extreme events will increase. Thus, a growing worry wins public opinion with regards to the impacts of these changes on natural resources and populations. Temperature and precipitation projections, in different scenarios, showed that climate change will have different impacts on the regions of the globe, with spatio-temporal changes in the occurrence and amounts of rainfall, but usually with increasing temperature (Barrios et *al.,* 2008; Dang et *al.*, 2007; IPCC, 2001; Meissner et *al.*, 2003; Snyder et *al.*, 2004; Tarhule, 2005). Therefore, the impacts of climate change vary according to regions and populations with space and time, depending on multiple factors, including non-climate stress and the extent of mitigation and adaptation (IPCC, 2014). Assessing future trends in local temperature and precipitation would be a prerequisite to support the development of adaptation and mitigation strategies.

In the recent past, the assessment of climate change in West Africa was made with the outputs of the General Circulation Models (GCMs) (IPCC, 2007). With grid ranging from 150 to 400 km^2, GCMs have great difficulties to take into account regional heterogeneities of variability and changes of climate. This means that these models are not suitable to produce climate projections at regional, national and local scale, which are necessary to assess the impacts of climate change and to develop adaptation policies (Paeth et *al.*, 2011). Faced with this situation, projects such as AMMA, ENSEMBLE and CORDEX AFRICA have been developed to produce variables at regional scale. Regional Climate Models (RCMs) were therefore forced by GCMs outputs in West Africa region with a spatial resolution of 50 km. Even though the RCMs take more or less into account the variability and regional heterogeneity of climate, it is well established that climate parameters obtained from simulations of these RCMs are subject to bias due for example to our limited understanding of process or to our lack of knowledge of the spatial resolution of these models (Rauscher et *al.*, 2010). There is therefore a necessity of a post

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treatment of this data before their use to study the impacts of climate change (Winkler et *al.*, 2011). In recent years, many studies have explored different treatment techniques of RCMs outputs in order to correct RCMs outputs so as to find the best estimates of observed parameters (Piani et *al.*, 2010a ; Piani et *al.*, 2010b ; Themeßl et *al.*, 2012; Hempel et *al.*, 2013; Fang et *al.*, 2015; Sunyer et *al.*, 2015; Sarr et *al.*, 2015; etc.). These downscaling techniques, despite their diversity, can be classified into two categories: dynamic and statistical (Hewitson and Crane, 1996; Miller et *al.*, 2009). The dynamical downscaling is physically linked to Regional Climate Models with high computational requirements (Giorgi et *al.*, 1994; Sylla et *al.*, 2009). They do not give significantly better results for temperature and precipitation, and are sometimes considered too expensive for operational use. As for the statistical method, it assumes a stationary state in the relationship predictor-predictand, and requires a robust relationship and sufficient data to test this hypothesis. Statistical methods are based on statistical relationships between the data from the GCM or RCM and observed data. If statistical methods seem to be easily accessible to all, their diversity poses a problem of choosing the ideal method for a given region. For this, comparative studies between several methods of statistical downscaling and the development of multi-method approach can be a great asset for improving estimates of observed parameters and their future projection. The purpose of this paper is to compare the performances of seven (07) downscaling methods for three (03) different RCMs in the Mekrou at Kompongou watershed to assess future impacts of climate change on precipitations.

2. Study area and data

The study area is the Mekrou watershed at the outlet of Kompongou. Covering an area of 5670 km^2, it is located in North of Benin between 1°30' and 2°15' of East Longitude and 10°20' and 11°30' of North Latitude (Figure 1). With an elongated shape, it covers three main cities that are Kérou, Kouandé and Péhunco.

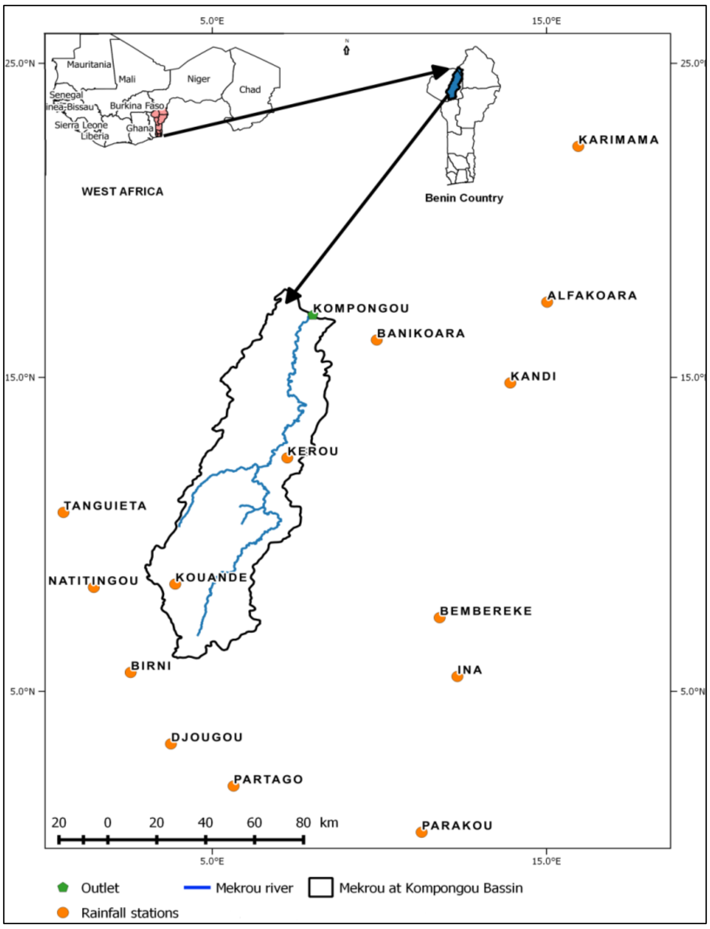

Figure 1: Study area

This watershed belongs to the Benin side of the Niger Basin. The highest point of the watershed is at Kampuya (641m) in around of Kouandé, while the lowest point (259m) is located in around of Kérou and precisely in the bed of the River Mekrou (Gaba et *al.*, 2015). The average slope is approximately 2.47%. The soils types encountered in the basin are: the ferruginous soils on crystalline bedrock, clay soil, loamy black shallows, swamps and fertile gallery forests (GLEauBe, 2012; Benoit, 1988). The analysis of

Kérou and Kouandé rainfall stations between 1952-2014 shows that the months of July, August and September are the wettest. At Kouandé the annual mean of rainfall is 1190 mm, while it is 978 mm in Banikoara which is a little further in the North (Gaba and *al*., 2015). The river discharge at the outlet of Kompongou range from 250 m^3s^{-1} in September to 0 m^3s^{-1} in April. The annual mean of flow is about 21m^3s^{-1}. High flows occur mostly during the summer (July-September).

The data used in this study are of two types: the observed and simulated data from RCMs. The first are mainly obtained at the National Directorate of Meteorology of Benin. Indeed, on the whole watershed 02 reliable rain gauges are available: these are gauges of Kouandé and Kérou. In addition to these two (02) gauges, twelve (12) rain gauges distributed all around the basin are also available (Figure 1) for a total of fourteen (14) rainfall stations. Over the period 1960-2014, all precipitation's stations are functional with few delay time for some of them.

The seconds are the historical and future projections (RCP4.5 and RCP8.5 scenarios) rainfall data of three regional models (SMHI-RCA4, MPI-REMO, DMI-HIRHAM5) from CORDEX Africa project. The historical data are considered for the period 1965 - 2005 (period of available observed data in the basin). For future projections the RCP4.5 and RCP8.5 scenarios are considered in the period 2006 - 2100.

3. Bias correction methods

There are a large number of downscaling methods. Seven (07) of these methods are compared in this study in order to obtain better estimates of rainfall in the basin. These methods are: Delta Change (DC), Scaling, Empirical Quantile Mapping (EQM), Adjusted Quantile Mapping (AQM), Gamma Distribution Quantile Mapping (GQM), Gamma-Generalized Pareto Distribution Quantile Mapping (GPQM) and ISI-MIP method. These methods can be classified into two (02) major groups.

The firsts are the scaling methods (DC and Scaling) which consist in using an additive or multiplicative factor of scaling to correct the model simulations. The DC method is the simplest and most widely used bias correction method (Graham et *al*., 2007; Moore et *al*., 2008; Sperna Weiland et *al*., 2010) and requires the scaling of observations for simulations corrected as shown by equation (1).

$$P_{c,i} = P_{o,i} \times \frac{\Delta_p}{\Delta_r} \tag{1}$$

where $P_{c,i}$ represent the corrected precipitations ; $P_{o,i}$ are the observed rainfalls and Δ_r and Δ_p are respectively the simulated mean data of the reference period and the mean data of the projection period. The Scaling method is very similar to the previous method except that it involves scaling up simulations of RCMs to get their corrections (Wetterhall et *al*., 2012; Fang et *al*., 2015.). It works with monthly correction values based on differences between the observed and simulated data. As with the Delta method, precipitation is usually corrected with a multiplying factor on a monthly basis (equation 2):

$$P_{c,m,j} = P_{RCM,m,j} \times \frac{\Delta_{o,m}}{\Delta_{RCM,m}} \tag{2}$$

where $P_{c,m,j}$ represent the j corrected precipitation of the month m; $P_{RCM,m,j}$ are simulated rainfall on day j of the month and $\Delta_{o,m}$ and $\Delta_{RCM,m}$ are respectively the observed mean data of the month m and the simulated mean data of that month.

The seconds are the non-parameter Quantile-Quantile methods which consist to adjust the values of the quantile model with those calculated from observations. At each point of the model and for each variable, one calculates the 99 percentile of the daily series, as well as the 99 percentiles of the observed series. Each variable is corrected independently and at daily step. The correction function consists to associate each model percentile to observed percentile. Four (04) variants of these methods have been used. These four variants can be classified into two groups that are: non-parametric methods (EQM and AQM) and parametric methods (GQM and GPQM).

The EQM method uses empirical distribution functions (Déqué, 2007; Sennikovs and Bethers, 2009; Michelangeli et *al*., 2009). This should produce the best correction, but depends on many degrees of freedom and cannot be stationary and therefore may violate this hypothesis in future periods. However, for applications on Climate Change, it is assumed that the transfer function remains constant with time (Piani et *al*., 2010a), which is a trivial event (Trenberth et *al*., 2003). The EQM method is constructed by calculating the Empirical Probability Distribution Functions (PDF) but uses the cumulative distribution functions (CDF) (equation 3) for the correction:

$$y = F_{obs}{}^{-1}(F_{RCM}(x)) \tag{3}$$

where y is the corrected meteorological parameter and x its simulated value by the model ; F_{RCM} is the CDF of simulated data by the RCM and F_{obs}^{-1} is the inverse of the CDF of the observed data.

The AQM method calculates changes, quantile by quantile in the CDFs of daily outputs of RCMs between a control period and a verification period. These changes are rescheduled based on the CDF of observed data for the same control period, then added, quantile by quantile, these observations to obtain new CDFs that transmit climate change signal (Amengual et *al*., 2012) .This method is translated by the following equations (equations 4, 5 and 6):

$$P_i = O_i + g\overline{\Delta} + f\Delta_i' \tag{4}$$

$$\Delta_i = S_{ci} - S_{fi} \tag{5}$$

$$\Delta_i' = \Delta_i - \overline{\Delta} \tag{6}$$

with P_i the corrected values, O_i the observed values, S_{ci} and S_{fi} are respectively the simulation of RCM for the period of control and the RCM simulations for the period of verification or future projection of the corresponding CDFs, Δi is the difference between the future and control raw *ith* quantiles, $\bar{\Delta}$ is the mean of Δ_i, f and g are the ratio respectively between mean and standard deviations between observations and simulations of RCM on the control period.

The GQM method (Piani et *al.*, 2010a), applied only to the precipitation, replace F by the Gamma distribution (Equation 7) in equation (3). The Gamma distribution is then adjusted separately to observed data and the RCM data. The Gamma distribution depends only on two parameters and is used for the representation of PDF precipitation (Yang et *al.*, 2010. Wilks, 2011).

$$f(x)=\frac{(x/\beta_g)^{\alpha_g-1}\exp(-x/\beta_g)}{\beta_g\Gamma(x)} \qquad x,\ \alpha_g,\ \beta_g>0, \qquad (7)$$

with α_g and β_g respectively the shape and scale parameters and Γ the Gamma function. The Gamma distribution is not defined for x = 0. The bias correction process is performed in two steps (Piani et *al.*, 2010a). The first step is to correct the number of dry days of the models, setting a precipitation threshold below which any value of rainfall is equal to 0 mm. Once the threshold is set, the two (02) parameters of the gamma distribution are, in a separated way, adjusted to observed and simulated wet days.

In GPQM method, the function F of equation 3 is replaced by a combination of Gamma Distribution and General Pareto distribution (Equation 8). The latter is an extreme values distribution (Coles, 2001). The assumption that underlies the GPQM method is that the combination of a gamma distribution for the current values and a distribution of extreme values is better suited for correct precipitation, in particular for the extreme values (Gutjahr and Heinemann, 2013). First, as in the case of GQM method, a precipitation threshold is set for the correction of dry days. Then a 95th percentile threshold, as proposed by Yang et *al*. (2010), is set for the choice of the distribution to be used. Thus, the 95th percentile lower values are expected to follow the Gamma distribution, while values exceeding this threshold are expected to follow the general Pareto distribution (Gutjahr and Heinemann, 2013).

$$y=\begin{cases} F^{-1}_{obs,gamma}(F_{RCM,gamma}), & if \quad x<95^{th}\ percentille \\ F^{-1}_{obs,DGP}(F_{RCM,DGP}), & if \quad x\geq 95^{th}\ percentille \end{cases} \qquad (8)$$

The multi- variables method 'ISI-MIP', proposed by Hempel et *al*. (2013) is a new method of bias correction developed within the project ISI-MIP (Inter-Sectoral Impact Model Inter-comparison Project) funded by the German Federal Ministry of Education and Research. This method has been developed to preserve the signal change (trend, climate change signal, etc.) and can be applied to several variables (precipitation, the mean, maximum and minimum temperature, radiation, pressure and humidity). For more detail see Hempel et *al*. (2013).

Corrections Performance's Evaluation

The general principle of performance analysis methods for correcting biases in climate models is to compare the similarities between the observed and corrected models data and between observed and non-corrected models data. Many criteria are used; we will retain the two (02) below in this study. In what follows $P_{i,obs}$ and $P_{i,calc}$ represent the observed and calculated (i.e. corrected) daily rainfall.

The Root-Mean-Square Error (RMSE)

$$RMSE=\sqrt{\frac{1}{n}\sum_{i=1}^{n}(P_{i,obs}-P_{i,calc})^2} \qquad (9)$$

The Root-Mean-Square Error between two series is the distance between the means of these two series. The RMSE is particularly close to zero as the two series are similar.

The Mean Absolute Error (MAE)

$$MAE=\frac{1}{n}\sum_{i=1}^{n}\left|P_{i,obs}-P_{i,calc}\right| \qquad (10)$$

The MAE of two series is the mean of absolute values of error between the data of the two series taken in pairs. Like the RMSE, it is even closer to zero as the two series considered are similar.

4. Results

4.1 Performance Analysis of bias corrections at daily scale

Figure 2 shows the MAE and RMSE calculated from the daily values of observed rainfall and bias corrected rainfall. Comparing these criteria with those obtained using the non-corrected data shows that Scaling, ISIMIP, AQM, EQM and DC methods improve the quality of simulated rain for REMO and HIRHAM5 models. But the methods Scaling and ISIMIP are most successful in correcting bias for these two (02) models. As for the RCA4 model, the Scaling method is the only method (of the seven) indicated for the simulated precipitation bias correction by this model in the field of study. Parametric methods (GQM and GPQM) have degraded the quality of simulated rainfall whatever the considered RCM. The assumptions that precipitation could follow the Gamma distribution (Piani et *al*., 2010a) or Gamma + Pareto distribution (Gutjahr and Heinemann, 2013) are not checked in this watershed. Note also that the ISIMIP method which is one of the best methods for HIRHAM5 and REMO models could not correct rainfall at the stations such as Alfakoara, Tanguiéta and Karimama for RCA4 model.

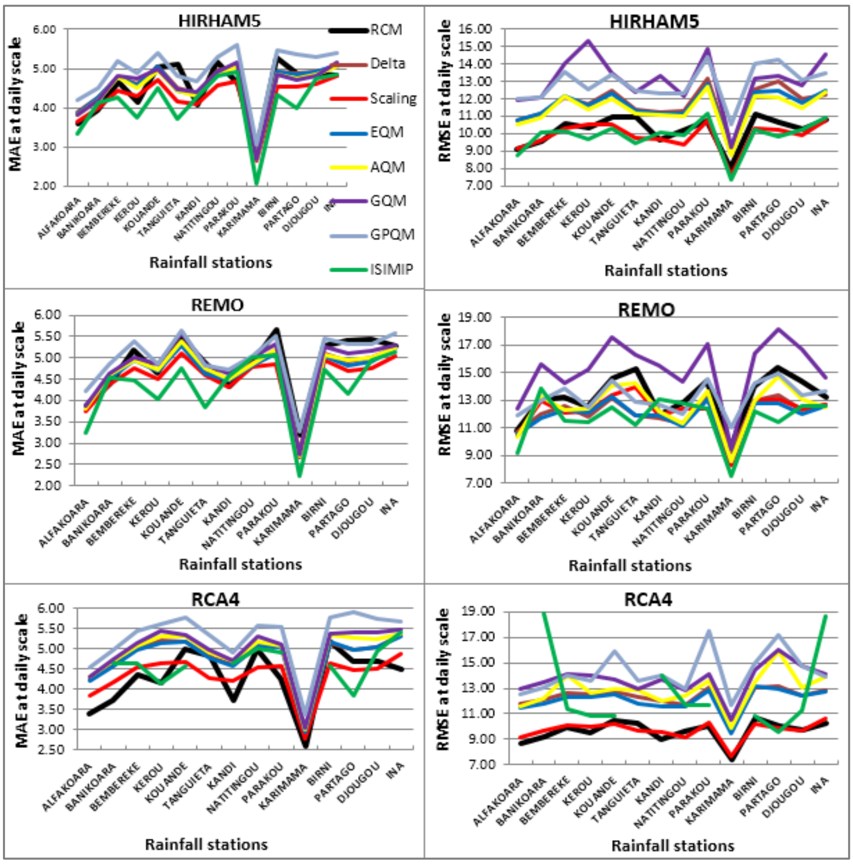

Figure 2: Performance of bias correction at daily scale

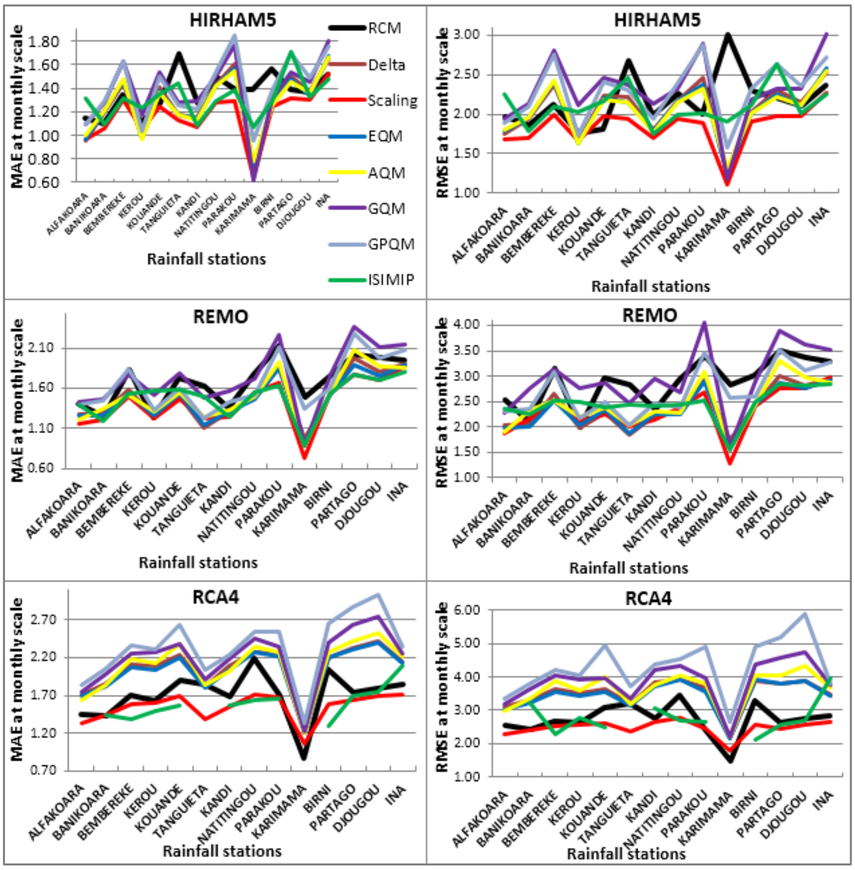

Figure 3: Performance of bias correction at monthly scale

4.2 Performance Analysis of bias corrections at Monthly scale

Figure 3 shows the performance of various correction methods applied by considering the monthly means of rainfall amounts. It appears from the analysis of this figure that the scaling method is still the best approach for correction. Nonparametric methods quantile-quantile (EQM and AQM) seem to better correct monthly rainfall amounts than daily rainfall. As a daily scale, parametric quantile-quantile methods (GQM and GPQM) degrade the quality of monthly precipitation amounts excepted Tanguiéta and Karimama stations for REMO and HIRHAM5 models.

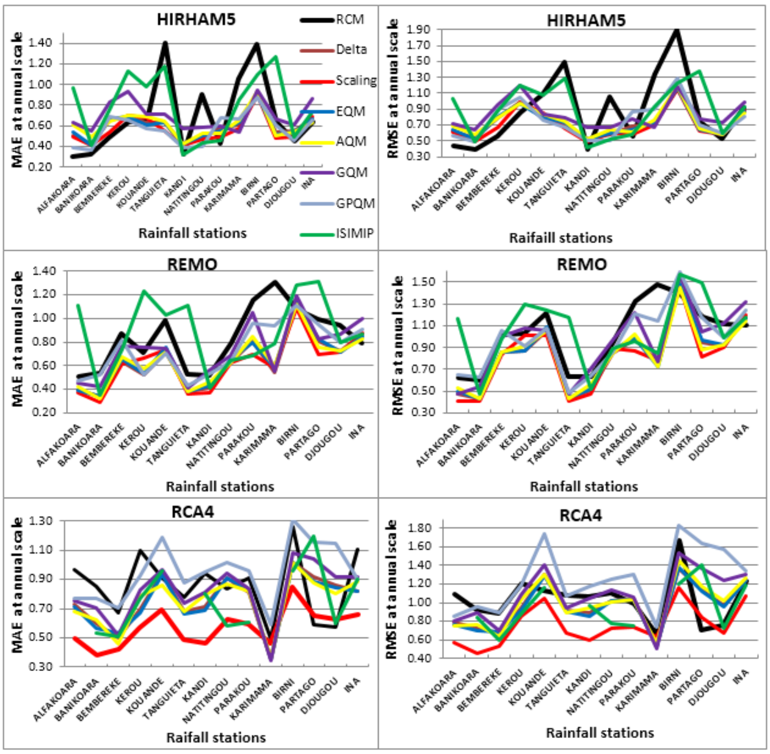

Figure 4: Performance of bias correction at annual scale

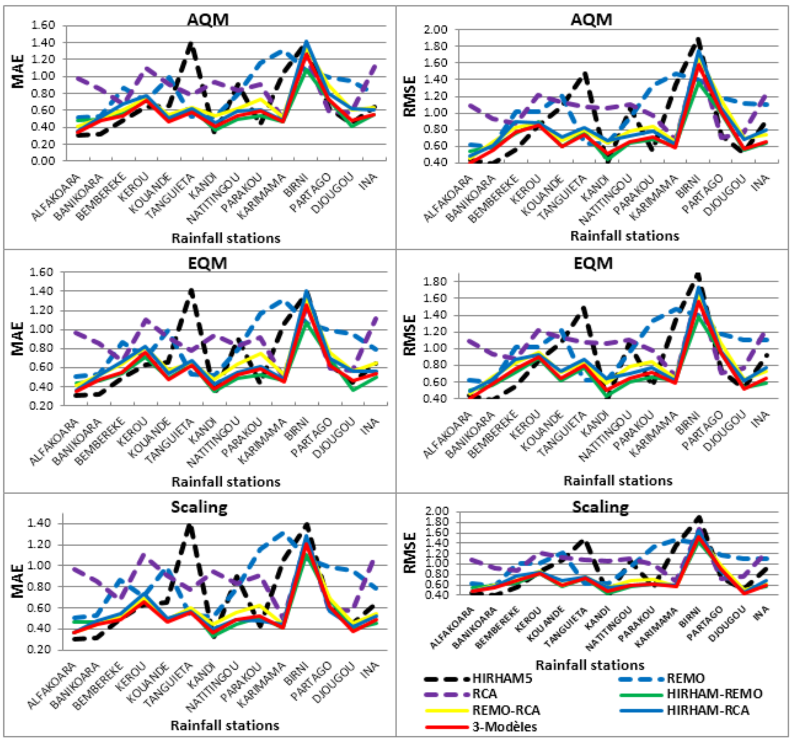

Figure 5: Performance of multi-RCMs

4.3 Performance Analysis of bias corrections at annual scale

Figure 4 shows the performance of correction methods applied by considering the means of annual rainfall amounts. At the annual scale, Scaling, EQM, AQM and Delta methods are all successful in correcting through REMO and HIRHAM5 models. On other hand the ISIMIP method is less efficient on annual basis. These results are also worse than those of GQM and GPQM methods. As for the RCA4 model, the Scaling method is the only method capable of reducing bias regardless of the precipitation station.

4.4 Analysis of the performance of couplings of RCMs

The findings of challenges for a single model to take into account all climate information and the existence of potential complementarities between models has led a number of authors (Frei et *al*., 2006. Fowler et *al.*, 2007; Tebaldi and Knutti, 2007; Déqué et *al*., 2012; etc.) to focus on the Multi-model methods (based on the combination of several models) in order to increase performance and reduce uncertainties simulations. This approach is also developed in this work in order to improve the simulated precipitation by the three RCMs. Analysis of the results (Figure 5) shows a decrease in MAE and RMSE of multi-RCMs compared to those obtained with the individual RCM whatever the method of bias correction and the rainfall station considered. Among the four (04) combinations of RCMs that were made, the combination of REMO and HIRHAM5 models and the combination of the three models show the best performances for all correction methods.

4.5 Analysis of future trends of precipitation

Changes in precipitation over the period 2006-2100 is analyzed using rainfall corrected by the EQM method. Trends by each RCM and trends of the combination of the three models were considered. According to the REMO model, for both RCP4.5 and RCP8.5 scenarios and for all rainfall stations, there would be a downward trend in annual mean rainfall amounts over the period 2006-2100 (Figure 6). However, the decrease is always more important for the RCP8.5 scenario than for RCP4.5 scenario. For example, for Banikoara and Kouandé rainfall stations, decrease in annual mean of rainfall amounts over the period 2006 - 2100, according to the RCP8.5 scenario, will be respectively about 0.6mm and 0.7mm (that represent 22.22% and 20% of rainfall amounts). The RCP4.5 scenario for the same rainfall stations, foresees a decrease of approximately 0.4mm and 0.1mm of annual rainfall amounts corresponding to 10.8% and 5% of rainfall amounts.

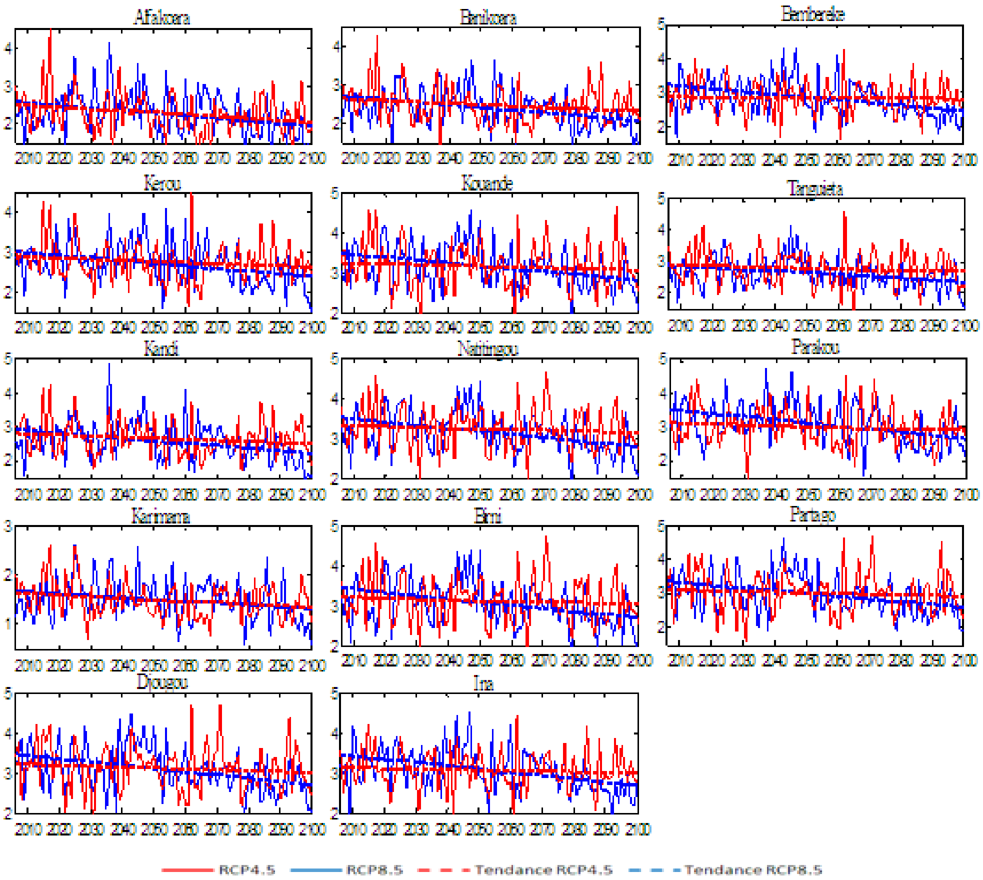

Figure 6: Linear trend in future projections of precipitation amounts by REMO (years in x-axis and precipitation amount in y axis)

In Contrary to REMO model which foresees a decreasing trend of future precipitation, HIRHAM5 and RCA4 models predict an increase trend of rainfall amounts for both RCP4.5 and RCP8.5 and for all rainfall stations (Figure 7 for HIRHAM5 model). Note that the increase of annual precipitation amount, under the RCP4.5 scenario is relatively small and is of the order of 4% and 3% at Banikoara and Kouandé. For the RCP8.5 scenario these increases are approximately 27% at Banikoara and 16% at Kouandé.

The combination of the three RCMs gives an upward trend of annual mean of rainfall amounts for RCP8.5 scenario and for all rainfall stations considered (Figure 8). For example, at Banikoara and Kouandé rainfall stations, the increased precipitation rates are around 25% and 14% respectively. On the other hand, for RCP4.5 scenario, the combination of three models provides a more or less constant trend of amounts of annual rainfall with time.

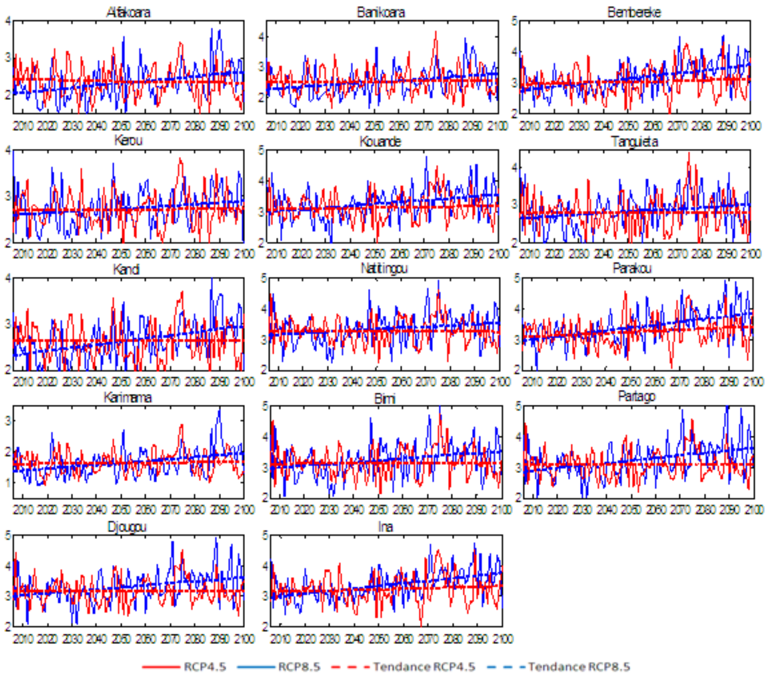

Figure 7: Linear trend in future projections of precipitation amounts by HIRHAM5 (years in x-axis and precipitation amount in y axis)

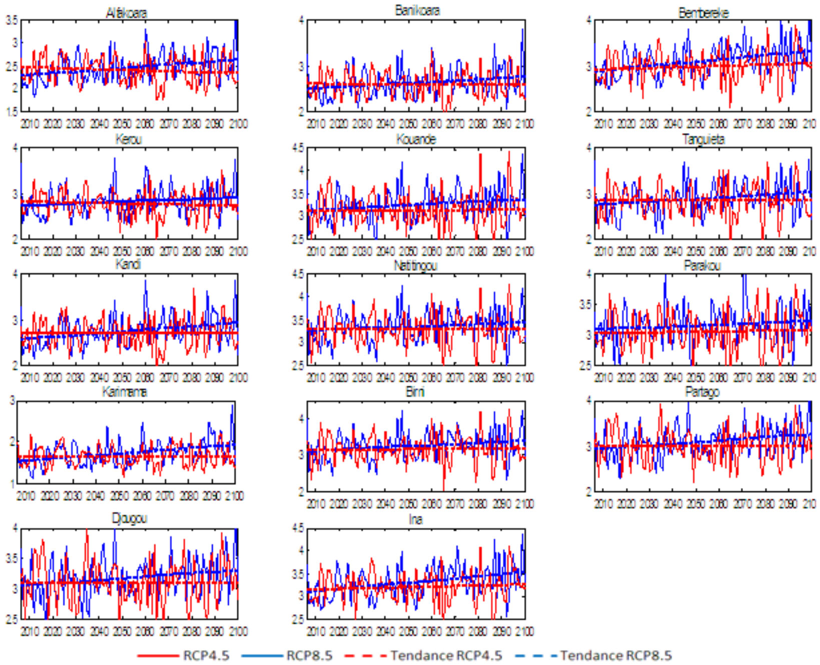

Figure 8: Linear trend in future projections of precipitation amounts by multi-RCMs (years in x-axis and precipitation amount in y axis)

5. Discussion

It is well established that climate parameters from RCMs simulations are subject to bias due for example to our limited understanding of the process or the lack of knowledge of the spatial resolution of these models (Rauscher et *al*., 2010). To correct these bias, numerous techniques have been developed and applied (Piani et *al.*, 2010a; Piani et *al.*, 2010b; Themeßl et *al.*, 2012; Hempel et *al.*, 2013; Fang et *al.*, 2015 ; Sunyer et *al.*, 2015 ; Sarr et *al.*, 2015; etc.). Seven (07) of these methods have been applied in this study and the fact is that three (03) only (Scaling, EQM, AQM) could reduce bias of the three (03) RCMs at different time scales. These results confirm that most of the bias correction methods have great difficulty in correcting rainfall in time and space, probably due to the high variability of precipitation (Piani et *al*., 2010a) or to the assumption of stationarity of bias (Maraun et *al*., 2010) basis of development of these methods, which hypothesis is not verified in some arid and semi-arid areas such as West Africa (Maraun, 2012). Nonparametric QM methods have also been used in many applications with satisfaction for bias correction of RCMs precipitations (Gudmundsson et *al.*, 2012; Themeßl et *al.*, 2011; Teutschbein and Seibert, 2012; etc.). Parametric QM methods (GQM and GPQM) have degraded the quality of simulations for all stations, time scale and RCMs. These results are consistent to those obtained by Gudmundsson et *al*. (2012) who found that parametric methods are the least efficient of all methods used in their study. The good quality of nonparametric methods compared to parametric would be due to their flexibility as they are related to any predetermined function (Gudmundsson et *al*., 2012) and this flexibility enables a good fit for any quantile-quantile relationship.

To improve the performance of bias correction methods, Multi-RCMs approach was developed. As shown in many studies (Frei et *al*., 2006. Fowleret *al.*, 2007; Tebaldi and Knutti, 2007. Déqué et *al.*, 2012), the multi-RCMs approach reduces biases compared to individual model. In the present study, the combinations of two (02) models and that of the 3 models gave in each case better performances as compared with those of the individual model. Note that the combination of REMO and HIRHAM5 models and of the 3 models gave the best results.

The upward trends in future annual precipitation amounts for the HIRHAM5 RCA4 models and the downward trend of REMO are consistent with the predictions of IPCC (2014), which provides large wider precipitation uncertainty in West Africa. These results also confirm those obtained by Kabore et *al*. (2015) who also found an increasing trend of annual rainfall amounts of future models with the period from 2006 to 2050. The downward trend of the evolution of annual rainfall amounts of REMO model is also in accordance with the results obtained by Mbaye et *al*. (2015) in Senegal with the same model. To better understand the implications of trends in population and propose adaptation measures, a study of the inter-annual variability of rainfall is essential to determine the duration and occurrence of rainy seasons, the frequency of extreme rainfall, etc. ., which are the factors taken into account in agricultural production.

Conclusion

Three of the seven bias correction methods showed real capacities of reducing the bias of RCMs at different time scales. The different combinations of RCMs performed also helped improve much more the performance of bias corrections. Finally the analysis of the future evolution of annual rainfall amounts shows for REMO model a downward trend for RCP4.5 and RCP8.5 scenarios with an emphasis on RCP8.5 scenario. As against for HIRHAM5 and RCA4 models, there is a tendency to increase of annual rainfall amounts. The combination of the three models reveals a rising trend of future annual precipitation for scenario RCP4.5 while the trend is almost constant for RCP4.5 scenario.

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