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Interactive comment on "Analyzing the future climate change of Upper Blue Nile River Basin (UBNRB) using statistical down scaling techniques" *by* Dagnenet Fenta Mekonnen and Markus Disse

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We thank Anonymous Referee #2 for his critical review, which added significantly to the discussion of the paper

The objective of this study is to analyze and better comprehend the possible future climate trend for UBNRB. If you select a set of representative climate scenarios that properly capture future climate variability, the results are reasonable and accepted for other colleagues. However, I do not believe that you can do a comprehend analysis with only a set of climate scenarios without a systematic techniques to select representative

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scenarios?

As climate models are differ from each other , particularly in the parameters and functions used to describe the physical processes of the ocean and atmosphere circulations. Forcing scenarios also differ from each other as they provide alternative hypotheses about the development of human society, through different demographic, social, political, technological, and environmental assumptions. High uncertainty is, therefore, expected in climate change impact studies if the simulation results of a single GCM and single scenario are relied upon.

To address uncertainty in projected climate changes, the (IPCC, 2014) thus recommends using a large ensemble of climate change scenarios produced from various combinations of Atmospheric Ocean General Circulation Model (AOGCMs) and forcing scenarios. Importantly, all climate change scenarios provided by IPCC should be considered plausible and illustrative, and do not have probabilities attached to them. It is thus standard practice to use, in any single study, several GCMs outputs in an ensemble framework . However, it can become prohibitively time consuming to assess the climate change, using simultaneously many climate change scenarios and many Statistical Down scaling models. As a result, researchers typically assess the climate change and its impacts under only one or a few climate change scenarios. Moreover, researchers often select climate change scenarios arbitrarily and provide little or no justification about their choice. Yet different modeling frameworks can lead to different projections of climate change, and possibly to conflicting interpretations. In this context, a critical question is which and how many climate change scenarios are required to carry out impact analyses that cover the range of possible climate futures. Surprisingly, there is no publication aimed at presenting and testing an objective method to select an appropriate subset of climate change scenarios among the wide range of possibilities(Casajus et al., 2016).

Therefore, given the importance of both taking into account the wide range of equally probable climatic futures and avoiding computationally prohibitive study designs, in this study, we applied multi model approach to see the uncertainties came from different GCMs. We produced future climate scenarios using output from six AOGCMs available through CMIP3 and one available through CMIP5. These six AOGCMs from CMIP3 were not chosen arbitrarily but systematically based on their performances representing the current climate of the study area. The MAGICC/SCEGEN computer program tool was used for the performance evaluation of the embedded 15 GCMs in LARS WG5.5 database, and those six best performed GCMs were selected (for details see Authors comment #1). In summary, we used six ensembles of best performed GCMs under all three SRES scenarios (A2, A1B, and B1) considered in the IPCC-AR4 report from the four scenario families (A1, A2, B1 and B2). Additionally, one CMIP5 GCM under four newly radiative scenarios of RCP2.6, RCP4.5, RCP6 and RCP8.5. In total, 21 future climate scenarios were produced for this study as summarized in the Table1 , which we might think representative to understand fully and to project the future climate change in the study area and to retain information about the full variability of GCMs. We will add a paragraph to the paper reflecting the discussion above.

The second issue is downscaling scheme you chose, LARS-WG and SDSM. LARSWG is a weather generator for a single site without consideration of spatial correlation. If you apply a single random number when you generate weather conditions for all stations, spatial correlation might be intrinsically preserved. If you applied LARS-WG for individual station, however, you significantly distorted the spatial correlation between stations. In this case, you need to check in validation.

We do fully agree with the Anonymous Referee #2 that LARS WG as it is a stochastic simulation tools that are commonly used to produce synthetic climate data of any length with the same characteristics as the input record, it simulate weather separately for single sites; therefore, the resulting weather series for different sites are independent of each other, whereas very strong spatial correlation exists in real weather data which can be lost during simulation.

To analyze the spatial auto correlation of station to station, the simple Pearson's correlation coefficient (R2) value was calculated and presented in the Fig.2 below. A 28 years for the period of 1984-2011, monthly data were analyzed for randomly chosen stations (Abaysheleko and Bahirdar) and the R2 values were plotted against the stations. The result from Fig.2 showed that R2 values of the simulated precipitation for the selected stations systematically decreased from the R2 value of the observed precipitation. The highest R2 value recorded was 0.83 for Bahirdar with Gondar and Dangila and the lower R2 value was 0.53 with Bedele for the observed precipitation values. While the highest R2 value was 0.73 both with Gondar and Dangila and the lowest value was 0.49 with Bedele for the simulated monthly precipitation of Bahirdar Station. The same trend was observed for Abaysheleko, in which the R2 value of the simulated precipitation decreased as compared to the observed precipitation. The highest R2 value was observed 0.71 with both Debre Tabor and Gondar and the lowest value was 0.43 with Bedele station for the observed precipitation, whereas, the highest R2 value was 0.64 with both Gondar and Debre Tabaor and lowest value was 0.46 with Bedele station after simulation. In general, the result of LARS WG revealed that the spatial correlation of the stations was distorted /decreased/ from the original to a lesser extent as expected.

Although, a few stochastic models have been developed to produce weather series simultaneously at multiple sites to regionalize the weather generators, mainly for daily precipitation, such as space–time models, non-homogeneous hidden Markov model and nonparametric models typically use a K-Nearest Neighbor (K-NN) procedure (King et al., 2015), they are complicated in both calibration and implementation and are unable to adequately reproduce the observed correlations (Khalili et al., 2007).

Even if, LARS WG has limitation to preserve the spatial correlation of climate variables, it can be applied for downscaling climate change scenario for the Upper Blue Nile River Basin satisfactorily. As spatial distribution of precipitation may have essential effects on the discharge of a river and the formation of floods, preserve the spatial correlation in simulations of the weather series corresponding to certain climate scenarios is necessary while preparing as input to impact models, especially for hydrological models and it would be the Author's future work. We will add a paragraph to the paper reflecting the discussion above as a limitation of the model.

In addition, I am not sure if it is reasonable to inter-compare the skill between weather generator (LARS-WG) and regression-based (SDSM) downscaling methods because SDSM considers sequencing of GCM but LARS-WG generates a new sequence. Lastly, the authors need to include more climate index for a comprehensive inter-comparison.

Many downscaling models (dynamic and statistical)have been developed in the past few decades, which all have strengths and weaknesses (Wilby et al., 2007). Statistical downscaling, which derives a statistical or empirical relationship between the large-scale climate features simulated by the GCM (predictors) and the fine scale climate variables (predictands) for the region is the priority of this study. Although many downscaling models have been developed in the past decade, it is not clear which one provides the most reliable estimates of climate variables, no single model has been found to perform well over all the regions and time scales. Thus, evaluations of different models are critical to understand the applicability of the existing models. Comparison of different statistical downscaling models have been conducted in many countries at various spatial and temporal scales (Dibike and Coulibaly, 2005; Ebrahim et al., 2013; Fiseha et al., 2012; Goodarzi et al., 2015; Hashmi et al., 2011; Khan et al., 2006; Qian et al., 2004; Wilby et al., 2004; Wilby and Wigley, 1997; Xu, 1999). However, it remains difficult to directly compare the skill of different downscaling models because of the range of different hydrological variables that have been assessed in the literature in both space and time domains, the large number of predictors used, and the different proposed evaluation metrics used for assessing model performances(Goly et al., 2014) .

Khan et al. (2006) have compared three downscaling modelsâĂŤnamely, artificial neural networks (ANNs), statistical downscaling model (SDSM), and the Long Ashton Research Station Weather Generator (LARS-WG) in terms of various uncertainty attributes exhibited in their own scaling results of daily precipitation and daily maximum and minimum temperature. The methods indicated that no single model performed better for all the attributes and that downscaling daily precipitation ANN model errors are significant at 95% confidence level for all months of the year. However, SDSM and LARS-WG model errors of only a few months were significant. Further, they showed that the estimates of means and variances of downscaled precipitation and temperature performed better for SDSM and LARS-WG, while ANN performed poorly.

Dibike et al. (2005) were also evaluated the performance of SDSM and LARS WG in reproducing the current three meteorological variables (Precipitation, maximum and minimum temperature). The result showed that, the mean daily precipitation is simulated by both SDSM and LARS-WG reasonably well and there is no much difference in their performance. In downscaling maximum and minimum temperature, the performance of both models is very good. However, SDSM slightly overestimates the temperatures for most months of the year while LARS-WG slightly overestimates for some months and underestimates for the remaining months of the year.

Fiseha et al. (2012) were evaluated the performances of two statistical downscaling models (i.e., SDSM and LARS WG) in terms of their ability to reproduce the mean values of current climate and future precipitation, and temperature data. In the case of temperatures (Tmin and Tmax), both models show identical results and capture the general trends of the mean values. While, for precipitation, the analysis of the results from the two models does not lead to an identical conclusion presumably due to the fact that the SDSM uses large scale predictor variables, but the LARS WG is analyzed by applying the change factors from the GCM to the observed climate.

Therefore, inclusion of multi-model approach and assessing the comparative performance of the downscaling model is essential to understand the applicability of the models and to minimize the uncertainties caused due to the downscaling models. Moreover, to best identify which model provides the most plausible and robust simulations for downscaling climate models for a specific study area and time periods. We will add a paragraph to the paper reflecting the discussion above. However, we deliberately avoided to include more climate index (such as extreme climate indices) for a comprehensive inter-comparison as it is not the main focus of the study.

All other comments that highlight the weakness of the format and structure of the paper presentation raised by the reviewer will be addressed in the revised version. For instance Figure 2a can be replaced with the below simple flow chart to enhance the quality and to understand easily. List of predictors in Table 3 are not the selected ones, they are all lists of predictors available in NCEP-NCAR on HadCM3 & canESM2 grid. Selection procedure of predictors is described in page 9 l 4-12 and the details can be found (Wilby et al., 2007).

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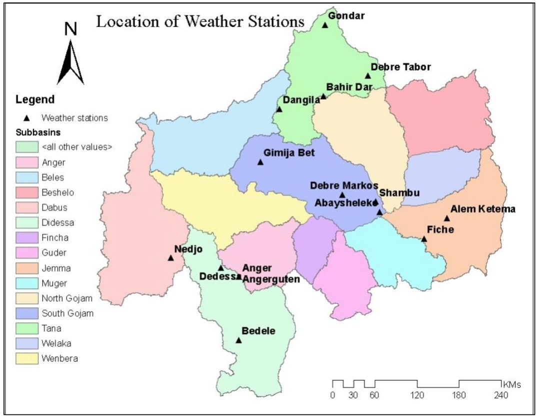

Figure1: Location of weather stations

Fig. 1.

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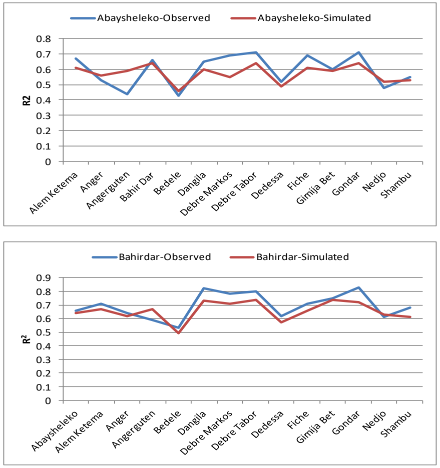

Figure2: Spatial correlation coefficient (R^2) of a) Abaysheleko (left) and b) Bahirdar (right) weather stations with others for monthly precipitation from 1984-2011.

Fig. 2.

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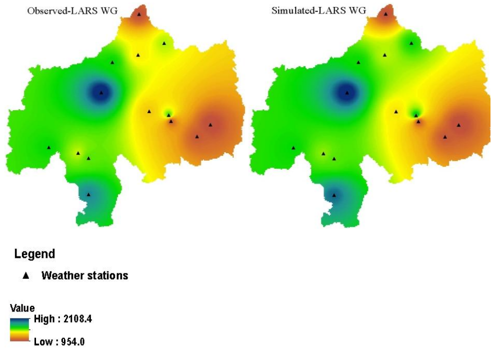

Figure 3: Long term mean annual precipitation(mm) simulated using LARS WG model

Fig. 3.

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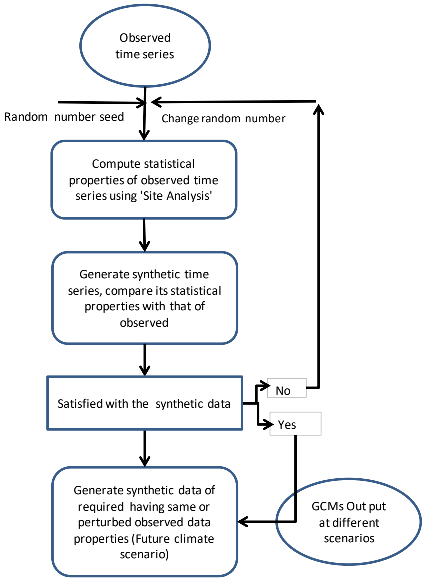

Figure 4 : Schematic diagram of LARSWG

Fig. 4.

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Table 1: Global climate models from IPCC AR4 and IPCC AR5 used for this study

Research center	Country	GCM	Model acronym	Grid Resoluti on	SRES scenario
1. LARS WG statistical downscaling model					
Common Wealth Scientific and Industrial Research Organization	Australi a	CSIRO-MK3	CSMK3	1.9x1.9°	A1B, B1
Max-Plank Institute for Meteorology	German y	ECHAM5-OM	MPEH5	1,9x1.9°	A1B,A2,B1
National Institute for Environmental Studies	Japan	MRI-CGCM2.3.2	MIHR	2.8x2.8°	A1B,B1
UK Meteorological Office	UK	HadCM3	HADCM 3	2.5x3.75°	A1B,A2,B1
Geophysical Fluid Dynamics Lab	USA	GFDL-CM2.1	GFCM21	2x2.5°	A1B,A2,B1
		CCSM3	NCCCS	1.4x1.4°	A1B,B1
2. SDSM statistical down scaling model					
UK Meteorological Office	UK	HadCM3	HADCM 3	2.5x3.75°	B2a,A2a
Canadian Centre for Climate Modeling and Analysis	Canada	canESM2	canESM 2	2.8125o x 2.8125o	RCp2.6,RCP4.5, RCP6, RCP8.5

Fig. 5.