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Review

Comparison of downscaling methods for mean and extreme precipitation in Senegal

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ABSTRACT

Study region: The study considers six precipitation stations located in Senegal, West Africa. Senegal is located in the Sahel, an area that is threatened by climate variability and change. Both droughts and extreme rainfall have been an issue in recent years.

Study focus: Two different statistical downscaling techniques were applied to the outputs of four regional climate models at six selected precipitation stations in Senegal. First, the delta-change method was applied to the mean annual precipitation as well as the 5, 10, 20, 50 and 100-year return period daily precipitation events. Second, a quantile–quantile transformation (QQ) was used to downscale the monthly distributions of precipitation simulated by regional climate models (RCMs). The 5, 10, 20, 50 and 100-year daily precipitation events were afterward calculated. All extreme events were calculated assuming that maximum annual daily precipitations follow the generalized extreme value (GEV) distribution. The two-sided Kolmogorov–Smirnov (KS) test was finally used to assess the performance of the quantile–quantile transformation as well as the GEV distribution fit for the annual maximum daily precipitation.

New hydrological insights for the region: Results show that the two downscaling techniques generally agree on the direction of the change when applied to the outputs of same RCM, but some cases lead to very different projections of the direction and magnitude of the change. Projected changes indicate a decline in mean precipitation except for one RCM over one region in Senegal. Projected changes in extreme precipitations are not consistent across stations and return periods. The choice of the downscaling technique has more effect on the estimation of extreme daily precipitations of return period equal or greater than ten years than the choice of the climate models.

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Contents

1. Introduction

Senegal is a semi-arid country located in the extreme west of the African continent. Its climate is characterized by a dry season from November to April and a wet season from May to October, regulated by the migrations of the InterTropical Convergence Zone (ITCZ) (Leroux, 1970). During the wet season, the ITCZ completely covers the study area as it moves towards the north to the edge of the Sahara until the months of August and September. Most of the rainfall is recorded in August, followed by July and then September (Sarr et al., 2013, 2014). As part of the Sahelian zone, Senegal has been hit by recurrent droughts leading to food shortage. Recently, the country also experienced frequent episodes of intense precipitations leading to urban flooding and casualties in Dakar, the country's capital, and in other urban centres. Between August 16 and August 22, 2005, Dakar has recorded 367 mm of rain, which is more than half of the average annual total rainfall. On August 26, 2012, Dakar received one quarter of the annual precipitation (168 mm) in less than an hour (Dacosta, 2012, personal communication). These precipitation events have caused considerable psycho-social and health impacts, which are eventual losses to vulnerable sectors such as agriculture, infrastructures and trades. The perceived increase in climate-related disasters has triggered fears that the frequency of extreme precipitations will be triggering more extreme events, characterized by their infrequency and their high magnitude.

The best way to develop cost-effective coping strategies is to generate information about future changes in mean and extreme precipitation indices (Nicholls and Murray, 1999; Manton et al., 2001). These indices are generally calculated with the outputs of a climate model running under a given scenario. Different emission scenarios and climate models simulations are available. In addition, different downscaling techniques exist, ranging from statistical methods (delta-change, regression-based, weather typing, neural networks, etc.) to the use of regional climate models (RCMs). Statistical downscaling can be applied to RCMs in an attempt to correct their biases. Given that for practical reasons an end user in a given region can only apply a few of the available techniques available, inter-comparison studies are helpful in pointing out the uncertainty associated with the choice of the downscaling technique. Burger et al. (2012) showed for the same location that downscaled climate extremes are more sensitive to the choice of the downscaling technique than the emission scenario, the RCM and the location. The choice of the downscaling technique, mainly in the field of regional planning and decision-making, is very important. Even if there are many downscaling techniques, they can be classified into two categories: dynamical and statistical (Hewitson and Crane, 1996; Miller et al., 2009). Dynamical downscaling is physically related to regional climate

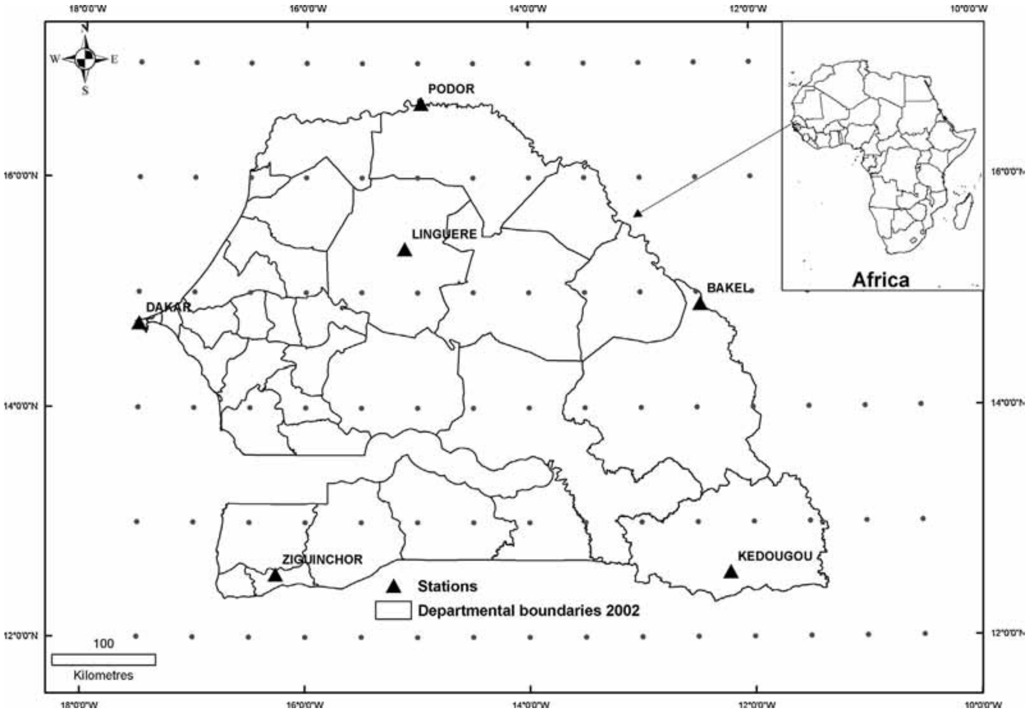

Fig. 1. The study domain and the selected stations.

models with high computational requirements (e.g. Giorgi et al., 1994; Sylla et al., 2009). Dynamical downscaling do not give significantly better results for temperature and precipitation and is often considered too expensive for operational use, but it does not require local calibration of their outputs. Statistical downscaling assumes stationarity in the predictor–predictand relationship, requires robust relationships and sufficient data to verify this assumption. Statistical downscaling results could be also strongly impacted by data errors if the predictor–predictand relationship does not consider important climatic features (such as large scale circulation and local characteristics of the study area), it generally focuses on precipitation (in the present paper) and/or temperature (e.g. Di Vittorio and Miller, 2013). Statistical methods are based on statistical relationships between the coarse GCM or RCM data and point measurement at an observation station. In practical terms, the statistical relationships are based on a calibration period, approved for a period of separate time, and then applied to other time periods, with the assumption of temporal stationarity (Di Vittorio and Miller, 2013).

The objective of this paper is to compare the impact of two downscaling techniques (the delta-change and quantile–quantile transformation) on projected changes, in average and extreme precipitation of the 2000–2050 period at six locations across Senegal (Fig. 1). Four RCMs and global climate models (GCMs) are sampled from Ensembles-based Predictions of Climate Changes and Their Impacts (ENSEMBLES) and African Monsoon Multidisciplinary Analyses (AMMA) experiments (Van der Linden and Mitchell, 2009; Redelsperger et al., 2006). The downscaling techniques were applied to estimate the mean daily precipitation and 5, 10, 20, 50 and 100-year daily precipitation events at the six locations in addition to the direction of change. The delta-change technique was selected because it is most widely used with RCM outputs (Maraun et al., 2010; Themeßl et al., 2011). The delta change technique is easy to apply (one just need to apply a coefficient to historical time series) and preserve important statistical characteristics (spatial correlations, interdependence) in downscaled time series. Its main limitation is that it does not allow for a change in variance in the future, and misses the risk generated by a possible change in climate variables distributions in the future. It is

Table 1
Selected climate stations.

ID	Name	Latitude	Longitude	Altitude (m)	Data availability
BK	Bakel	14.9	−12.5	25	1950–2007
DK	Dakar	14.7	−17.5	24	–
LG	Linguère	15.4	−15.1	20	–
KG	Kédougou	12.6	−12.2	116	–
PD	Podor	16.6	−14.9	6	–
ZG	Ziguinchor	12.5	−16.3	26	–

well known that the correct reproduction of these statistical characteristics is required for a realistic modelling of biophysical impacts. The choice of the QQ correction is motivated by the fact that it tries to correct the distributions of the variables, therefore potentially reducing the bias of extreme events estimators in climate model simulations. When it is applied to several variables generated by an RCM, the spatial correlation and interdependence in RCM outputs are inherited by downscaled time series. Regression based downscaling techniques such as the Statistical DownScaling Model (SDSM) were not used given their reported low explained variance in reproducing daily precipitation statistics during the historical period (reportedly from 6% to 45%): Wilby et al. (1998), Wilby and Dawson (2008) and Nguyen et al. (2004). The delta-change was applied to both the mean and extreme precipitations indices calculated using historical data; The QQ-transformation was applied to historical data before the mean and extreme precipitation indices were calculated for future periods.

The remainder of the paper is organized as follows: the two downscaling methods are described in Section 2. The results are discussed in Section 3, and a conclusion is finally given in Section 4.

2. Methodology

2.1. Observed precipitation

Daily precipitation time series spanning from 1950 to 2007 at six climatic stations were collected from the Senegalese meteorological service for the study (Table 1). The stations were selected to provide a good spatial coverage of the different climatic zones across Senegal: Dakar (DK) in the west and Ziguinchor (ZG) in the southwest are located on the fringe of the Atlantic Ocean. Podor (PD) and Linguère (LG) in the north of the country; Bakel (BK) in the east is representative of the more arid areas, while Kédougou (KG) at the southeast experiences a relatively wet climate (Fig. 2). Stations in Senegal hold the oldest data in West Africa. However, these data are missing, inconsistent or erroneous because of a bad management of materials and staff who made the measurements. Only stations containing less than 2% of missing values were retained in the study. Many other stations are not considered because many years were missing. The rainy season in Senegal generally extends from May to October, with the heaviest precipitations occurring between July and September. A decreasing trend was detected in the mean annual precipitation at all stations using a Mann–Kendall test at 95% of confidence level, but no trend was found in maximum daily precipitations.

2.2. Regional/global climate models combinations

AMMA-ENSEMBLES is an international collaborative model intercomparison experiment that provides a set of RCM simulations results covering most of the African continent at a resolution of 50 km (Paeth and Diederich, 2011a,b). The RCMs are driven by either the ERA-INTERIM reanalysis, or by global climate models outputs simulated under the SRES A1B emission scenarios (Paeth and Diederich, 2011a,b). The data sets are available for free in the online database (http://ensemblesrt3.dmi.dk/). Four different RCM/GCM combinations (listed in Table 2) are selected from the AMMA-ENSEMBLES database to include three different RCMs (HIRHAM, REMO and RCA) driven by two different GCMs (HADCM3 and ECHAM5) (Paeth and Diederich, 2011a,b). All RCMs are run under the SRES A1B scenarios. The simulated precipitation time series of the four GCM/RCMs combinations are extracted for each of the six cities and used in the analysis. The use of an ensemble of different climate simulations allows

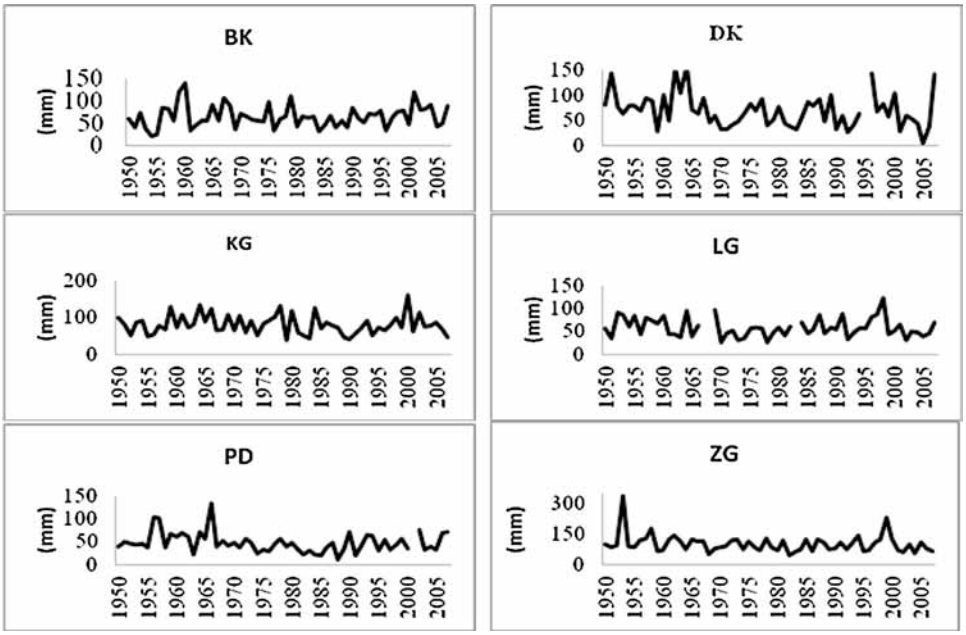

Fig. 2. Time-series of the annual precipitation extremes for each station.

the evaluation of the uncertainties in the individual projections coming from the RCM/GCM models combination.

2.3. T-year precipitation estimate

In this study, the generalized extreme value distribution (GEV) is used to model maximum daily precipitations. The GEV distribution has an interesting asymptotical behaviour and is commonly used to model extreme events. The extreme value theory (EVT) provides the convergence of the extremes to the GEV distributions despite the original distribution of the daily data. The GEV distribution combines the Gumbel, Fréchet and Weibull distributions of extreme values (Jenkinson, 1955):

$$F(x)=\begin{cases}\exp\left[-\left(1-\dfrac{\kappa}{\alpha}(x-\mu)\right)^{1/\kappa}\right]; & \kappa\neq 0\\[2ex] \exp\left[-\exp\left(-\left(\dfrac{x-\mu}{\alpha}\right)\right)\right]; & \kappa=0\end{cases} \tag{1}$$

where μ, α and κ are the location, the scale and the shape parameters, respectively. When $\kappa<0$, the GEV corresponds to the Fréchet distribution and can be fitted to heavy tailed behaviour. The $\kappa>0$ represents the Weibul distribution and is used to fit left skewed samples. The case, $\kappa=0$ corresponds to the Gumbel distribution and has moderate right tail with two parameters, scale and location (Katz et al.,

Table 2
Selected GCM/RCM combinations.

Acronym	RCM	Driving GCM	Simulation period
DMI-HIRHAM5	HIRHAM5	ECHAM5-r3	1989–2050
MPI-M-REMO	REMO	ECHAM5-r3	1950–2050
METNOHIRHAM	RCA	HadCM3-Q0	1990–2050
INMRCA3	HIRHAM	HadCM3-Q0	1951–2099

2002). The GEV parameters are estimated with the generalized maximum likelihood (GML) method. The GML method is based on the same principle as the maximum likelihood (ML) method with an additional constraint on the shape parameter, to eliminate potentially invalid values (El Adlouni et al., 2007). A prior distribution of κ adapted to hydro-meteorological series was introduced by Martins and Stedinger (2000). The prior for κ has a Beta distribution (with shape parameters $\alpha = 3$ and $\beta = 6$) defined on the interval [−0.5, +0.5], with a mode at −0.12.

2.4. The delta-change technique

The technique is based on the ratio between the periods 2001–2050 and 1950–2000 of the *T*-year precipitation calculated using RCM simulations. For a given station and a given RCM, the delta-change technique is applied in a similar way as in Tramblay et al. (2012) using the following steps:

1. Maximum daily precipitations of each year in the historical precipitation time series are extracted from the observed data.
2. The GEV distribution is fitted to the samples to calculate the *T*-year return period precipitation ($P_{T,hist,obs}$) for $T = 5$, 10, 20, 50, 100 years using the maximum likelihood estimator.
3. Maximum daily precipitations of each year in the RCM-simulated precipitation time series for the historical period are extracted.
4. The mean daily precipitation and the *T*-year return period precipitation ($P_{T,hist,RCM}$) for $T = 5$, 10, 20, 50, 100 years are calculated using the GEV distribution for which parameters are obtained using their maximum likelihood estimator.
5. Maximum daily precipitations of each year in the RCM-simulated precipitation time series for the future period are extracted.
6. The mean daily precipitation and the *T*-year return period precipitation ($P_{T,hist,RCM}$) for $T = 5$, 10, 20, 50, 100 years are calculated using the GEV distribution which's parameters are obtained using their maximum likelihood estimator.
7. The future *T*-year precipitation is estimated as

$$P_{T,fut,delta} = P_{T,fut,RCM} \frac{P_{T,hist,obs}}{P_{T,hist,RCM}} \quad (2)$$

2.5. The quantile–quantile transformation (QQ)

The quantile–quantile transformation (also called quantile mapping) (Maraun et al., 2010; Themeßl et al., 2011) was applied on a monthly integrals to obtain statistical distributions of a given climate variable as close as possible to the statistical distribution of the observed variable on the historical period. The procedure for a given month and precipitation variable is explained below:

1. The historical data is split in a calibration period (1950–1988) and a validation period (1989–2007). The daily time series of the month are extracted for both periods from both observations and RCM simulations
2. An empirical cumulative distribution function F_{obs} is developed using the observations on the calibration period; another cumulative distribution function F_{RCM} is developed using the RCM outputs on the calibration period.
3. Corrected RCM simulations are generated on the validation period and future periods using the following transformation: $X_{CORR} = F_{obs}^{-1}(F_{RCM}(X_{RCM}))$ where X_{RCM} is the variable extracted from raw RCM simulations and X_{CORR} is the corrected variable.
4. The probability mass function (PMF) of precipitation occurrence (defined as intensity > 1 mm/day) as well as the PDF of precipitation intensity on rainy days are built. If the PDF (or PMF) of corrected variable is closer to the probability density function (PDF) of the observations than the PDF (or PMF) of the non-corrected variable, the quantile–quantile transformation is applied to future RCM simulations of that particular variable.

Table 3
Combination of stations and models selected to carry-on extreme precipitation estimation after QQ-transformation (OK = the station is selected).

Model	Stations					
	Bakel	Dakar	Linguère	Kédougou	Podor	Ziguinchor
DMI-HIRHAM5			OK		OK	
MPI-M-REMO			OK			OK
METNOHIRHAM		OK	OK			
INMRCA3					OK	

5. A two-sample Kolmogorov–Smirnov (KS) test is used to compare the PDF of the observations to the PDF of the corrected precipitation on both the calibration and validation period (Simard and L'Ecuyer, 2011). The null hypothesis is that the two data sets are from the same continuous distribution. The alternative hypothesis is that they are from different continuous distributions. The distributions are assumed different if the *p*-value is below 5%.

3. Results and discussion

3.1. Validation of the quantile–quantile transformation in the historical period

The hypothesis that the uncorrected RCM outputs have the same distribution as the observations was systematically rejected by the KS test at all stations on both the calibration and validation period, supporting the assumption that a distribution correction is needed. As expected the hypothesis that the corrected RCM outputs have the same distribution as observed was never rejected on the calibration period across all variables and stations. The QQ-downscaling is carried on at a station only if the null hypothesis is not rejected for any of the three months of the rainy season where the maximum precipitation occurs in Senegal (July, August and September). Results show that the null hypothesis was however rejected on the validation period at some of the stations for some of the months, and that the rate of rejection varied greatly across models and stations: for instance, no model was retained for the cities of Bakel and Kédougou because for each of the models under consideration, the null hypothesis was rejected for at least one month in the rainy season (Table 3); only model DMI-HIRHAM5 was retained for Dakar, and only one model (out of four) was rejected for the station of Linguère. The complete list of model-station combinations retained to carry-on the QQ-transformation can be found in Table 3. No RCM is selected at the two eastern stations of Bakel and Ziguinchor, while only one is selected at Dakar, two at Podor and Ziguinchor and three at Podor (Table 3). No RCM is selected at more than two stations, making it difficult to draw a general conclusion about potential zones of better performances for the climate models. Therefore we cannot recommend a particular RCM for Senegal based on this study. The rejections may be due to undetected anomalies such as outliers in either the observed data, or the RCM data.

The QQ-transformation always improved the fit between RCM simulations and observation. Even when the KS test led to the rejection of the null hypothesis on the validation period, the *p*-value obtained when comparing corrected RCM outputs to observations was higher than the *p*-value obtained when comparing uncorrected RCM values to observations. An example of such improvement is presented in Fig. 3 where probability of rainfall occurrence at Dakar for each month from June to October plotted for the observations, a RCM (METNOHIRHAM in this case) outputs and QQ-transformed RCM outputs. The graphs are presented for the calibration (left panels) and validation (right panels) periods. The dark blue bars represents the precipitation occurrence probability for the month in the observations; the light blue bars represent the precipitation occurrence probability calculated using the uncorrected outputs of the RCM; the green bars represent the precipitation occurrence probability calculated using the QQ-corrected outputs of the RCM; the orange and red bars present the same results for the uncorrected and corrected RCM on the 2000–2050 period. It can easily be seen that the green bars (corrected RCM) are always closer to the dark blue bars (observations) than the light blue bars (uncorrected RCM). Furthermore, the projected rainfall occurrence probabilities for the

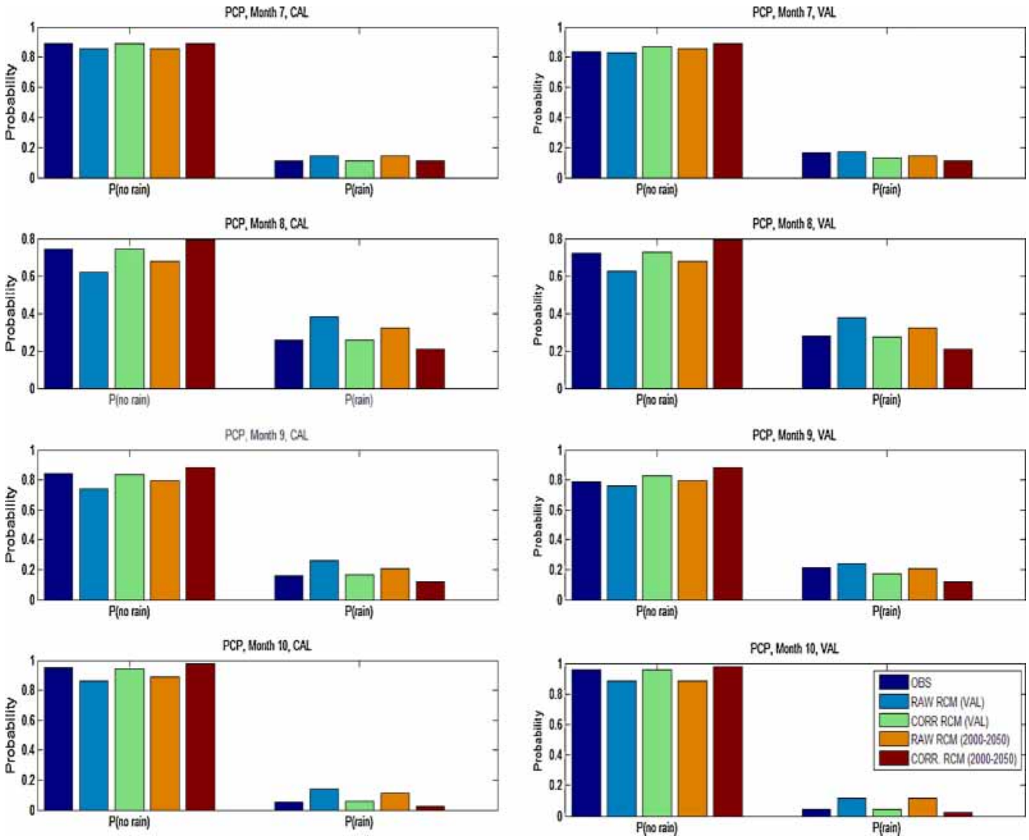

Fig. 3. Probability mass function of precipitation occurrence for Dakar, RCM METNOHIRHAM.

2000–2050 period are significantly different of those of the uncorrected RCM. The probability density of wet days precipitations for the same city (Dakar) and the same RCM (Fig. 4). On that figure, the thick blue lines represent the observations; the dotted green lines represent the uncorrected RCM; the dashed orange lines represent the QQ-corrected RCM. The continuous green line and the dash-dot violet lines represent the uncorrected and corrected RCM on the 2000–2050 period. Once again, it can be seen that the distribution of the corrected RCM outputs are closer that of the observations than the distribution of the uncorrected RCM outputs.

3.2. Downscaling results

By construction, no performance can be calculated for the delta-change, since it is the modification of the observed data according to a climate change signal; the QQ technique in the other hand allows the modeller to evaluate its ability to correct probability distributions. Results show that the two sided KS test lead to the discarding a significantly high number of stations-model combinations (Table 3). In similar applications of the QQ transformation (e.g. Amadou et al., 2014; El-Khoury et al., 2015), the authors have found that the transformation works much better with temperatures than with precipitation. It is assumed that the difference in performance is due to the highly skewed shape of precipitation transformation, the QQ transformation having trouble reproducing the tail of the distribution, since it is a non-parametric method thus heavily dependent on the calibration period. The mean precipitation and the extreme precipitations of the historical (1950–2000) and future (2001–2050) periods for the

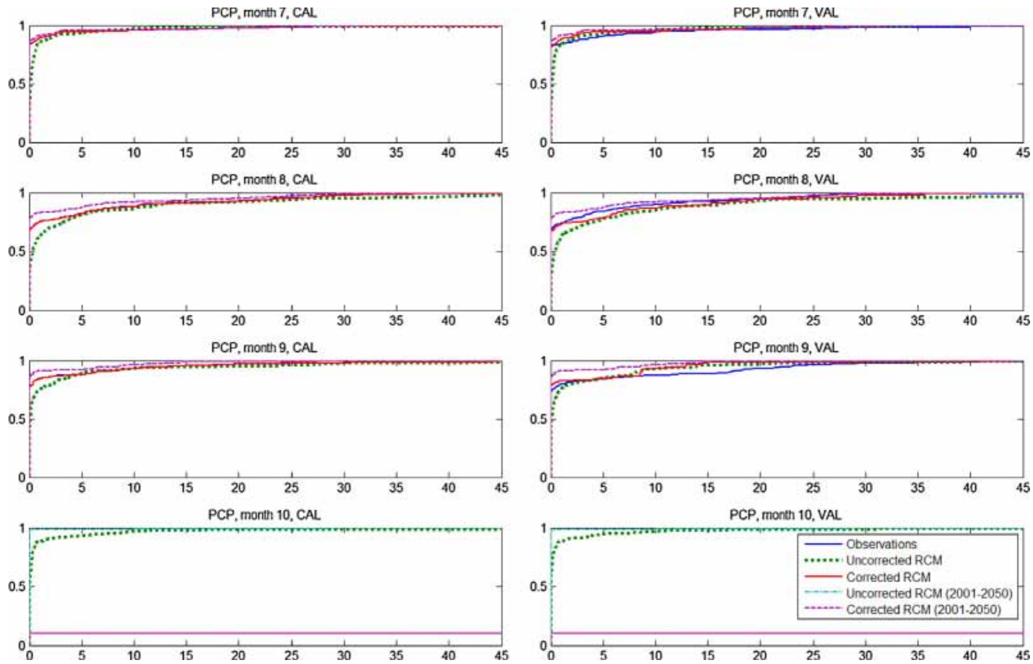

Fig. 4. Empirical probability density of wet days precipitation for Dakar, RCM METNOHIRHAM.

models that passed the KS-test screening are presented in Table 4 (Dakar), Table 5 (Linguère), Table 6 (Podor) and Table 7 (Zinguichor). Each table is organized as follow: the first and second columns represent the climate model and the indices (either the mean precipitation or a *T*-year precipitation). Columns 3–8 represent the following methods of estimation of the indices: GEV fit on observations (column 3), GEV fit on uncorrected climate model outputs on the historical period (columns 4), GEV fit on QQ-corrected climate models outputs on the historical period (columns 5), GEV fit on uncorrected climate model outputs on the future period (columns 6), GEV fit on QQ-corrected climate models outputs on the future period (columns 7) and finally the delta-change technique (column 8). Each climate model is represented by seven lines. The results of the KS-test comparing the fitted GEV distribution to the empirical distribution of annual maximum precipitation are presented on the first line. When 'S.D.' (similar distribution) appears in one column, it means that the KS-test did not lead to the rejection of the null hypothesis. The *p*-value is presented as well. The second line presents the mean daily precipitation while the third to the seventh lines represent the *T*-year quantile for $T = 5$, 10, 20, 50 and 100 years, and the column represents a future period (columns 7 and 80, a percentage of increase over the same quantity calculated with the observations is provided). The following general conclusions can be drawn:

1. The annual maximum daily precipitation time series can be considered GEV-distributed since the null hypothesis was never rejected.
2. The range of projected changes ranges from very small values (less than 2%) with is within the data uncertainty range to quite large values (from −41.6% to +18.7%). While smaller changes of a few percents can be considered non significant, those above 10% strongly suggest an impact in the future.

Then, the following location-specific conclusions can be drawn:

Table 4

Current and future estimates of extreme daily precipitations for Dakar (*M*: annual precipitation in mm; *T* = *X*: *X*-years return period precipitation).

RCM/GCM	Return period	Historical period (1950–2000)			Future (2001–2050)		
		Observations	GCM/RCM	GCM/RCM + QQ	GCM/RCM (uncorrected)	GCM/RCM + QQ	GCM/RCM + delta-change
	KS test	S.D. (p = 0.879)	S.D. (p = 0.879)	S.D. (p = 0.411)	S.D. (p = 0.832)	S.D. (p = 0.926)	
METNOHIRHAM	M	298.935	401.5	292	328.5	182.5 (−39%)	255.5 (−18.2%)
	T = 5	86.5	103.1	73.2	88.0	55.9 (−35.4%)	73.78 (−14.7%)
	T = 10	108.9	129.9	112.1	118.7	74.74 (−31.3%)	99.41 (−8.7%)
	T = 20	130.1	157.8	174.5	154.9	98.28 (−24.5%)	127.67 (−1.9%)
	T = 50	157.3	197.4	319.4	214.1	139.35 (−11.4%)	170.64 (+8.5%)
	T = 100	177.4	229.8	509.9	269.9	180.52 (+1.7%)	208.43 (+17.5%)

Table 5
Current and future estimates of extreme daily precipitations for Linguère (M: annual precipitation in mm; $T=X$: X-year return period precipitation).

RCM/GCM	Return period	Historical period (1950–2000)			Future (2001–2050)		
		Observations	GCM/RCM	GCM/RCM + QQ	GCM/RCM (uncorrected)	GCM/RCM + QQ	GCM/RCM + delta-change
DMI-HIRHAM5	M	337.26	547.5	365	474.5	292 (−13.5%)	292 (−13.5%)
	$T=5$	76.8	42.4	80.2	39.8	74.17 (−3.4%)	71.99 (−6.2%)
	$T=10$	91.5	45.7	84.1	43.7	81.17 (−11.2%)	87.41 (−4.4%)
	$T=20$	108.2	48.4	86.3	47.1	86.01 (−20.5%)	105.39 (−2.6%)
	$T=50$	134.7	51.1	87.8	51.0	90.38 (−32.9%)	134.33 (−0.3%)
	$T=100$	158.8	52.8	88.4	53.6	92.65 (−41.6%)	161.06 (+1.5%)
RCM/GCM	KS test	S.D. ($p=0.879$)	S.D. ($p=0.879$)	S.D. ($p=0.640$)	S.D. ($p=0.620$)	S.D. ($p=0.617$)	
MPI-M-REMO	M	0.969	0.9	1.0	0.9	0.9(−7.2%)	0.6(−9.7%)
	$T=5$	83.5	123.5	80.1	112.9	75.88 (−9.1%)	76.35 (−8.5%)
	$T=10$	99.9	186.2	97.0	178.9	90.53 (−9.4%)	96.03 (−3.9%)
	$T=20$	115.2	269.6	113.8	274.5	104.95 (−8.9%)	117.34 (+1.8%)
	$T=50$	134.4	426.1	136.3	472.3	124.17 (−7.6%)	148.94 (+10.8%)
	$T=100$	148.3	594.3	153.8	705.5	139 (−6.2%)	175.9(+18.7%)
RCM/GCM	KS test	S.D. ($p=0.928$)	S.D. ($p=0.928$)	S.D. ($p=0.902$)	S.D. ($p=0.935$)	S.D. ($p=0.959$)	
METNOHIRHAM	M	0.922	0.7	0.9	0.7	0.8(−13.3%)	0.9(−0.3%)
	$T=5$	74.6	70.2	87.0	72.3	82.15 (+10.1%)	76.82 (+3.0%)
	$T=10$	89.0	95.7	111.4	92.9	98.38 (+10.6%)	86.3 (−3.0%)
	$T=20$	105.7	127.6	139.3	115.3	113.88 (+7.7%)	95.51 (−9.6%)
	$T=50$	132.7	183.0	183.5	148.7	133.86 (+0.9%)	107.81 (−18.8%)
	$T=100$	157.8	238.4	223.9	177.4	148.78 (−5.7%)	117.41 (−25.6%)

Table 6
Current and future estimates of extreme daily precipitations for Podor (*M*: annual precipitation in mm; $T = X$: *X*-years return period precipitation).

RCM/GCM	Return period	Historical period (1950–2000)			Future (2001–2050)		
		Observations	GCM/RCM	GCM/RCM + QQ	GCM/RCM (uncorrected)	GCM/RCM + QQ	GCM/RCM + delta-change
	KS test	S.D. ($p = 0.449$)	S.D. ($p = 0.449$)	S.D. ($p = 0.690$)	S.D. ($p = 0.780$)	S.D. ($p = 0.297$)	
DMI-HIRHAM5	*M*	210.605	255.5	182.5	182.5	109.5 (−48.1%)	146 (−29%)
	$T = 5$	64.2	34.4	56.3	35.4	50.48 (−21.3%)	65.84 (+2.6%)
	$T = 10$	69.6	35.9	63.5	39.6	58.51 (−16.0%)	76.9 (+10.5%)
	$T = 20$	73.0	36.8	69.3	43.1	64.89 (−11.1%)	85.52 (+17.2%)
	$T = 50$	75.6	37.4	75.3	46.7	71.58 (−5.4%)	94.36 (+24.7%)
	$T = 100$	76.8	37.7	79.0	48.9	75.65 (−1.6%)	99.61 (+29.6%)

Table 7
Current and future estimates of extreme daily precipitations for Zinguichor (*M*: annual precipitation in mm; *T* = *X*: *X*-years return period precipitation).

RCM/GCM	Return period	Historical period (1950–2000)			Future (2001–2050)		
		Observations	GCM/RCM	GCM/RCM + QQ	GCM/RCM (uncorrected)	GCM/RCM + QQ	GCM/RCM + delta-change
	KS test	S.D. (p = 0.861)	S.D. (p = 0.86)	S.D. (p = 0.435)	S.D. (p = 0.842)	S.D. (p = 0.256)	
IMETNOHIRHAM	*M*	1226.035	985.5	1131.5	985.5	1131.5 (−7.8%)	1241 (−0.3%)
	T = 5	121.8	144.1	134.8	153.6	124.7 (+2.4%)	129.87 (+6.6%)
	T = 10	148.0	186.7	138.9	189.8	134.4 (−9.2%)	150.46 (+1.7%)
	T = 20	175.9	237.9	140.7	227.4	141.08 (−19.8%)	168.11 (−4.4%)
	T = 50	216.7	323.5	141.5	280.4	147.08 (−32.1%)	187.82 (−13.3%)
	T = 100	251.1	405.7	141.8	323.6	150.19 (−40.2%)	200.3 (−20.2%)
RCM/GCM	KS test	S.D. (p = 0.504)	S.D. (p = 0.50)	S.D. (p = 0.833)	S.D. (p = 0.960)	S.D. (p = 0.491)	
MPI-M-REMO	*M*	3.581	2.8	3.5	3.0	3.6(0.5%)	3.8(6.9%)
	T = 5	125.1	221.1	123.9	247.3	134.42 (+7.5%)	139.91 (+11.8%)
	T = 10	150.9	280.2	138.4	291.2	143.21 (−5.1%)	156.84 (+4.0%)
	T = 20	178.6	344.5	150.4	330.4	148.94 (−16.6%)	171.3 (−4.1%)
	T = 50	219.4	440.4	163.8	377.1	153.77 (−29.9%)	187.81 (−14.4%)
	T = 100	254.0	523.1	172.4	409.3	156.11 (−38.5%)	198.74 (−21.8%)

3.2.1. Dakar

Only one RCM (METNOHIRHAM) was selected for this station. The KS-test comparing the fitted GEV distribution to that of the annual maximum daily precipitation did not lead to the rejection of the null-hypothesis in any data set. The two techniques results project a reduction of the magnitude of both the mean precipitation and extreme precipitation events with a return period equal to or below 20 years, but the QQ-transformation provide a larger decrease for the future (−39% versus −18.2%). According to the QQ-transformation, the 50-year event is also set to decrease while the delta-change predicts a change in the opposite direction. Both techniques predict an increase in the 100-year event, but the increase suggested by the QQ-transformation is ten times smaller (+1.7% versus +17.5%). Given that lower quantiles are set to decrease and higher quantiles set to increase, the variability of precipitation in Dakar will be increasing.

3.2.2. Linguère

Three RCMs (DMI-HIRHAM5, MPI-M-REMO, METNOHIRHAM) were selected for this station. The two sided KS test comparing the fitted GEV distribution to that of the annual maximum daily precipitation did not lead to a significant difference for all data set. All RCMs and both downscaling techniques provide a reduction of the mean precipitation in a range between −13.5% and −0.3%. There is however a disagreement between models and downscaling techniques about the directions of changes of the quantiles. When applied to the outputs of DMI-HIRHAM5 and MPI-M-REMO, the QQ-transformation predicts a decrease of the quantiles for all return periods while the delta-change technique points to a decrease in lower return periods and an increase in higher return periods. The two downscaling techniques agree on the direction of change of the quantiles when they are applied to the outputs of METNOHIRHAM: they point to an increase in lower return periods quantiles and a decrease in higher return periods quantiles.

3.2.3. Podor

Two RCMs (INMRCA3 and DMI-HIRHAM5) were selected for this station. The two sided KS-test comparing the fitted GEV distribution to that of the annual maximum daily precipitation did not lead to the same result of the absence of significant differences. All RCMs and both downscaling techniques provide a reduction of the mean precipitation in a range between −29% and −48.1%. The delta-change suggests an increase in all quantiles while the QQ-transformation systematically suggested a change in the opposite direction.

3.2.4. Ziguinchor

Two RCMs (METNOHIRHAM and MPI-M-REMO) were selected for this station. METNOHIRHAM predicted a reduction of the mean precipitation (−7.8% with the QQ-transformation; −0.3% with the delta-change) while MPI-M-REMO points to an increase of the mean precipitation (+0.5% with the QQ-transformation; +6.9% with the delta-change). Independently of the downscaling technique used, both climate models show an increase of lower return periods of the quantiles and a decrease of higher return period of the quantiles.

3.3. Discussion

The most important finding of this study is that for a given location, depending on the climate model and downscaling technique used, one can get two opposite conclusions. It is therefore highly hazardous to rely on only one model or only one downscaling technique when designing adaptation options to climate change based on model simulations. As shown in previous studies, combining different climate models can increase the consistency of model projections (Frei et al., 2006; Fowler et al., 2007a; Tebaldi and Knutti, 2007; Déqué et al., 2012). However, it must be noted that when the same RCM is used with both techniques, the delta-change and the QQ-transformation always agreed in the direction of the projected change for the mean annual precipitation (predicted downward in seven out of eight cases in this study), but not for the change in magnitude. On the opposite, the two downscaling techniques can disagree on the direction of change for extreme precipitation quantiles, even when applied to the same RCM. Several authors have previously shown that the difference in the

Table 8
p-Value and rank of each factor after the ANOVA analysis (bold values represents significant influence; (*M*: annual precipitation in mm; *T* = *X*: *X*-years return periods precipitation).

Index	City	GCM	RCM	Downscaling technique
M	**1.33e−007** (rank = 1)	5.99e−001 (rank = 3)	7.92e−001 (rank = 4)	4.37e−001 (rank = 2)
T = 5	**1.09e−005** (rank = 1)	2.47e−001 (rank = 4)	1.38e−001 (rank = 3)	8.27e−002 (rank = 2)
T = 10	**8.57e−005** (rank = 1)	1.31e−001 (rank = 4)	6.68e−002 (rank = 3)	**1.93e−00s2** (rank = 2)
T = 20	**1.25e−003** (rank = 1)	1.01e−001 (rank = 4)	5.16e−002 (rank = 3)	**9.83e−003** (rank = 2)
T = 50	**2.45e−002** (rank = 2)	1.02e−001 (rank = 4)	5.60e−002 (rank = 3)	**8.50e−003** (rank = 1)
T = 100	**4.79e−002** (rank = 2)	1.24e−001 (rank = 4)	7.17e−002 (rank = 3)	**1.08e−002** (rank = 1)

climate change signal between bias-corrected and uncorrected RCMs could be low for mean values of hydrological variables such as precipitation (Chen et al., 2011), but may be high in the case of extreme values (Hagemann et al., 2011; Dosio et al., 2012). This finding is confirmed in the present study with RCM, indicating that future projections of extreme events may be associated with a high uncertainty. The main sources of uncertainty in regional climate change are the choice of the RCM and the choice of the forcing GCM (Déqué et al., 2012). In addition, the bias-correction of climate model outputs relies on the hypothesis of stationarity of the bias (Maraun et al., 2010). Several authors have shown that this hypothesis was not fulfilled for some arid regions (Maraun, 2012) or for considering different time periods concerning the validation and the calibration of the method (Lafon et al., 2013). Given that some climate models have been discarded after failing the KS-test in validation, the only station where the results for different RCMs (HIRHAM5 and REMO) driven by the same GCM (ECHAM5) can be compared is Linguère (Table 5). The differences between the projected variations in mean precipitation is less affected by the choice of downscaling techniques (predicted changes differed of 0.0% and 2.5% of the historic mean depending of the RCM) than by the choice of the RCM (6.2% and 3.8% of the historic mean depending of the downscaling technique). A similar comparison can be done but may be misleading for extreme precipitations since the GEV fit on extreme precipitation is calculated with the corrected outputs of DMI-HIRHAM5 at Linguère which is one of the worst one in the data set (with a *p*-value of 0.574 while *p*-values for other data sets are in the 0.9–1 range). Finally, in order to identify which factor has more impact on the downscaled mean and extreme precipitation among the location, the driving GCM, the RCM or the downscaling technique, a four-ways fixed effect ANOVA analysis was performed. The location factor has four levels (Dakar, Podor, Linguère and Ziguinchor) corresponding to the cities for which one model was retained at least. The GCM factor has two levels (ECHAM5 and HADCM3), the RCM factors have three levels (HIRHAM, RCA, REMO) and finally the downscaling factor has two levels (delta-change and quantile–quantile transformation). The *p*-values of the significance of each factor for each of the indices (mean and extreme precipitations) and their rank in a decreasing order of influence are listed in Table 8. At a 95% confidence level, only the location significantly affects the mean precipitation and the 5-year return period daily precipitation. The downscaling becomes significant for return periods above 10 year. It takes the second rank after the location factor for return periods 10 years and 20 years. The downscaling technique takes the first rank and the location of the second rank for return periods 50 years and 100 years. The GCM and the RCM techniques did not have a significant impact (*p*-value below 0.05) on any of the indices, although the *p*-value of the RCM is always close to 0.05 which is the threshold value for return periods above 10 years. These results should be taken with care as the size of the data set used for the ANOVA is small (16 combinations). Results suggest that one could use any of the models and any of the downscaling techniques to estimate the mean and 5-year precipitation at any of the stations. For *T*-year daily precipitation with *T* larger or equal to 10 year, the choice of the downscaling technique matters. Despite the fact that recent study showed that the bias-correction method can improve the reproduction of the historical climate by RCMs, it is hard to tell if one downscaling technique is better than the other: several studies (Tebaldi and Knutti, 2007; Reifen and Toumi, 2009) mentioned that the performance of climate models at reproducing the past is not a guarantee of better skills at making accurate projections. Our recommendation is to use both in order to capture the uncertainty associated with the downscaling technique.

4. Conclusion

This study presents the first evaluation of the projected changes in precipitation in Senegal with RCMs and two downscaling techniques. The daily data observed at six stations between 1950 and 2007 as well as four RCM simulations driven by two different GCMs are taken into account to evaluate the impact of future climate changes under the emission of greenhouse gases scenario A1B. GEV distributions are fitted to the precipitation extremes observed and projected to provide an analysis based on quantiles for different return periods. Results show that the two techniques generally agree on the direction of the change when applied to the outputs of same climate model, but sometimes lead to very different projections of the direction and magnitude of the change in extreme precipitations. Projected changes in the mean precipitation are downward except for one RCM in one city. Projected changes in extreme precipitations are not consistent across stations and return periods.

Results also suggest that the choice of the downscaling technique has more effect on the estimation of extreme daily precipitations of return period equal or greater than ten years than the choice of the climate models. Because of the great variability in the future projections obtained with the set of 4 RCMs considered herein, further work in the same region should consider a larger ensemble of climate models to evaluate if a larger ensemble provides similar results.

Conflict of interest

None declared.

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