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Modelling blue and green water availability under climate change in the Beninese Basin of the Niger River Basin, West Africa

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Abstract

The aim of this study was to quantify climate change impact on future blue water (BW) and green water (GW) resources as well as the associated uncertainties for 4 subbasins of the Beninese part of the Niger River Basin. The outputs of 3 regional climate models (HIRHAM5, RCSM, and RCA4) under 2 emission scenarios (RCP4.5 and RCP8.5) were downscaled for the historical period (1976–2005) and for the future (2021–2050) using the Statistical DownScaling Model (SDSM). Comparison of climate variables between these 2 periods suggests that rainfall will increase (1.7% to 23.4%) for HIRHAM5 and RCSM under both RCPs but shows mixed trends (−8.5% to 17.3%) for RCA4. Mean temperature will also increase up to 0.48 °C for HIRHAM5 and RCSM but decrease for RCA4 up to −0.37 °C. Driven by the downscaled climate data, future BW and GW were evaluated with hydrological models validated with streamflow and soil moisture, respectively. The results indicate that GW will increase in all the 4 investigated subbasins, whereas BW will only increase in one subbasin. The overall uncertainty associated with the evaluation of the future BW and GW was quantified through the computation of the interquartile range of the total number of model realizations (combinations of regional climate models and selected hydrological models) for each subbasin. The results show larger uncertainty for the quantification of BW than GW. To cope with the projected decrease in BW that could adversely impact the livelihoods and food security of the local population, recommendations for the development of adequate adaptation strategies are briefly discussed.

KEYWORDS

adaptation, climate change, interquartile range, statistical downscaling, uncertainty, water resources

1 | INTRODUCTION

Stern (2010) identified climate change and poverty as the two major challenges of our time. Modelling future climate change has led to the development of multiple general circulation models (GCMs) and regional climate models (RCMs) along with various downscaling techniques (Ahmed et al., 2013; Gudmundsson, Bremnes, Haugen, & Engen-Skaugen, 2012; Hagemann et al., 2011; Hay, Wilby, & Leavesley, 2000; Piani et al., 2010; Piani, Haerter, & Coppola, 2010; Salathé, Mote, & Wiley, 2007) to solve the issues of the coarse GCMs and RCMs scales (Fowler, Blenkinsop, & Tebaldi, 2007; Wood, Leung, Sridhar, & Lettenmaier, 2004).

Statistical and dynamical downscaling are the two common methods used for the disaggregation of GCMs and/or RCMs outputs. Whereas dynamical downscaling disaggregates GCM outputs from the global scale to the regional scale using climate models, the statistical approach downscales GCM and RCM outputs to the local and point scales using statistical functions. The former is less attractive because it is computationally demanding and not easily transferable to new regions. Notwithstanding, dynamical downscaling has the advantages of providing RCM outputs consistent with the host GCM (Wilby & Dawson, 2007), and better representation of orographic precipitation (Haensler, Hagemann, & Jacob, 2011) and extreme events (Fowler et al., 2007). Statistical downscaling is favoured because of its parsimony, easier transferability to other regions, and lesser demand on computer resources.

Although climate change is a global phenomenon, regions are not affected the same way (UNFCCC, 2007). West Africa is one of the most exposed and vulnerable regions to the adverse effects of climate change (IPCC, 2007a, 2007b, Niasse, Afouda, & Amani, 2004). The economy of this region is mainly based on rainfed agriculture, and any change in the climate regime would directly affect the income at the country level as well as the livelihood of local populations (Läderach, Martinez-Valle, Schroth, & Castro, 2013; Schroth, Läderach, Martinez-Valle, Bunn, & Jassogne, 2016; Sultan & Gaetani, 2016). The high sensitivity of the West African region to climate hazards is illustrated by the severe consequences of the drought of the 1970s and 1980s (Amogu et al., 2010; Badou, Kapangaziwiri, Diekkrüger, Hounkpè, & Afouda, 2016; Lebel et al., 2009) and the floods at the end of the 2000s and the beginning of the 2010s (Aich et al., 2015; Descroix et al., 2012) on agricultural production and livelihoods of local population (Bonou, 2016; Hounkpè, Diekkrüger, Badou, & Afouda, 2016; Liersch et al., 2013).

Although the adverse impacts of climate hazards felt by the West African population are known, the extent to which future climate change will impact water resources is still an open question. Lebel and Ali (2009) reported wetter conditions since 1990 after the drought of 1970s and 1980s in the eastern and central Sahel, whereas dry conditions are still prevailing in the western part. Other studies (Badou et al., 2016; Laprise et al., 2013; Sylla et al., 2010; Vizy, Cook, Crétat, & Neupane, 2013) have shown a decrease in rainfall in the western Sahel and an increase in the eastern part. However, Oyerinde et al. (2016) and Kaboré/Bontogho et al. (2015) reported an intensification of the hydrological cycle in the eastern and central Sahel respectively. For Oyerinde et al. (2016), climate change in the future will be beneficial for hydropower production caused by an increase in precipitation and streamflow despite an increase in potential evapotranspiration for more than 70% of the Niger River Basin (2.2 million km^2), the largest river basin in West Africa.

Mbaye et al. (2015) working in western Sahel over the Senegal River Basin showed that precipitation would decrease by the end of the century for most parts of the study area with the exception of the southern part (Guinean Highlands). Potential water yield (the difference between precipitation and potential evapotranspiration) would decrease as well.

However, other studies have reported unclear impacts on the hydrological cycle in response to climate change (Carter & Parker, 2009; Druyan, 2011; Vetter et al., 2015; Yira, Diekkrüger, Steup, & Bossa, 2017). A comparison of 10 climate studies over West Africa showed that the direction in which rainfall will vary during the current century is uncertain (Druyan, 2011). Carter and Parker (2009) compared the impacts of climate change, population growth, and land use/land cover changes on groundwater in Africa. They found out that population growth would have the most severe impact, whereas climate change would have significant impacts albeit with uncertainties (both in direction and magnitude). Comparing the impacts of climate change on the streamflows of four large African basins, Aich et al. (2014) found that the Niger and the Limpopo river basins will experience a mixed trend with respect to their mean river discharge—an increase of high flows and a reduction of low flows—for most of the investigated climate models. Yira et al. (2017) also pointed out the unclear behaviour of future climate change for the Dano Basin of Burkina Faso as they found that downscaled data from six RCMs are nonconsistent regarding future direction of rainfall and discharge.

Hence, more research is needed to better understand, with less uncertainty, the direction and magnitude of climate change impacts over West Africa. In that sense, multimodel assessment approach is thus expected to capture the uncertainties in the modelling of climate change impacts (Mbaye et al., 2015; Oyerinde et al., 2016; Yira et al., 2017). The objectives of this study are therefore, for the Beninese part of the Niger River Basin, to

1. statistically downscale the outputs of RCMs and assess future climate trends;
2. quantify the impact of climate change on future blue water (BW) and green water (GW) availability; and
3. quantify the uncertainty associated with the evaluation of BW and GW.

2 | MATERIALS AND METHODS

Following the defined three objectives, the methodology of the study can be split into three parts. The first part addresses how future climate change was assessed over the study area, namely, how three RCMs products were statistically downscaled and analysed. The second part addresses how climate change impacts on future BW and GW were assessed. This includes how a set of four calibrated and validated hydrological models was applied. The third part addresses the quantification approach of uncertainties associated with the evaluation of future BW and GW. Prior to a detailed description of these three parts, the current section provides a brief description of the study area and the applied climate data.

2.1 | Study area

The Beninese part of the Niger River Basin consists of four adjacent and poorly gauged subbasins—the Coubéri (13,217 km^2), Gbassè (8,038 km^2), Yankin (8,171 km^2), and the Kompongou (5,670 km^2)—located in northern Benin, situated between 1°50′E and 3°75′E longitude and 10°0′N and 12°30′N latitude (Figure 1). Its climate is Sudanese in the south and Sudano-Sahelian in the north. The mean

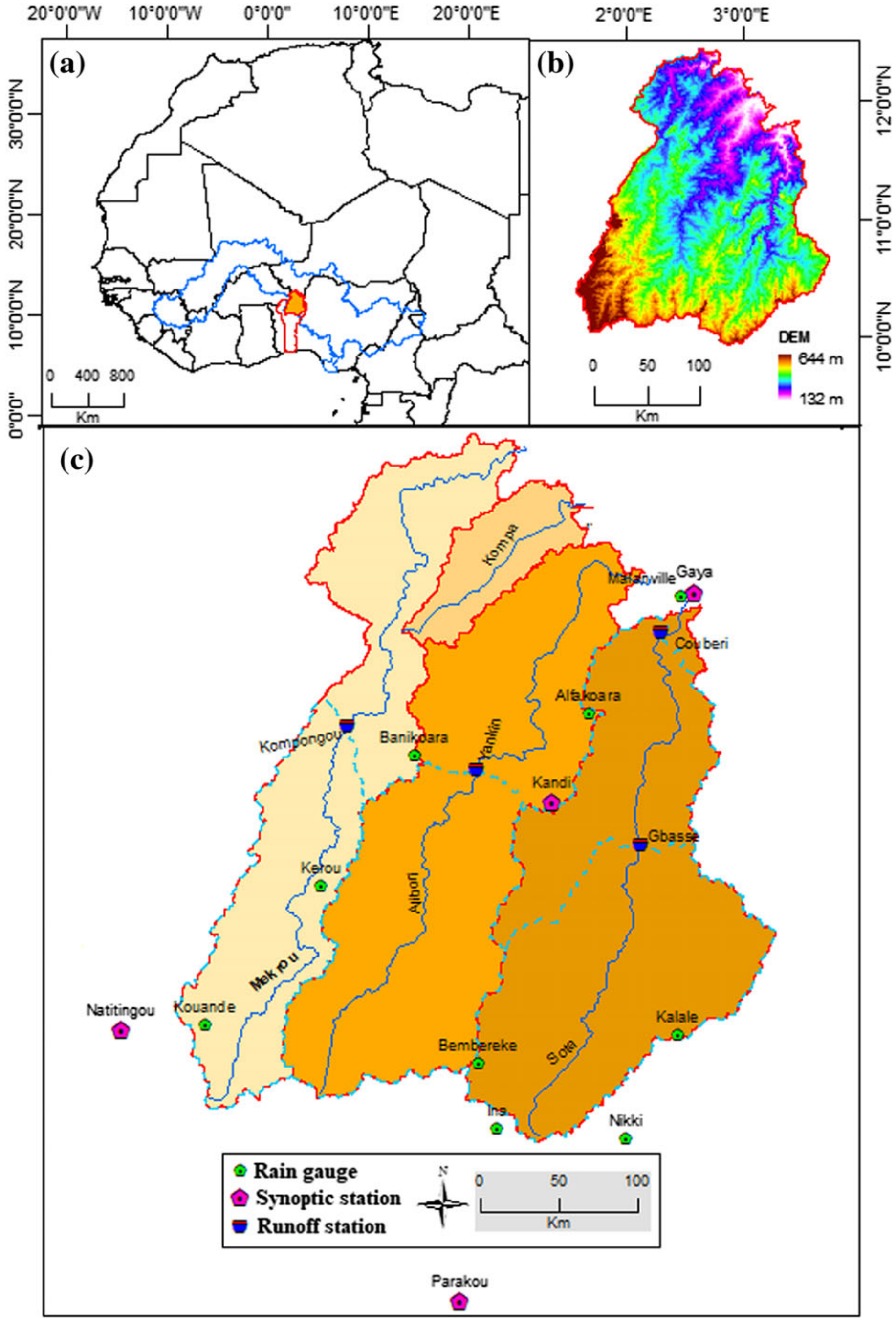

FIGURE 1 (a) Location of the Beninese part of the Niger River Basin in West Africa; (b) digital elevation model; and (c) Coubéri, Gbassè, Yankin, and Kompongou subbasins, and the climate and streamflow networks

annual rainfall for the period of 1971–2010 is about 936 mm, whereas the mean minimum and mean maximum temperatures are 21.54 °C and 34.55 °C, respectively (Badou, 2016).

2.2 | Climate data

In this study, a statistical downscaling technique was implemented. A critical step of the method is the choice of the large-scale predictors to be used for downscaling a given predictand (Gutiérrez et al., 2011; Wilby & Dawson, 2007). This choice of predictors requires a sound knowledge of the relationship between the predictors and the predictands of interest. There is, however, an alternative of using RCM outputs as predictors following a direct predictor–predictand relationship. For example, to downscale the temperature of a given gauge (predictand), one can use the temperature from an RCM as predictor (Kebede, Diekkrüger, & Moges, 2013). This alternative seems particularly interesting in hydrological modelling because RCMs outputs can be disaggregated to the hydrological local impact assessment scale. In this study, following Gobiet, Suklitsch, and Heinrich (2015); Kebede et al. (2013); and Themeßl, Gobiet, and Heinrich (2011), RCM outputs were used as predictors. RCMs that provide not only precipitation and temperature but also wind speed, humidity, and radiation data were preferred because some of the hydrological models (UHP-HRU, SWAT, and WaSiM) used in this study require these variables. Table 1 gives a summary of the characteristics of the RCMs used. All three RCMs were developed in the framework of the CORDEX AFRICA (Giorgi, Jones, & Asrar, 2009).

Furthermore, observed data from 12 in situ climate stations were used as reference data for the downscaling (Table 2). Radiation data were derived from sunshine duration information using the formula of Amoussa (1992).

2.3 | Statistical downscaling

The Statistical DownScaling Model (SDSM) Ver 4.2 (Wilby & Dawson, 2007) was selected for the downscaling of climate data. SDSM is reported to be a robust model (Kebede et al., 2013; Wetterhall, Bárdossy, Chen, Halldin, & Xu, 2006; Wilby & Dawson, 2012) and has been successfully applied worldwide (Wilby & Dawson, 2007). SDSM is "a hybrid of the stochastic weather generator and transfer function methods" (Wilby & Dawson, 2007). The model has to be run for each climate variable and each gauging station, which makes it easy to implement but at the same time tedious. Further details on the model are provided in the user manuals and the notes of Wilby and Dawson (2015, 2013, 2007, 2004).

The calibration process searches for the best statistical relationship allowing the predictors to fit as much as possible the predictands for the present day climate. To obtain such a fit, a trial and error technique was used. The empirical relationship obtained after the calibration is tested for an independent historical period during the validation stage. Upon a successful validation, the empirical predictor–predictand relationship is used to downscale ensembles of the same local variables for the future climate.

The RCMs data cover the period 1950–2100. The period 1976–2005 (with 1976–1995 as the calibration period and 1996–2005 for validation) was chosen as the baseline period, and the future period spans from 2021 to 2050.

To account for the stochastic nature of climate variables (Biao, Alamou, & Afouda, 2016) and as a result of limited computer resources, a total of 20 ensemble simulations were generated for each downscaled variable. Ensemble means were used for the comparison of downscaled and observed variables and to derive the statistics (Kebede et al., 2013).

2.4 | Future BW and GW availability

The calibration and validation of the hydrological models and the identification of the hydrological models adequate for the simulation of BW and GW are described in detail in Badou (2016). This author identified in a set of four hydrological models the ones adequate for the simulation of the BW and GW of the research area.

By definition, BW is the sum of streamflow (which includes shallow groundwater), deep aquifer recharge, and water storage (lakes, ponds, wetlands, etc.). However, BW in this study was restricted to the sum of streamflow and deep aquifer recharge. This was constrained by the crucial challenge related to hydrological data availability and acquisition in the region (Kapangaziwiri, Hughes, & Wagener, 2012). Streamflow (including shallow groundwater) is

TABLE 1 Summary of some characteristics of the RCMs used in this study

GCM	Centre	RCM	Scenario
Earth System Model ICHEC EC-EARTH	Danish Meteorological Institute (DMI)	HIRHAM5	RCP 4.5 and 8.5
MPI-ESM-LR	Max Planck Institute (MPI)	RCSM	RCP 4.5 and 8.5
NOAA-GFDL-GFDL-ESM2M	Swedish Meteorological and Hydrological Institute (SMHI)–Rossby Centre	RCA4	RCP 4.5 and 8.5

Note. ICHEC is the Irish Centre for High-end Computing; EC-EARTH is the Earth system model; MPI-ESM-LR is the max Planck institute–Earth system model running on low-resolution grid; NOAA-GFDL-GFDL-ESM2M is the National Oceanic and Atmospheric Administration–Geophysical Fluid Dynamics Laboratory–Earth System Model; and RCSMs the regional climate system models.

TABLE 2 Observed climate data used during the downscaling

Stations	Elev. (m)	Lat. (degree)	Long. (degree)	Rain. (mm)	Mean temp. (°C)	Rel. hum. (%)	W. speed (m/s)	Rad.* (Wh/m^2)
Gaya	202	11.88	3.45	+	+	+	+	+
Kandi	290	11.13	2.93	+	+	+	+	+
Natitingou	460	10.32	1.38	+	+	+	+	+
Parakou	392	9.35	2.6	+	+	+	+	+
Alfakoara	282	11.45	3.07	+	–	–	–	–
Banikoara	310	11.3	2.43	+	–	–	–	–
Bembéréké	491	10.2	2.67	+	–	–	–	–
Ina	358	9.97	2.73	+	–	–	–	–
Kalalé	410	10.3	3.38	+	–	–	–	–
Kouandé	442	10.33	1.68	+	–	–	–	–
Malanville	160	11.87	3.4	+	–	–	–	–
Nikki	402	9.93	3.2	+	–	–	–	–

Note. + Indicates that data are available and – indicates that they are not. The data length is 1976–2005.

readily available (Dettinger & Diaz, 2000) and was therefore taken as a proxy for BW. Green water has two components, green water flow (which is actual evapotranspiration) and green water storage (which is soil moisture). Soil moisture being the primary source of actual evapotranspiration (i.e., green water flow), in this study, GW was defined as the sum of soil moisture and actual evapotranspiration, and soil moisture was taken as a proxy for GW. Having no observed soil moisture data, satellite soil moisture data of the European Space Agency Climate Change Initiative (http://www.esa-cci.org/) was used (Badou, 2016).

Badou (2016) found that HBV-light, UHP-HRU, SWAT, and WaSiM hydrological models were adequate for the simulation of the daily streamflow of the Coubéri and Kompongou subbasins; HBV-light and SWAT for the Gbassè subbasin; and WaSiM, HBV-light, and UHP-HRU for the Yankin subbasin (see Table 3). For the simulation of soil moisture, UHP-HRU and SWAT were identified as adequate for the Coubéri, Gbassè, and Kompongou subbasins, and UHP-HRU, SWAT, and WaSiM for the Yankin subbasin (see Table 3). A description of the four hydrological models is given in the Supporting Information (Table S1) along with their performances (Tables S2–S6). A quality control was conducted prior to the selection of the calibration and validation periods of the hydrological models, which span from 1977 to 2010 (Tables S2–S5). This period has limited missing for model driving climate data, and streamflow and soil moisture data, which are used as reference data. Note that the periods of calibration and validation of the statistical downscaling tool, SDSM, 1976–2005 (see Section 2.3), and that of the hydrological models (WaSiM, SWAT, UHP-HRU, and HBV-light), 1977–2010, are not interlinked and therefore different. Also due to missing data, the periods of calibration and validation of the hydrological models vary from one subbasin to the other but fall within the period 1977–2010 (see Table S2–S6).

For each subbasin, the hydrological models were run with the downscaled data from the three RCMs, HIRHAM5, RCSM, and RCA4, and future BW was evaluated only with the hydrological models that were successfully validated for the simulation of streamflow, whereas future GW was evaluated solely with the hydrological models validated for the simulation of soil moisture. Doing so enabled the exploitation of the strengths of each of the hydrological models used.

TABLE 3 Capacity of the hydrological models to simulate daily streamflow and soil moisture, modified after Badou (2016)

Subbasin	Coubéri	Gbassè	Yankin	Kompongou
Streamflow				
HBV-light	+	+	+	+
UHP-HRU	+	−	+	+
SWAT	+	+	−	+
WaSiM	+	−	+	+
Soil moisture				
HBV-light	−	−	−	−
UHP-HRU	+	+	+	+
SWAT	+	+	+	+
WaSiM	−	−	+	−

Note. The sign + signifies that the model is adequate (see Tables S2–S5 and S6) for the simulation of the variable, the sign—that it is not.

As downscaling was effective (see Section 4.1), observation-based hydrological simulations and downscaled RCMs data-based historical simulations can interchangeably be used as reference for computing changes. In this paper, to quantify climate change impacts, observation-based BW and GW of the hydrological models calibration and validation periods were averaged to obtain, for each case, a mean value used as reference for the historical period and compared with future BW and GW. In reality, BW and GW resulting from running the hydrological models with observed climate data are more representative (and less uncertain) of the processes occurring across the study area. An alternative would have been to use BW and GW resulting from running the hydrological models with RCMs data for the historical period as reference, but this would have led to higher uncertainties in quantifying BW and GW changes.

2.5 | Uncertainty quantification

The uncertainty analysis focused on the overall predictive uncertainty, which implied lumping all the sources of uncertainties (i.e., input data, reference data, hydrological models, hydrological models parameters, climate models, and emissions scenarios). Such analysis of predictive uncertainty helps in capturing the overall range of expected uncertainty propagated through the modelling. The two emission scenarios (RCP4.5 and RCP8.5), the three RCMs (HIRHAM5, RCA4, and RCSM), the four hydrological models (HBV-light, UHP-HRU, SWAT, and WaSiM), and the N behavioural solutions of the hydrological models (see Tables S2–S5) were considered to compute the number of model realizations (NMR), which is the total number of simulations and is given in Equation (1) below.

$$NMR = 2\times3\times4\times N \tag{1}$$

The overall uncertainties were presented in the form of box-plots drawn with all the elements of the NMR and discussed in terms of interquartile ranges (the difference between the 75th and 25th percentiles). The interquartile range expresses how scattered the data are, and is therefore used as a measure of uncertainty. Thus, the higher the interquartile range is, the wider the box-plot are, implying the degree of uncertainty of the results.

3 | RESULTS

3.1 | Downscaled climate variables

Although radiation, humidity, and wind speed data were also downscaled, only the results of the downscaling of precipitation and temperature are presented because previous studies mainly focus on these two variables. Downscaled radiation, relative humidity, and wind speed are shown in Figures S1–S3, respectively.

3.1.1 | Precipitation

Figure 2 compares RCMs and observed precipitation. The left- and right-hand side panels of the diagram show raw and bias-corrected rainfall, respectively.

In general, the RCMs rainfall captured the unimodal rainfall regime of the study area with the maximum peak in August well defined. However, for the stations located in the south (Nikki, Ina,

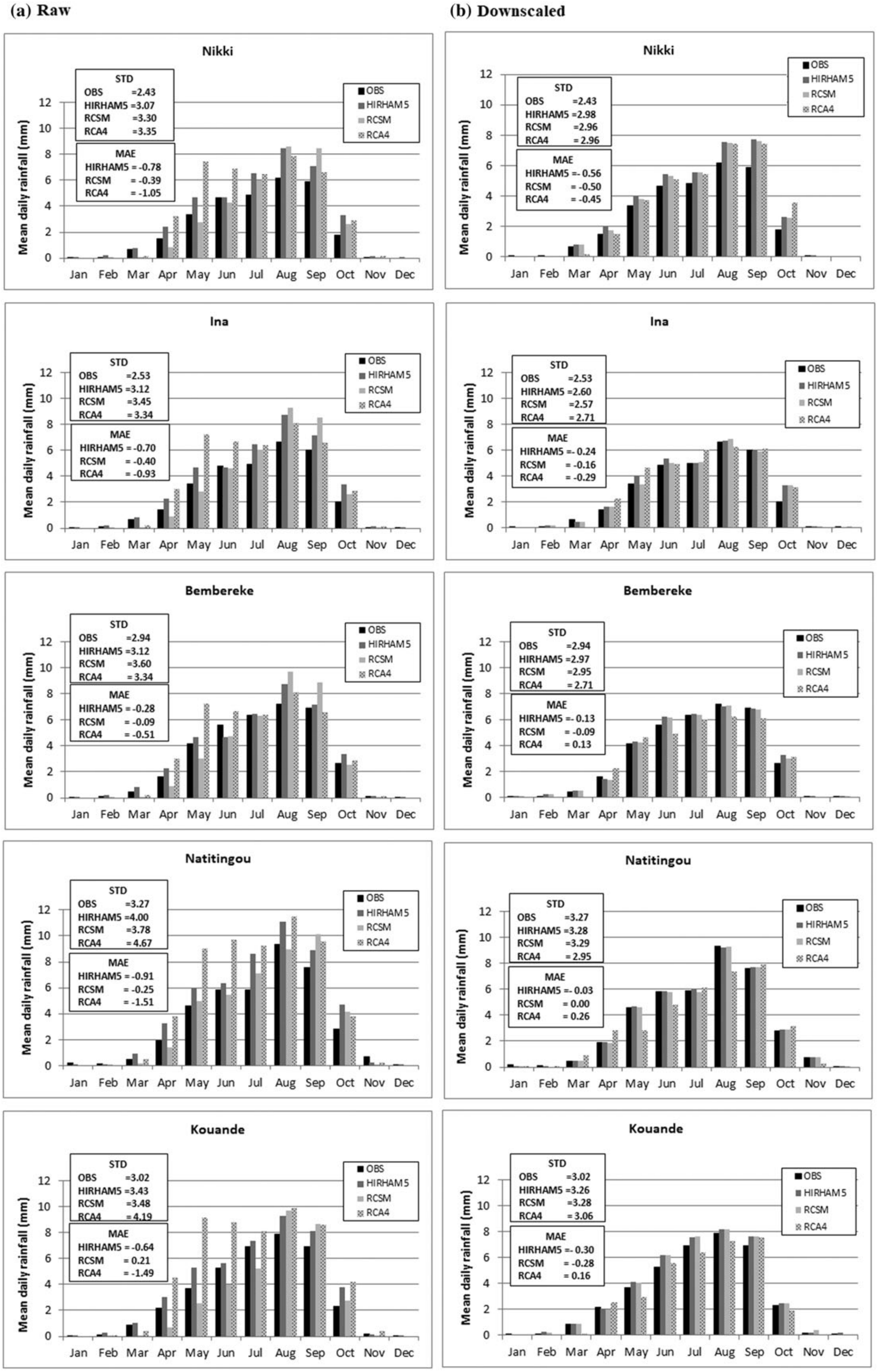

FIGURE 2 Comparison of raw (left panel) and downscaled (right panel) rainfall of the baseline period (1976–2005). Stations are ordered from the south to the north of the study area. STD = standard deviation; MAE = mean absolute error

Bembereke, Natitingou, and Kalale), RCA4 overestimates the rain during the April to October season. Comparison of raw and downscaled RCM rainfall shows that biases in the raw data are successfully corrected especially for HRHAM5 and RCSM (but to a lesser extent for RCA4). A clear difference is noted between the statistical properties of raw and downscaled rainfall whose standard deviations fall

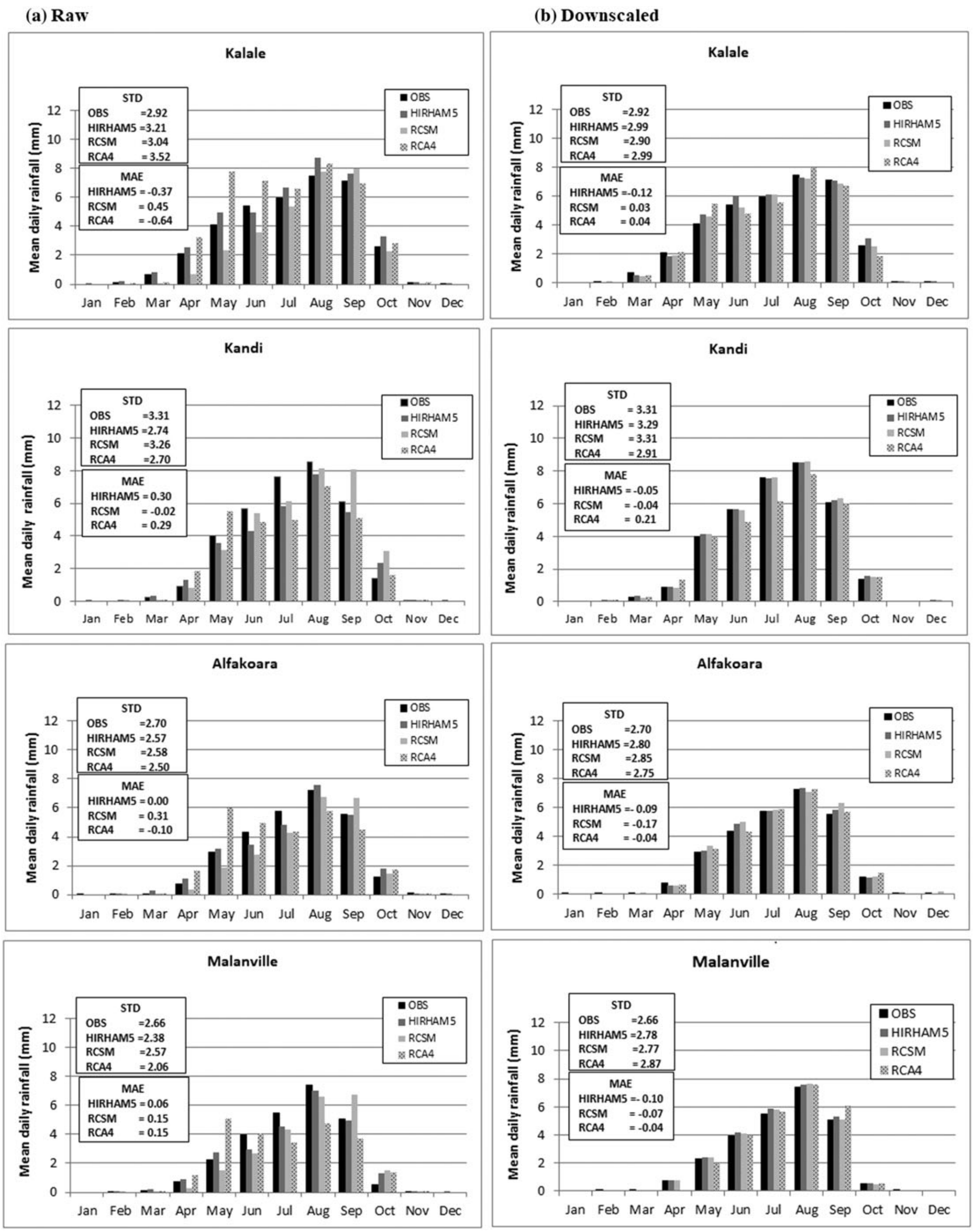

FIGURE 2 Continued.

within the intervals (2.06, 4.67) against (2.57, 3.31), and absolute values of the mean absolute errors within the intervals (0, 1.51) against (0, 0.56). Yet this difference in statistical properties does not imply an alteration of the climate signal (Figure 2). Therefore, the conclusion was that SDSM is appropriate for downscaling rainfall over the study area.

Downscaled RCMs projections are presented as changes relative to the baseline period (Figure 3). Under RCP4.5, rainfall exhibits a positive trend for HIRHAM5 (47 to 265 mm, i.e., 4.6% to 23.4%) and RCSM (22 to 264 mm, i.e., 1.9% to 23.3%) but a mixed trend for RCA4 (−66 to 215 mm, i.e., −7.7% to 17.3%).

Under RCP 8.5, similar trends are projected with slight change in the magnitudes: 47 to 265 mm (4.5% to 23.4%) increase for HIRHAM5, 19 to 265 mm (1.7% to 23.4%) increase for RCSM, and −73 to 205 mm (−8.5% to 16.2%) for RCA4. Half of the stations depict negative trends particularly with RCA4 model (Figure 3).

3.1.2 | Temperature

Figure 4 displays the mean temperature before and after downscaling (left and right panels, respectively). The three RCMs reproduced well the seasonal cycle of observed temperature; however, they underestimated the magnitude. This is particularly so for RCSM, which depicts the strongest underestimation during the months of January and December. Downscaled temperature matches reasonably well the observed temperature for the three RCMs with low standard

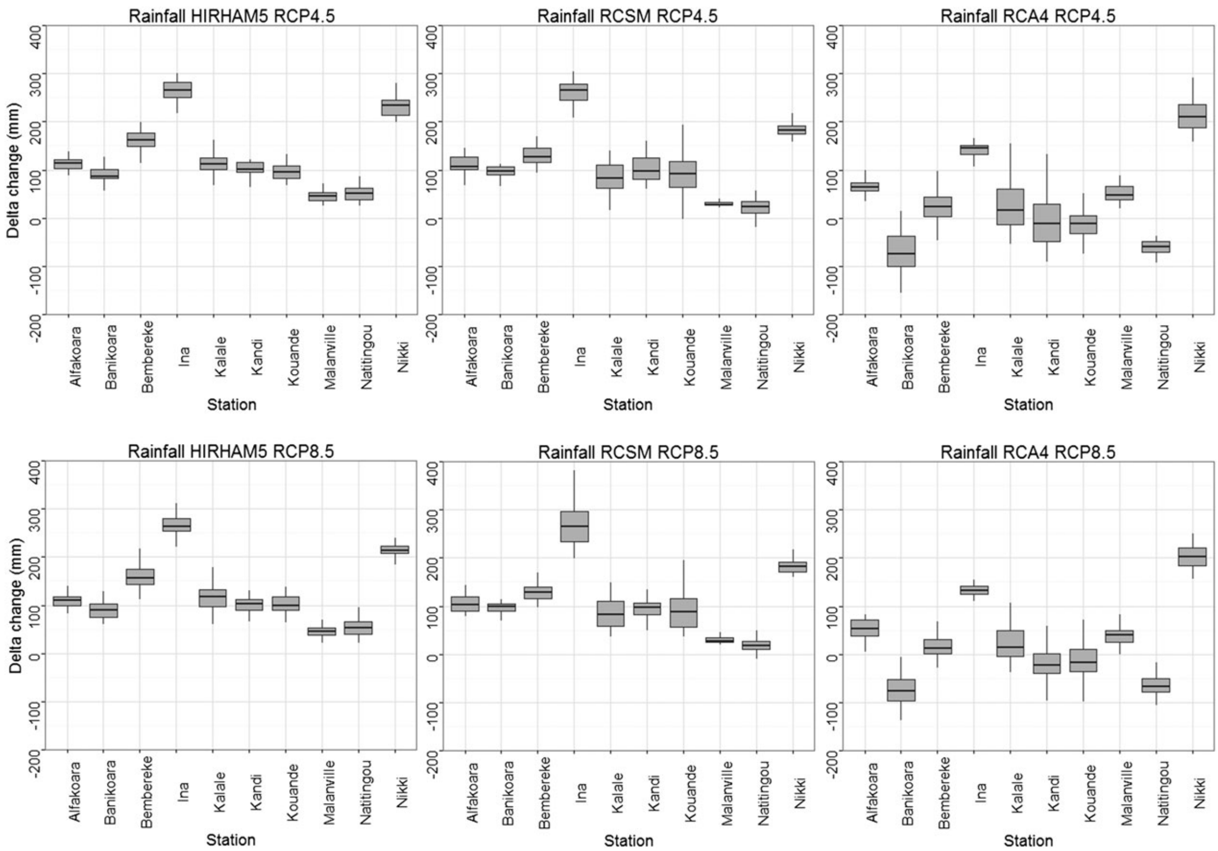

FIGURE 3 Box plots of the projected change (2021–2050) in annual mean rainfall relative to the baseline period (1976–2005) under RCP 4.5 (upper panel) and RCP 8.5 (lower panel)

deviation and low MAE values (Figure 4). These results thus indicate that SDSM is suitable for the downscaling of the temperature over the study area.

Figure 5 shows the expected changes in mean temperature for the future period (2021–2050) relative to the historical period (1976–2005). Regardless of the scenario, HIRHAM5 and RCSM exhibited positive trends with RCA4 showing negative trends. As an order of magnitude, the changes equal 0.02 to 0.38 °C and 0.04 to 0.35 °C for HRHAM5 under RCP4.5 and RCP 8.5, respectively. In the case of the RCSM model, changes of −0.01 to 0.48 °C and −0.02 to 0.45 °C are projected under RCP 4.5 and RCP 8.5, respectively. The changes are expected to reach −0.34 up to 0.09 °C and −0.37 up to 0.04 °C under RCPs 4.5 and 8.5 for the RCA4 model. It is interesting to note that the station at Parakou will experience both the highest temperature increase (HIRHAM5 and RCSM) and the highest temperature decrease (RCA4).

3.2 | Future BW and GW availability

Projected BW and GW are presented in Figures 6–9 for the first and last decades of the future time horizon for the Coubéri, Gbassè, Yankin, and Kompongou subbasins, respectively. Some variables (e.g., GW in Figures 6a,d, and BW in Figures 7b and 8c) are not shown because the hydrological models were not suitable for the predictions of these variables.

Over the Coubéri subbasin, the ensemble of hydrological models predict a negative trend of BW by midcentury. For SWAT and UHP-HRU, the decrease is in the same order of magnitude for both RCPs (Figures 6b,c). However, HBV-light and WaSiM project a decrease under RCP8.5 that is slightly higher than under RCP4.5 (Figures 6a, d). GW is expected to increase in the subbasin with an increase under RCP4.5 nearly twice that under RCP8.5. Overall, compared with the reference period, rainfall will vary between −0.6% (RCP4.5) and −1.5% (RCP8.5), which will result in a decrease in BW of −37.5% (RCP4.5) and −36.8% (RCP8.5) and an increase in GW of 4.7% (RCP4.5) and 3.4% (RCP8.5).

For the Gbassè subbasin, both HBV-light and SWAT predict a decrease in BW but with different magnitudes. The decrease will be between 17% and 39% for the HBV-light and even higher for the SWAT model (Figures 7a,c). Future trend in GW is consistent across the models with both UHP-HRU and SWAT predicting an increase in GW especially under RCP4.5 (Figures 7b,c). Altogether, the deviation from the reference period can be summarized as follows: a variation of rainfall by ±4.2% under RCP4.5 and ±3.4% under RCP8.5 that will induce a reduction in BW by −50.6% under RCP4.5 and −49.3% under RCP8.5 and an increase in GW by 16.3% under RCP4.5 against 15.0% under RCP8.5.

The expected change in BW and GW resources relative to the reference period, across the Yankin subbasin, is presented in Figure 8 along with the change in rainfall. Rainfall is expected to increase for HIRHAM5 and RCSM (with a higher increase under RCP4.5) but to decrease for RCA4 (along with a higher decrease under RCP8.5). Regardless of the climate models and the RCP, BW will decrease but GW is simulated to increase. In addition, the decrease in BW is slightly

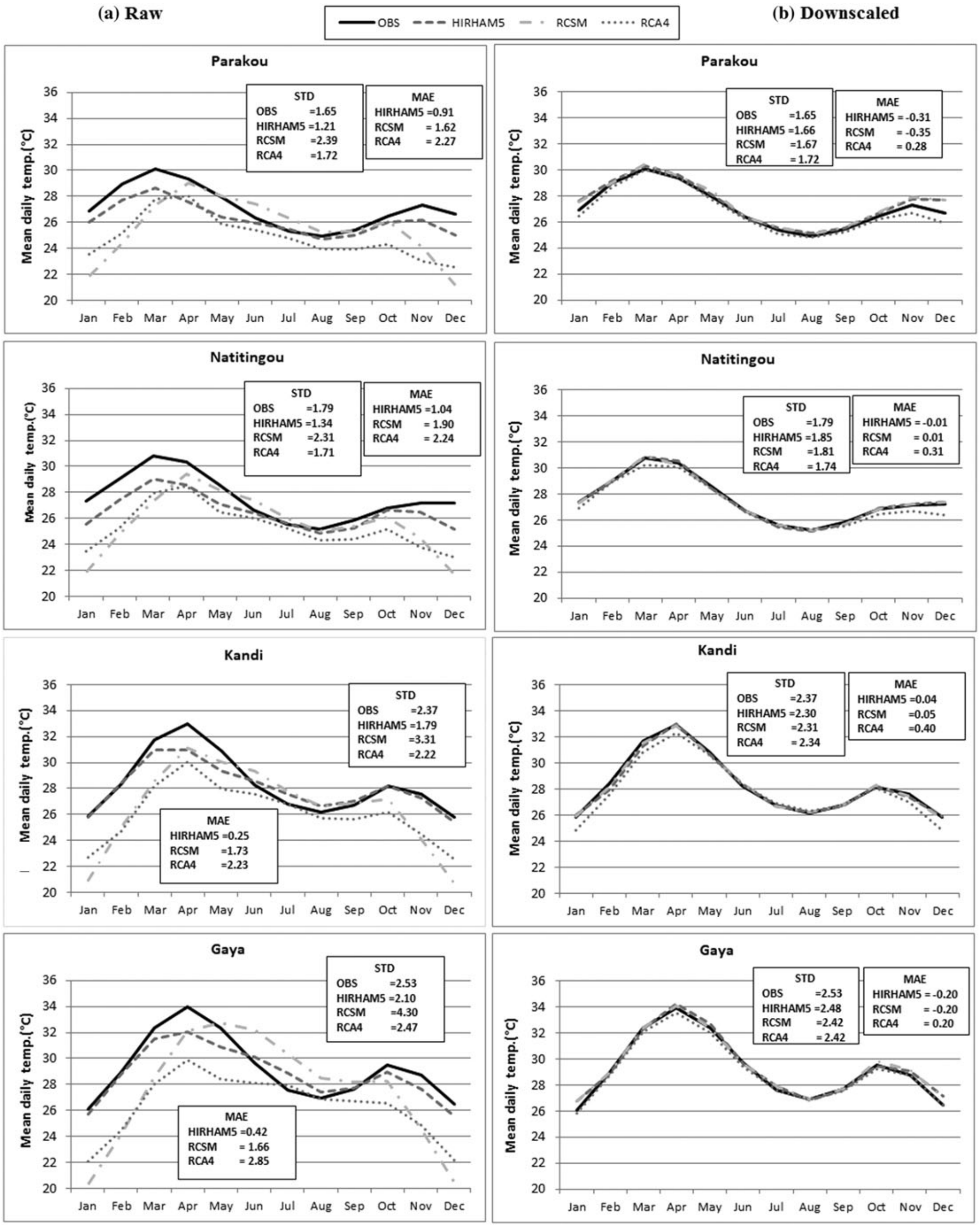

FIGURE 4 Comparison of raw (left panel) and downscaled (right panel) mean temperature of the baseline period (1976–2005). Stations are ordered from the south to the north of the study area. STD = standard deviation; MAE = mean absolute error

higher under RCP8.5, whereas the increase in GW is slightly higher under RCP8.5. On the whole, rainfall will likely increase by 5.6% under RCP 4.5 and by 5.1% under RCP8.5. This change in rainfall will be accompanied by a reduction in BW of −25% under RCP4.5 and −26.0% under RCP8.5 but by an increase in GW of 10.9% under RCP4.5 and 10.1% under RCP8.5.

The projected BW and GW of the Kompongou subbasin (Figure 9) have different trends from the three other subbasins. The first difference is that, unlike the other subbasins, rainfall will increase for all climate and hydrological models with the exception of UHP-HRU run with RCA4. The second peculiarity of the Kompongou subbasin is that a mixed trend (an increase and a decrease) and not a decrease (as it was the case for the other subbasins) in BW is projected. Also, unlike the other subbasins, UHP-HRU showed a decrease in GW when run with RCA4 and RCSM data.

Of the four subbasins, the highest increase in rainfall and the lowest decrease in BW are simulated for the Kompongou subbasin. Overall, compared with the reference period, rainfall will increase by between 9.1% (RCP4.5) and 8.9% (RCP8.5). This change in rainfall will lead to a change in BW of −8.4% (RCP4.5) and −6.2% (RCP8.5) but to an increase in GW by 5.5% (RCP4.5) and 4.9% (RCP8.5).

3.3 | Uncertainty quantification

The uncertainty quantification of the Coubéri subbasin was based on 90 model realizations. The result is presented in Figure 10.

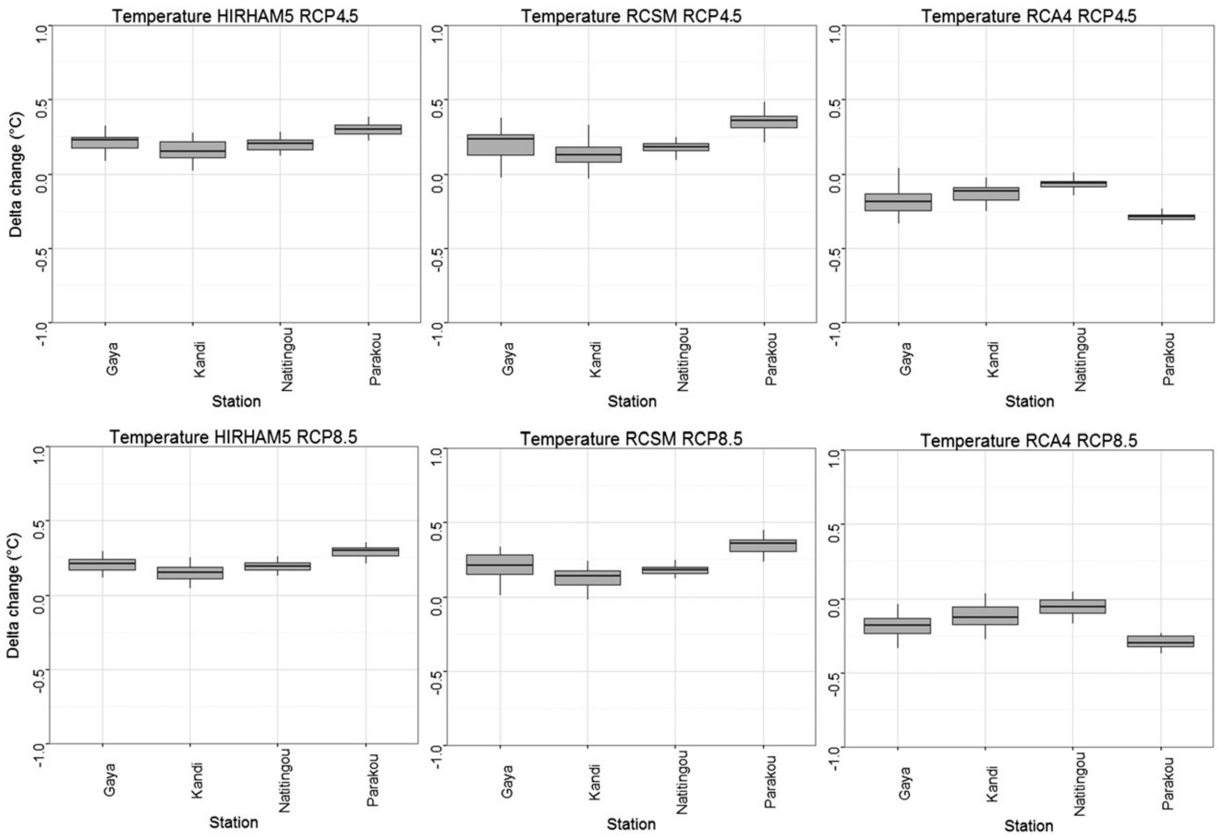

FIGURE 5 Box plots of the projected change (2021–2050) in annual mean temperature relative to the baseline period (1976–2005) under RCP 4.5 (upper panel) and RCP 8.5 (lower panel)

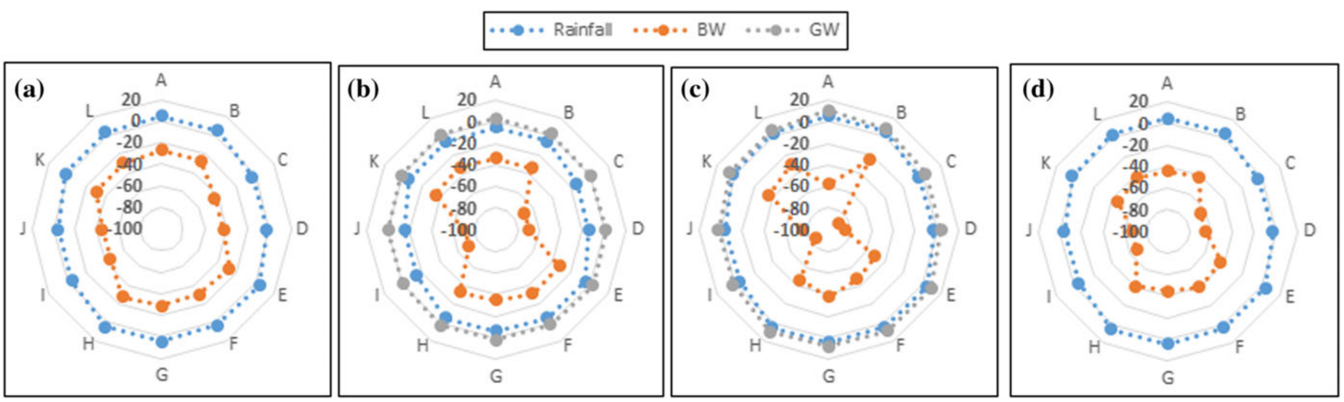

FIGURE 6 Simulated changes (%) in rainfall, blue water (BW), and green water (GW) under RCP4.5 and RCP8.5 climate scenarios in the Coubéri subbasin by the HBV-light (a), UHP-HRU (b), SWAT (c), and WaSiM (d) hydrological models. *A: HIRHAM5_RCP4.5_2021–2030, B: HIRHAM5_RCP4.5_2041–2050, C: RCA4_RCP4.5_2021–2030, D: RCA4_RCP4.5_2041–2050, E: RCSM_RCP4.5_2021–2030, F: RCSM_RCP4.5_2041–2050, G: HIRHAM5_RCP8.5_2021–2030, H: HIRHAM5_RCP8.5_2041–2050, I: RCA4_RCP8.5_2021–2030, J: RCA4_RCP8.5_2041–2050, K: RCSM_RCP8.5_2021–2030, L: RCSM_RCP8.5_2041–2050*

Rainfall is predicted to decrease by a median of −2.9% to −4.0% with an interquartile range between 8.7% and 9.2%. The median of BW will also decrease by between −38.4% to −41.3% with an interquartile range of 16.1% to 21.6%. The median projected change in GW is approximately 1.5% to 2.5% with an interquartile range of 2.2% to 2.7%. The values of the interquartile ranges show that the GW evaluation is associated with lesser uncertainty than that of rainfall, whereas the assessment of BW is the least certain.

For the Gbassè subbasin, 48 model realizations were used to assess the uncertainty (Figure 11). The median of rainfall is predicted to increase by between 5.2% and 6.3% along with an associated interquartile range of 8.2% to 8.72%. Similarly, the median of GW will increase by 12.4% to 14.0% with an interquartile range of 18.4% to 19.1%. The median of BW is, however, predicted to decrease between −21.3% and −23.2% with an interquartile range of 18.5% to 20.2%. Thus, the evaluation of change in rainfall is associated with lesser uncertainty than the quantification of BW and GW.

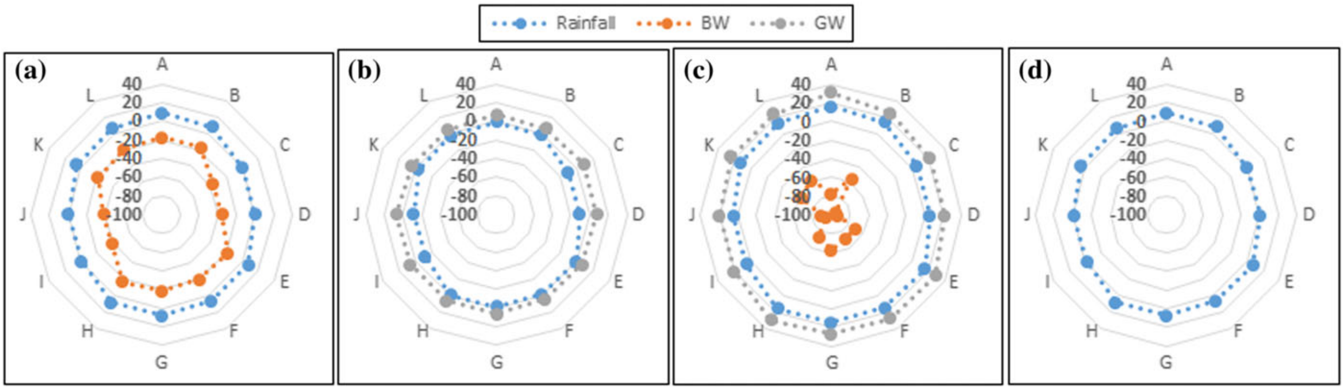

FIGURE 7 Simulated changes (%) in rainfall, blue water (BW), and green water (GW) under RCP4.5 and RCP8.5 climate scenarios in the Gbassè subbasin by the HBV-light (a), UHP-HRU (b), SWAT (c), and WaSiM (d) hydrological models. *A: HIRHAM5_RCP4.5_2021–2030, B: HIRHAM5_RCP4.5_2041–2050, C: RCA4_RCP4.5_2021–2030, D: RCA4_RCP4.5_2041–2050, E: RCSM_RCP4.5_2021–2030, F: RCSM_RCP4.5_2041–2050, G: HIRHAM5_RCP8.5_2021–2030, H: HIRHAM5_RCP8.5_2041–2050, I: RCA4_RCP8.5_2021–2030, J: RCA4_RCP8.5_2041–2050, K: RCSM_RCP8.5_2021–2030, L: RCSM_RCP8.5_2041–2050*

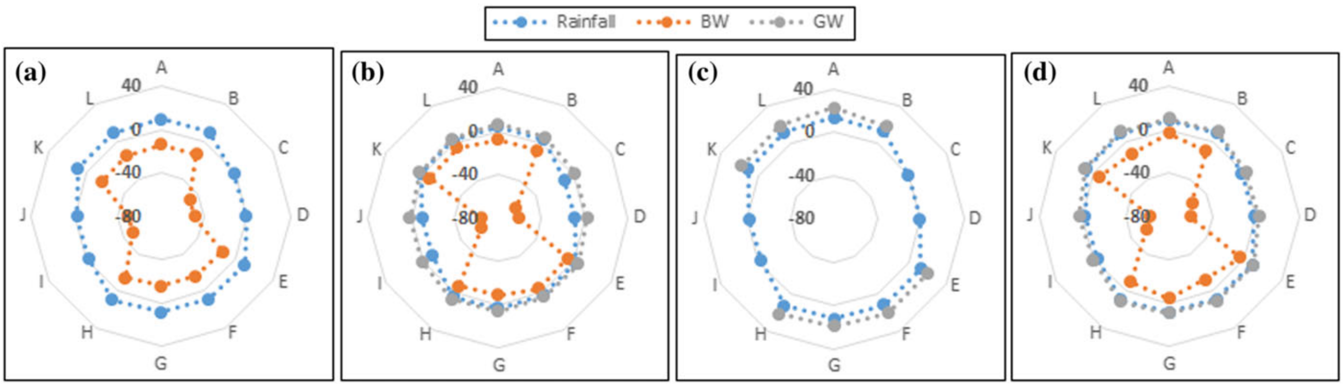

FIGURE 8 Simulated changes (%) in rainfall, blue water (BW), and green water (GW) under RCP4.5 and RCP8.5 climate scenarios in the Yankin subbasin by the HBV-light (a), UHP-HRU (b), SWAT (c), and WaSiM (d) hydrological models. *A: HIRHAM5_RCP4.5_2021–2030, B: HIRHAM5_RCP4.5_2041–2050, C: RCA4_RCP4.5_2021–2030, D: RCA4_RCP4.5_2041–2050, E: RCSM_RCP4.5_2021–2030, F: RCSM_RCP4.5_2041–2050, G: HIRHAM5_RCP8.5_2021–2030, H: HIRHAM5_RCP8.5_2041–2050, I: RCA4_RCP8.5_2021–2030, J: RCA4_RCP8.5_2041–2050, K: RCSM_RCP8.5_2021–2030, L: RCSM_RCP8.5_2041–2050*

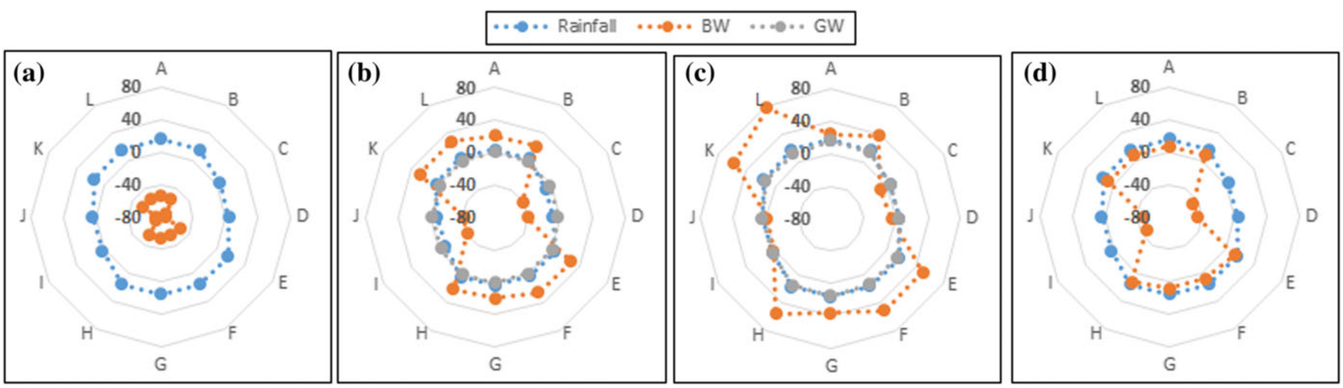

FIGURE 9 Simulated changes (%) in rainfall, blue water (BW), and green water (GW) under RCP4.5 and RCP8.5 climate scenarios in the Gbassè subbasin by the HBV-light (a), UHP-HRU (b), SWAT (c), and WaSiM (d) hydrological models. *A: HIRHAM5_RCP4.5_2021–2030, B: HIRHAM5_RCP4.5_2041–2050, C: RCA4_RCP4.5_2021–2030, D: RCA4_RCP4.5_2041–2050, E: RCSM_RCP4.5_2021–2030, F: RCSM_RCP4.5_2041–2050, G: HIRHAM5_RCP8.5_2021–2030, H: HIRHAM5_RCP8.5_2041–2050, I: RCA4_RCP8.5_2021–2030, J: RCA4_RCP8.5_2041–2050, K: RCSM_RCP8.5_2021–2030, L: RCSM_RCP8.5_2041–2050*

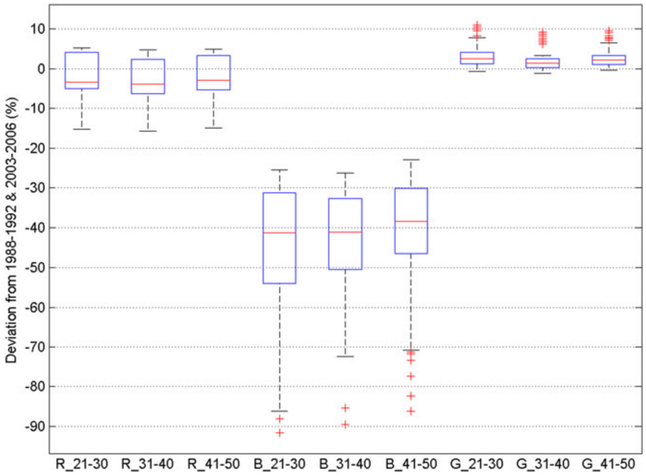

FIGURE 10 Ensemble percentiles (lower, median, and upper quartile) projected interannual rainfall, blue water, and green water trends relative to 1988–1992 and 2003–2006 in the Coubéri subbasin. X_21–30, X_31–40, X_41–50 denotes the values of rainfall (X = R), blue water (X = B), and green water (X = G) during the decades 2021–2030, 2031–2041, and 2041–2050

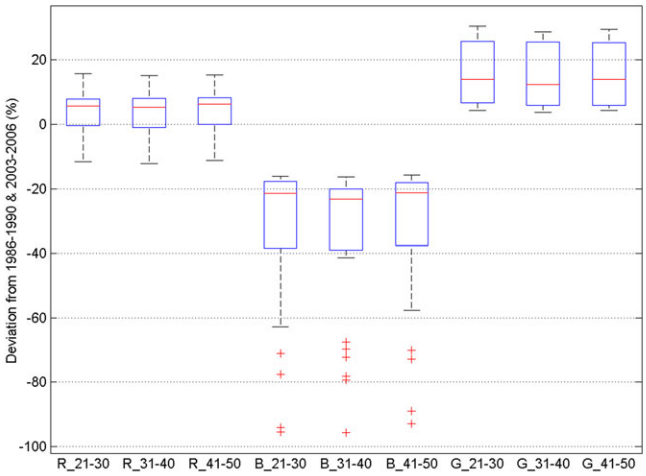

FIGURE 11 Ensemble percentiles (lower quartile, median and upper quartile) projected interannual rainfall, blue water, and green water trends relative to 1986–1990 and 2003–2006 in the Gbassè subbasin. X_21–30, X_31–40, X_41–50 denotes the values of rainfall (X = R), blue water (X = B) and green water (X = G) during the decades 2021–2030, 2031–2041, and 2041–2050

In the case of the Yankin subbasin, 78 model realizations were used to assess the uncertainty. An inspection of Figure 12 reveals that rainfall change will exhibit positive trends of 7.7% to 8.6% changes of the median along with an interquartile range of 10.5% to 11.2%. However, the median of the BW is predicted to decrease by −15.2% to −17.8%, whereas the median of the GW is projected to increase by 9.3% to 10.0%. The associated interquartile ranges are predicted as of the order of 36.5% to 42.2% and 6.8% to 7.3% for BW and GW, respectively. As in the case of the Coubéri subbasin, GW evaluation is associated with lesser uncertainty than the evaluation of rainfall, whereas while the assessment of BW resources is the least certain.

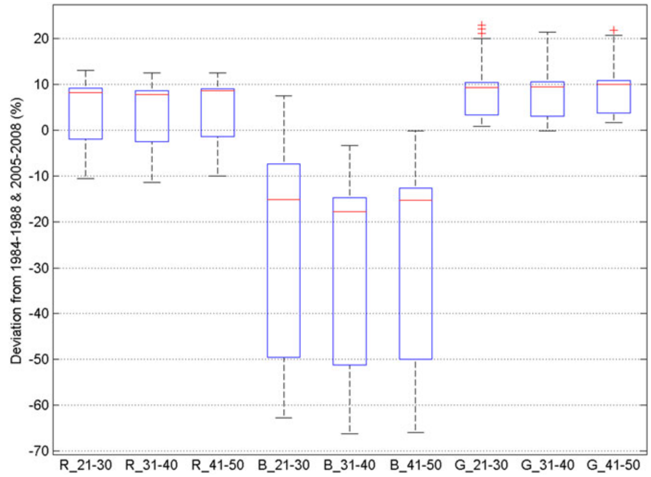

FIGURE 12 Ensemble percentiles (lower, median, and upper quartile) projected interannual rainfall, blue water, and green water trends relative to 1984–1988 and 2005–2008 in the Yankin subbasin. X_21–30, X_31–40, X_41–50 denotes the values of rainfall (X = R), blue water (X = B), and green water (X = G) during the decades 2021–2030, 2031–2041, and 2041–2050

For the Kompongou subbasin, the combination of climate models, emissions scenarios, hydrological models, and behavioural hydrological models parameters resulted in 24 model realizations, which is the smallest NMR of all subbasins. The reason is that only one behavioural hydrological model parameter set was retained after the calibration and validation procedure (see Section 4.3 and Tables S2–S5). The analysis of the uncertainty is presented in Figure 13. The median projected change in rainfall is approximately 8.8% to 10.2% with an interquartile range of 11.9% to 12.4%. This increase in rainfall will lead to an increase in both BW and GW. Whereas the median of the BW is predicted to increase by 0.2% to 4.5% with an interquartile range of 70.7% to 73.1%, that of GW is predicted to increase by 2.0% to 2.8% along with an interquartile range of 12.7% to 13.2%. Thus, the evaluation of BW is associated with the largest uncertainty in comparison with the assessment of rainfall and GW for which the interquartile ranges are smaller.

4 | DISCUSSION

4.1 | Downscaled climate variables

4.1.1 | Precipitation

The findings presented above are consistent with recent downscaling studies over Africa. The projected increase in rainfall for HIRHAM5 and RCSM is consistent with the conclusions of Oyerinde et al. (2016) who reported an increase of 2% (RCP 4.5) and 5% to 10% (RCP 8.5) from the middle to the end of the century over the Niger River Basin. Similarly, Kaboré/Bontogho et al. (2015) found that in the Massili Basin of Burkina Faso, rainfall will slightly increase for the period 2006–2050 in comparison with the period 1975–2000. Besides, the mixed trend of rainfall projected by RCA4 is comparable with the findings of Kebede et al. (2013) who reported that in the Baro-Akobo Basin of Ethiopia, downscaled rainfall by the model

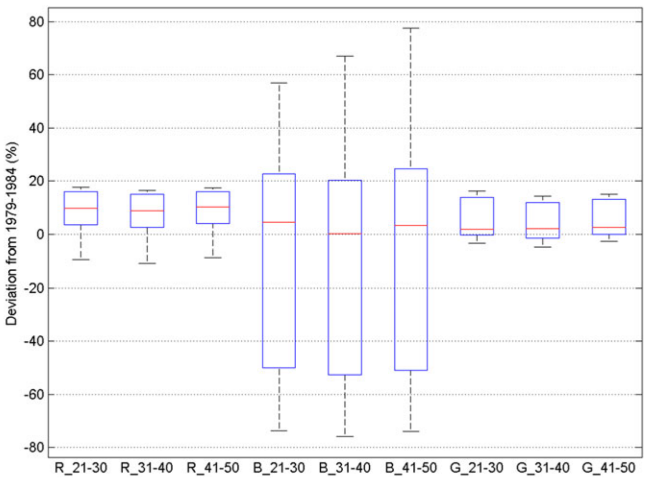

FIGURE 13 Ensemble percentiles (lower, median, and upper quartile) projected interannual rainfall, blue water, and green water trends relative to 1979–1984 in the Kompongou subbasin. X_21–30, X_31–40, X_41–50 denotes the values of rainfall (X = R), blue water (X = B), and green water (X = G) during the decades 2021–2030, 2031–2041, and 2041–2050

REMO (A1B and B1 scenarios) resulted in a change of −2% to 21%. The negative rainfall trend projected for some stations (Figure 3) is consistent with the results found for the Ouémé Basin of Benin, where a 9% to 12% decrease in rainfall was expected when REMO rainfall (A1B which is similar to RCP6.0 scenario and B1 which is similar to the RCP4.5 scenario) was bias-corrected (Bossa, Diekkrüger, & Agbossou, 2014).

However, the fact that stations exhibit both positive and negative rainfall trend relaunches the discourse on the importance of the direction (rather than the magnitude) of change of future rainfall over West Africa (Druyan, 2011; Yira et al., 2017).

4.1.2 | Temperature

The projected increase in temperature for the models HIRHAM5 and RCSM corroborates the conclusions of Kaboré/Bontogho et al. (2015) and Oyerinde (2016) where the former reported that temperature will increase by 1.8 °C (RCP4.5) and 3.0 °C (under RCP8.5) from 1971 to 2050 in Massili basin of Burkina Faso, and the latter found that the Niger River Basin will experience a temperature increase of between 5% and 10% under RCP4.5 and 5% and 20% under RCP8.5 from the beginning to the end of the century.

On the contrary, the negative trend of temperature projected for the climate model RCA4 contrasts the continuation of warming during the rest of the century reported in IPCC (2013). However, it is not the first time that a decrease in temperature is reported in the literature. For example, Kebede et al. (2013) downscaled the minimum and maximum temperatures of the GCM CGCM 3.1 (A1B scenario) and the RCM REMO (A1B and B1 scenarios) and obtained almost similar results. The results of Kebede et al. (2013) showed that the majority of the investigated stations will experience a decrease in maximum temperature (for CGCM3.1) and half of the stations will exhibit a decrease in minimum temperature (for REMO).

Another aspect that requires attention is that higher temperatures are projected under RCP4.5 than under RCP8.5. These results are surprising because the opposite was expected. However, Kebede et al. (2013) also found almost similar results when they reported higher maximum temperature under B1 than under A1B for half of the stations and higher minimum temperature under B1 than under A1B for 40% of the stations. Given that the same downscaling model, SDSM is used by Kebede et al. (2013) as well as in this study, one wonders if the results imply an internal artefact (or systematic error) of the model.

4.2 | Future BW and GW availability

On average, a decrease in BW is projected and GW is predicted to increase. The increase in GW is linked to the projected warming and the intensification of the hydrological cycle. In the context of increasing rainfall, the warmer the atmosphere, the greater the evaporative demand, which leads to an increase in GW. This in turn leads to less water to run off and/or to percolate and reach the deep aquifer so the decrease in BW. These results are partly in agreement with the conclusions of some previous studies in nearby basins. Using four hydrological models, Cornelissen, Diekkrüger, and Giertz (2013) investigated the impact of climate change (REMO under A1B and B1 scenarios) and land use change on the water balance of the Térou Basin, a tributary of the Ouémé River in Benin. Regardless of the emissions scenarios, two models (UHP-HRU and GR4J) predicted a decrease in discharge (which is the most important part of the BW), whereas the two others (SWAT and WaSiM) predicted an increase in discharge. Bossa (2012) conducted a study with the SWAT model to evaluate the influence of climate (REMO under A1B and B1) and land use changes on the sediment yield and the water balance of the Donga-Pont and the Ouémé-Bonou basins in Benin, and the results indicated a decrease in water yield, surface run-off and groundwater flow, and actual evapotranspiration. However, land use change would induce an increase in surface run-off and water yield (depending on the type of change envisaged) but a decrease in the others' water balance components. Zannou (2011) reported that the Ouémé Basin will experience a 41% decrease in water resources by 2025. Oyerinde et al. (2016) used eight GCM products and found that annual streamflow would slightly increase by the end of the century at the run-off stations at Malanville and Kainji located in the Niger River Basin. Finally, Touré, Diekkrüger, and Mariko (2016) found that climate change will lead to a decrease in groundwater resource in the Klela Basin of Mali.

4.3 | The particular case of the Kompongou subbasin

Unlike the three other subbasins, in the Kompongou subbasin, rainfall is expected to increase (with the exception of UHP-HRU run with RCA4 data), GW to decrease when UHP-HRU is run with RCA4 and RCSM data, and BW to have a mixed trend (not a decrease as it was the case for the other subbasins). This unique behaviour could be explained by the difference in climate conditions between the calibration/validation period (1979–1984) and the future time horizon (2021–2050). In the subbasin, the calibration (1979–1984) of hydrological models was satisfactory but the validation (2007–2010) was not. Kompongou is the subbasin with the largest percentage of missing data in the historical streamflow records. As a result, there was a difference of nearly 30 years between the calibration period (1979–1984) and the validation period (2007–2010). During these 30 years, the subbasin might have undergone many changes in its characteristics making validation very difficult if not impossible. Subsequently, comparison with the future was limited to the calibration period, which actually was a period of severe drought (Badou et al., 2016). Hence, when compared with that period of drought, some models (e.g., SWAT and WaSiM when run with HIRHAM5 and RCSM data) simulate an increase in future BW and UHP-HRU when driven by RCA4 and RCSM data predicts a decrease in GW.

4.4 | Uncertainty quantification

The key outcome of the uncertainty analyses is that BW quantification is associated with larger uncertainty than GW evaluation. Two main reasons can explain it. First, BW evaluation was done with four hydrological models of very distinct structures: a conceptual lumped model (HBV-light), two conceptual semidistributed model (UHP-HRU and SWAT), and a distributed physically based model (WaSiM). On the contrary, GW was assessed solely with the hydrological models (UHP-HRU, SWAT, and WaSiM) having a more or less physically meaningful soil moisture routine. Second, and most importantly, although the approaches used by the models to compute evapotranspiration (i.e., GW) are nearly similar, the approaches used to derive the streamflow components (i.e., BW) are very different. UHP-HRU, SWAT, and WaSiM use the Penman–Monteith method (Monteith, 1965; Penman, 1956) to compute Potential evapotranspiration. To derive surface run-off (a component of BW), HBV-light uses a typical tank-type approach, WaSiM a method based on the Richards equation, and UHP-HRU and SWAT the SCS CN method (Badou, 2016).

5 | RECOMMENDATIONS

The main finding of this study is that though rainfall may have a positive trend in the future, increase in rainfall will be accompanied by a decrease in BW resources, the easily accessible water resources but with an increase in GW resources. Given the current population growth in the study area, from 1,579,006 in 2014 to 5,600,000 expected in 2050 (Badou, 2016), this is rather crucial information for decision makers and water planners. Less BW resources imply less water for municipal, domestic, and industrial uses; less water for agriculture and possibly more conflicts between farmers and cattle rangers (Lougbegnon, Dossou, Houessou, & Teka, 2012); and less water for fishery. Two sets of solutions could be explored to address the problem. This first set deals with BW and the second with GW.

In order to meet the increasing water demand with the predicted decrease in BW, a rational use of BW is mandatory. In the study area, traditional belief in the “gods” is still very strong and often, hazards are seen as the gods' curses (Vissin, 2007). The solution, therefore, is more sociological than technical, implying that more attention should be given to the sociological dimension of adaptation to a changing climate. Wherever a technical solution is necessary, the human dimension should also be included. Unfortunately, this aspect is often not taken into account in most recommendations. More research is needed to bridge the gap between technical solution and their relevance for the people to implement them. Another solution to address the issue of the projected decrease in BW is the use of grass and alfalfa lands to dampen run-off (Kharel, Zheng, & Kirilenko, 2016). This technique limits run-off and increases deep aquifer recharge, which has a buffer effect against climate change (Vouillamoz, Lawson, Yalo, & Descloitres, 2015).

The second set of solutions is based on the projected increase in GW. An increase in GW implies an increase in either transpiration and/or evaporation (both resulting in increased water losses). To face the probable increase in evaporation, more research is needed to reverse the situation, by, for example, implementing techniques of soil and water conservation that can easily be applied in the study area. Rodriguez-Juan, Sbai, and El Harradji (2015) conducted such as study for the Mestferki Basin located in North-East of Morocco.

6 | CONCLUSION

A proper estimation of future water availability is vital information for water planners. This study explored alternative avenues for more informative and robust hydrological prediction of the water resources of the Benin Portion of the Niger River Basin, a conglomerate of four subbasins, which is rich in terms of ecosystem services but poorly gauged. Water resources were treated as BW and GW. The products of three RCMs (HIRHAM5, RCSM, and RCSM) under RCPs 4.5 and 8.5 were statistically downscaled and used to run four different hydrological models. Whereas BW was predicted using only the most suitable hydrological models for the simulation of streamflow, GW assessment depended on those models found to be more behavioural for the simulation of soil moisture storage. It was found that

1. rainfall will likely increase (1.7% to 23.4%) for HIRHAM5 and RCSM under both RCPs but will show mixed trends (−8.5% to 17.3%) for RCA4. Mean temperature will also increase up to 0.48 °C for HIRHAM5 and RCSM but decrease for RCA4 up to −0.37 °C.
2. as a result of global warming, GW will increase in all the four investigated subbasins and BW will only increase in the Kompongou subbasin. The median decrease in BW is projected to approximate −38% to −41% in the Coubéri subbasin, −21% to −23% in the Gbassè subbasin, and −15% to −18% in the Yankin subbasin, but a median increase of 0.2% to 4.5% is predicted in the Kompongou subbasin. The median increase in GW will approximate 2% to 3% in Coubéri, 12% to 14% in Gbassè, 9% to 10% in Yankin, and 2% to 3% in Kompongou.
3. using interquartile ranges, BW evaluation is associated with larger uncertainty than GW quantification. A variation of the interquartile ranges of 16% to 21% in BW against 2% to 3% in GW for the Coubéri subbasin, 19% to 20% in BW against 18% to 19% in GW for the Gbassè subbasin, 37% to 42% in BW against 7% in GW for the Yankin subbasin, and 71% to 73% in BW against 13% in GW for the Kompongou subbasin was noted.

The projected increase in rainfall will be accompanied by a decrease in BW resources, the easily accessible water resources but with an increase in GW resources. If technical solutions (use of grass lands to dampen run-off and increase deep aquifer recharge, techniques of soil and water conservation) are necessary, more attention should be given to the sociological dimension of adaptation to a changing climate.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

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