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Quantification and allocation of uncertainties of climate change impacts on hydropower potential under 1.5 °C and 2.0 °C global warming levels in the headwaters of the Benue River Basin, Cameroon

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ABSTRACT

Hydropower is the world's largest producer of renewable energy and represents more than 43% of the low-carbon energy. However, it is sensitive to climate variability and change. This study evaluates the climate change impacts on hydropower potential in the headwaters of the Benue River Basin (HBRB) under 1.5 °C and 2.0 °C global warming levels (GWLs) and quantifies the main sources of uncertainty in the modeling chain. Precipitation and temperature from 17 members of the Coordinated Regional Downscaling Experiment over the Africa domain (CORDEX-Africa) under two representative concentration pathways (RCPs 4.5 and 8.5) were used to run two calibrated Lumped-conceptual hydrological models (HMs) (Hydrologiska Byrans Vattenavdelning (HBV-Light) and HYdrological MODel (HYMOD)). An analysis of variance (ANOVA) decomposition was used to quantify the uncertainties related to each impact modeling chain step in the hydropower potential calculation process. Results reveal a high uncertainty in both climatic and hydrologic parameters. The change in precipitation associated with an increase in potential evapotranspiration (PET) causes a significant decrease in hydropower generation associated with a large uncertainty range. The ANOVA sensitivity test reveals that the dominant contributing source to hydropower projections uncertainty varies with GWL. Given the likely breach of GWL 1.5 by the early 2030s, these findings contribute information for consideration in water and energy planning in the region over the next decade, and stresses that these considerations are urgent for the socio-economic well-being of the region.

1. Introduction

Climate change is now a major concern around the World and there is a clear agreement that temperature increases will affect different mechanisms of the climate system. Since the middle of the 1990s, discussions about setting targets to limit global warming by a predefined threshold have been actively pursued, when the so-called tolerable global temperature window (ranging from 9.9 °C to 16.6 °C) was introduced at the First Conference of the Parties (COP) of the United Nations Framework Convention on Climate Change (UNFCCC) in Berlin in 1995 [1]. In 2015, the Paris Agreement (COP21) was adopted with the main goal to pursue efforts to limit the global-mean temperature at 1.5 °C and well below 2 °C above pre-industrial levels, which would significantly decrease the risks and impacts of climate change [2,3]. To

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achieve the Paris Accord, renewable energy sources are being promoted which are clean and increasingly competitive energy sources. They are distinct from fossil fuels mainly by their variety, affluence and potential for worldwide use, but especially in the fact that they do not produce greenhouse gases - the cause of climate change. They also present an opportunity for economic development and the achievement of the UN's Sustainable Development Goals (SDGs,7 and 13 [4]). Hydropower is the world's largest producer of renewable energy and represents more than 43% of low-carbon energy and 16% of the total electricity budget [5]. It is an efficient, flexible, reliable and environmentally friendly renewable source of energy, and is an option for climate change mitigation and adaptation in many regions [6]. The International Renewable Energy Agency (IRENA [7]) suggests that to meet the 2.0 °C target, we need about 850 GW of additional hydropower capacity by 2050, while to reach the 1.5 °C target, we will need at least another 1200 GW. The International Hydropower Association (IHA [5]) show that 26 GW of new hydropower capacity was put into operation, up on 21 GW installed in 2020's.

Although hydropower generation is known as an important option for climate change mitigation and adaptation, it is extremely sensitive to climate variability and change because small, sometimes insignificant climatic variations often result in significant changes in the availability and regularity of water in reservoirs, the main drivers of hydroelectric production [8–10]. Therefore, it is of paramount importance to understand the effects of climate change and variability on hydropower generation.

It has been demonstrated that some regions around the world are more vulnerable to climate change than others even if they are least culpable for greenhouse gases emissions [2]. This is particularly true for Africa continent, which is already experiencing increasing anomalies in climate patterns and is expected to face more climate risks and water shortages for the rest of this century [11]. In many parts of Africa, a reduction of water resources will have a significant impact on socio-economic development through agriculture, which employs 55–62% of the workforce and 95% of the cropland is rain fed [11], and hydropower that contributes to more than 80% of electricity production in countries such as the Democratic Republic of Congo, Ethiopia, Malawi, Mozambique, Uganda, and Zambia [12].

Although several studies have been conducted in West, Southern and East Africa regions that evaluate the potential impacts of climate change on hydropower generation (e.g. Refs. [13–15]), very few studies have been conducted in Central Africa. Moreover, there is a lack of studies that focus on the impacts of climate change on hydropower energy under different GWLs in Africa and especially in Central Africa. This is even though recent studies [16,17] provided evidence that Central Africa precipitation and temperature as well as climate extremes will be significantly impacted at different GWLs, which will increase heat stress and the proportion of population at risk of discomfort [18]. Furthermore, the sixth report of the Intergovernmental Panel on Climate Change (IPCC) establishes, albeit with limited confidence, that Central Africa is expected to experience an increase in extreme events under global warming [19]. For instance, the intensity and frequency of the hottest daily maximum temperature events are projected to robustly increase whereas those of the coldest daily minimum temperature are expected to decrease. Increases in the intensity and frequency of heavy precipitation and dry spell events are also projected. Without adaptation, such changes would have disastrous consequences for countries such as Cameroon [20] whose socio-economic activities' depend highly on natural resources (rain-fed agriculture [21,22], hydroelectric power generation [23], transportation, fisheries, etc.) and where Malaria transmission follows the seasonal cycle of rainfall [24,25]. Therefore, the projected impacts of climate change on river discharge and hydropower generation in Cameroonian catchments are highly important to understand in order to develop new adaptation strategies for water resource management.

However, the impact of climate projections on river discharge is associated with large uncertainties. These arise from the different steps of the modeling chain which include emission scenarios, global climate models (GCMs), downscaling techniques (dynamical or statistical), hydrological models' structure and parameter uncertainty [26]. For better water management and for science-based decision making, the quantification of uncertainty sources in climate-impact studies is of great importance. In the last decade, numerous previous studies have been focused on climate change impacts on hydrology and their sensitivity to the different sources of uncertainty [26–33]. Despite this, to date only few studies have been conducted over African catchments in general and specifically in Cameroonian catchments. In addition, few studies address the impacts of relatively low magnitudes of global warming - this is of great importance because seemingly small differences in temperature will have a strong impact in specific regions and ecosystems [26].

The study pursues three objectives: (i) to assess the consequences of climate change on hydro-climatic components and hydropower generation in the Headwaters of the Benue River Basin (HBRB) under GWLs of 1.5 °C and 2.0 °C above preindustrial levels; (ii) to quantify the total uncertainty in both projected climatic and hydrologic parameters and (iii) to quantify individual or combined uncertainties that come from different sources in the modeling chain (see Fig. 1). This paper is organized as follows, after the introduction, the study area and the data sources are described in section 2; section 3 provides the applied methodology while the results and discussions are given in section 4. The study ends with the summary and conclusions in section 5.

2. Study area and data

2.1. Study area

The study is performed for the Headwaters of the Benue River Basin (HBRB), the second-biggest basin in Cameroon, situated in the northern Cameroon (Fig. 2) among latitudes 7°N and 11°N, and Longitudes 12°E and 16°E, with a drainage area of 30 650 km^2 at the stream gauging station Riao. It rises at an altitude of 1300 m on the Adamawa plateau and represents the biggest water provider of the Niger basin [34]. The HBRB is the only perennial river in northern Cameroon where many rivers are seasonal and dry up a few months after the end of the wet season. It is important to the socioeconomics of the Northern region thanks to its potential to sustain different water resources activities such as irrigated agriculture, hydroelectricity production, navigation, industry, domestic use and breeding [35]. Moreover, in 1982, the Lagdo dam was built with an installed capacity of 72 MW and there is an ongoing project that aims to increase hydropower and irrigation capacity of the dam to supply electricity to other countries, including the Chad Republic, northern Nigeria and part of the Central African Republic [36]. However, this basin experiences water-related hazards such as droughts and floods [37–40]. Additionally, recent research showed an increase/decrease trend in annual air temperature/precipitation [41–43], and an increase of drought magnitude and intensity under changing environmental conditions [44,45]. This suggests the region is likely to experience drier conditions [23], making the HBRB region (in particular) an important case study.

The basin enjoys a tropical humid climate with two main seasons: the rainy season stretches from May to October and the dry season from November to April. It's a unimodal rainfall region (maximum in August) with annual rainfall ranges between 900 and 1500 mm [43] which decreases gradually from the south (the highland of the Adamawa plateau) to the north of the basin (Chad plain). In contrast to rainfall, temperature in the basin increases gradually from the south to the north with the annual mean temperature of 28 °C. The savanna is the predominant vegetation in the area and the elevation varies between 220 and 2260 m, characterized by major hills, including Adamawa Plateau, Alantika and Mandara mountains [43].

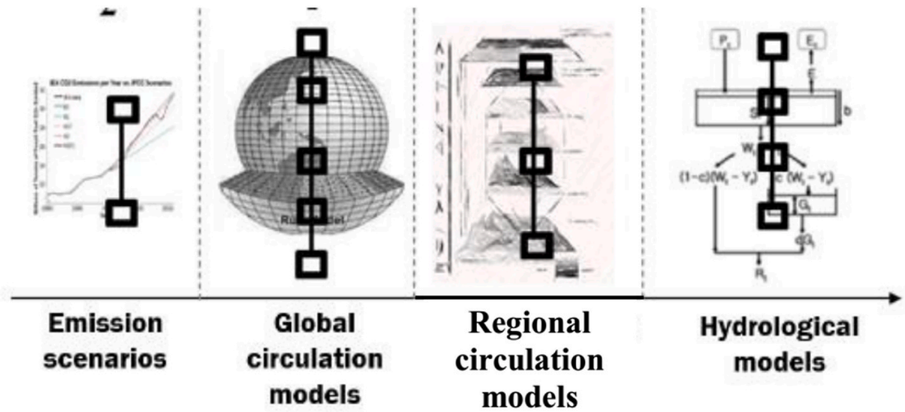

Fig. 1. Impact modeling chain for hydrological projections used in this study (adopted and modified from Ref. [31]).

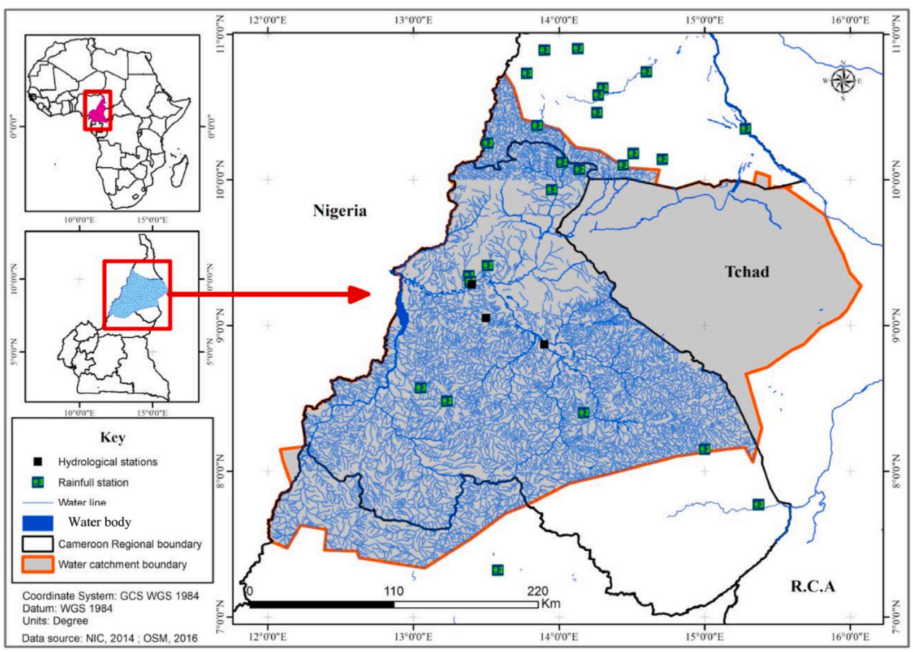

Fig. 2. Study catchment: basin drainage area and rainfall and hydrological stations.

2.2. Observed hydrometeorological data

In this study we used both daily meteorological and hydrological data to calibrate and validate the hydrological models. The meteorological data include rainfall for 25 stations and mean air temperature from 4 stations located in the basin. These data were provided by the Department of the National Meteorology of Cameroon (DNM) while the potential evapotranspiration (PET) was computed using the Hamon temperature-based method [46]. This method has been extensively used in climate change impact studies [23,47,48] and has been found to be one of the most sustainable temperature-based methods in the Benue River Basin [49]. Names, geographic positions, data record periods as well as data quality assessment can be found in Refs. [49,50].

Daily streamflow data measured at the Riao gauging station located in the basin were obtained from the environmental information system for water resources (SIEREM) database ([51], http://hydrosciences.fr/sierem). Streamflow records were available from 1950 to 1999 equivalent to 591 months with 08.97% of missing months.

2.3. Climate models data

The daily meteorological variables required for the hydrological analysis of projected water resources and hydropower generation variability (precipitation and mean air temperature), were obtained from 17 CORDEX-Africa climate simulations. CORDEX is a global programme whose aim is to downscale coarse-scale global climate model projections (GCMs) to finer scales over every continental land mass of the world and make these data freely available for download on the Earth System Grid Federation (ESGF). In this study we use CORDEX-Africa data from 5 regional climate models (RCMs) that downscaled 9 GCMs of the 5th Coupled Model Intercomparison Project (CMIP5 [52]) under two representative concentration pathways, RCPs 4.5 and 8.5, to a resolution of 0.44°. These data were extracted over our region of interest and used to force the hydrological model. We adopt a Global Warming Levels (GWLs) analysis method as described in Ref. [53]. Here, the period 1861–1890 is used to define the pre-industrial period against which each GWL is calculated. The timing of GWLs for each GCM is defined as the first time the center year of a 30-year moving average of projected global temperature is above 1.5 or 2 °C compared to the pre-industrial temperature. Thereafter, for each RCM downscaling, the same GWL timing of the corresponding driving GCM is used to extract data from a 30-year period for the analysis. For example, if a GCM exceeds 1.5° the pre-industrial temperature in 2035 according to the method described above, 30 years of daily data from the RCM that downscaled that GCM, centered on 2035 is extracted for use in the hydrological modelling. The 1.5 °C and 2 °C responses are extracted from transient experiments by selecting time samples at the date when the 30-year running mean global temperature reaches 1.5 °C or 2.0 °C compared to a control period (CTL), 1971–2000. A list of RCM–GCM combinations and the future 30-year periods of GWLs 1.5 °C and 2.0 °C are given in Table 1.

To ascertain the possible scenario of avoiding the impacts of higher warming at 2.0 °C above pre-industrial levels, the avoided impacts (AI) caused by additional 0.5 °C warming is computed using Eq. (1):

$$AI = \left[\frac{GWL_{2.0} - GWL_{1.5}}{GWL_{2.0}}\right] \times 100 \quad (1)$$

The good performance of the models considered in the representation of the mean state of the Central African climate has been extensively evaluated in previous studies (e.g. [54–61]: among others).

3. Material and methods

3.1. Hydrological models

In this study, we used two hydrological models namely HBV-Light [62] and HYMOD [63,64]. There are Conceptual-Lumped rainfall-runoff models working at the daily time-step and simulating discharge using day-to-day precipitation and PET as inputs and differ from their structures and complexities. HBV-Light model is a nine-parameters model and consists of three main routines including snow and snow cover, soil moisture and evaporation, and groundwater and response processes represented by two mains reservoirs. The HYMOD is a five-parameter model based on the probability-distributed theory proposed by Ref. [65] which assumes that the soil moisture reservoirs within a catchment have variable depths. Additionally, HYMOD consists of two main routines, including soil moisture and evaporation routine, represented by a nonlinear soil moisture reservoir and response routine represented by three fast-flow reservoirs and one slow-flow reservoir. Table 2 provides the definition of the parameters used to simplify the hydrological processes considered in the models as well as their initial ranges while the schematic representation of these processes is shown in Fig. 3.

The model calibration and uncertainty analysis were conducted using the Monte Carlo procedure [66]. Using the random number from a uniform distribution within the initial ranges of each model parameter, 50 000 parameter sets were generated. For each parameter set, the model was run, and the simulations were screened into behavioral and non-behavioral parameter sets using a threshold value of Kling–Gupta efficiency ($KGE \geq 0.75$ [67]) for very good simulations. To test the reproducibility of the best optimized parameter set during the validation period, both graphical (visual hydrograph comparison as well as flow duration curves) and statistical performance criteria were used. This include in addition to KGE, Nash and Sutcliffe Efficiency (NSE [68]), Percent Bias (PBIAS [69]), Pearson correlation coefficient (R^2 [69]), standardized root mean square error (RSR [69]). Descriptions and

Table 2
Description of parameters of the two conceptual rainfall–runoff models and their ranges used for the Monte Carlo procedure [62,64].

Hydrological model name	Parameter name	Definition	unit	Initial range
HBV-Light	FC	Maximum value of soil moisture storage	mm	50–500
	LP	Fraction of FC above which actual ET equals potential ET	–	0.3–1
	β	Shape parameter for the soil moisture distribution function	–	1–6
	K_0	Near-surface flow routing rate constant	day^{-1}	0.05–0.5
	K_1	Interflow routing rate constant	day^{-1}	0.01–0.3
	K_2	Baseflow routing rate constant	day^{-1}	0.001–0.1
	UZL	Threshold for Q_0 flow	mm	0–100
	PERC	Coefficient of percolation between the upper and lower groundwater boxes	day^{-1}	0.01–0.1
	MAXBAS	Length of triangular weighting function in routing routine	day	1–5
HYMOD	*SM,max*	Maximum soil storage capacity of a catchment	mm	1–500
	Bexp	Degree of spatial variability of soil moisture capacity	–	0.1–2
	Alpha	Partitioning factor between fast and slow routing reservoirs	–	0.1–0.99
	RF	Residence time of quick-flow reservoirs	day^{-1}	0.1–0.99
	RS	Residence time of slow-flow reservoir	day^{-1}	0.001–0.1

Table 1
Timing of 30-year period of targeted GWLs as a function of RCPs and corresponding driving GCM and RCM.

Driving GCMs	RCMs	RCP4.5		RCP8.5	
		1.5 °C	2.0 °C	1.5 °C	2.0 °C
CanESM2	SMHI-RCA4	2002–2031	2017–2046	1999–2028	2012–2041
IPSL-CM5A-MR	SMHI-RCA4	2002–2031	2020–2049	2002–2031	2016–2045
CNRM-CM5	SMHI-RCA4 CLMcom-CCLM4-8-17	2021–2050	2042–2071	2015–2044	2029–2058
CSIRO-Mk3-6-0	SMHI-RCA4	2020–2049	2033–2062	2018–2047	2030–2059
EC-EARTH-r12	SMHI-RCA4 CLMcom-CCLM4-8-17	2010–2039	2031–2060	2005–2034	2021–2050
EC-EARTH-r3	DMI-HIRHAM5	2009–2038	2030–2059	2006–2035	2023–2052
EC-EARTH-r1	KNMI-RACMO22E	2006–2035	2028–2057	2003–2032	2021–2050
HadGEM2-ES	SMHI-RCA4 CLMcom-CCLM4-8-17 KNMI-RACMO22E	2016–2045	2032–2061	2010–2039	2023–2052
MIROC5	SMHI-RCA4	2026–2055	2059–2088	2019–2048	2034–2063
MPI-ESM-LR	SMHI-RCA4 CLMcom-CCLM4-8-17 MPI-CSC-REMO2009	2006–2035	2029–2058	2004–2033	2021–2050
NorESM1-M	SMHI-RCA4	2027–2056	2062–2091	2019–2048	2034–2063

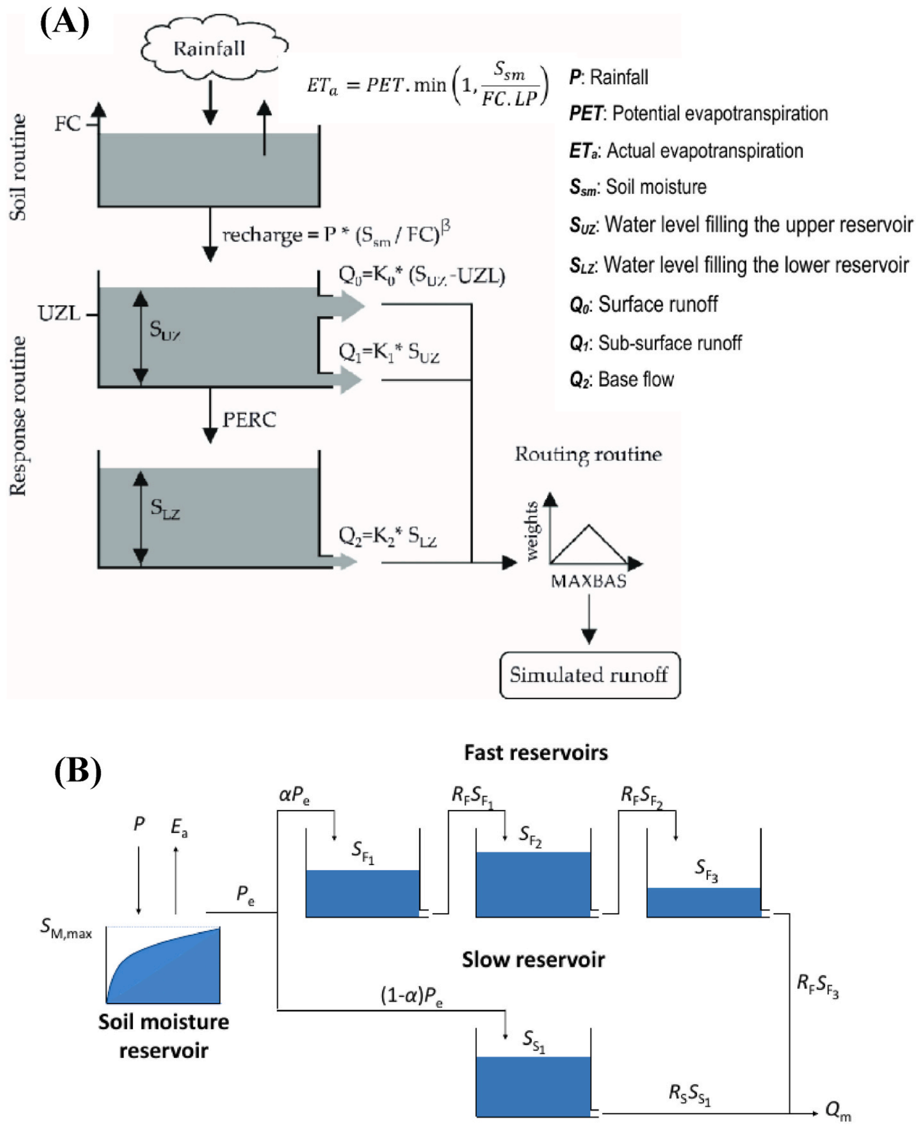

Fig. 3. Schematic representation of the different hydrological processes in the two hydrological models: (A) HBV-Light model [62] and (B) HYMOD [64].

formulations of these statistical criteria can be found in Refs. [49,50,69].

3.2. Assessment of the impacts on hydropower potential

The projected impacts of climate change on the gross hydropower potential were evaluated in Lagdo dam, which has an installed capacity of 72 MW and with an average head fall of 25 m. The gross hydropower potential is the total amount of electricity that could potentially be generated if all available water resources were devoted to this use. It is obtained by converting the potential and kinetic energy of water into electrical energy by electromechanical means (turbines and generators). Hydropower potential is estimated based on the streamflow, hydraulic head i.e. elevation gradient in this case and the total plant efficiency, as shown in Eq. (2) [8,70]:

$$N_p = Q \times H \times \rho_w \times g \times \eta \tag{2}$$

where N_p is the gross hydropower potential (W), Q is the streamflow (m^3/s), H is the hydraulic head (m), ρ_w is the water density ($kg/\,m^3$), g is the gravitational acceleration (m/s^2) and η is the total plant efficiency (%).

Historical and future stream flows simulated by the two calibrated hydrological models were used to estimate both historical and future hydropower potential through Eq. (2).

3.3. Uncertainty quantification and decomposition: ANOVA sensitivity test

In this study, we use a sensitivity test based on the ANalysis Of VAriance (ANOVA [71]) to allocate and quantify the main sources of uncertainty in the modeling chain. ANOVA is a statistical test for detecting differences in group means when there is one parametric dependent variable and one or more independent variables [26]. In ANOVA, the total sum of squares (SST, Eq. (3)) is used to express the total variation that can be attributed to the various groups [26]. The four groups used for variance decomposition in this study are the GCMs, RCMs, HMs and RCPs:

$$SST = \sum_{i=1}^{N_{RCP}} \sum_{j=1}^{N_{GCM}} \sum_{k=1}^{N_{RCM}} \sum_{l=1}^{N_{HM}} \left(X_{ijkl} - \overline{X}\right)^2 \tag{3}$$

where X_{ijkl} is the value of hydro-climate variable X corresponding to RCP i, GCM j, RCM k and HM l respectively and $\overline{X}$ is the overall mean.

SST can be further divided into four main effects (SS_{RCP}, SS_{GCM}, SS_{RCM} and SS_{HM}, the squared deviations of single values from their appropriate factor mean) which are effects directly attributable to RCPs, GCMs, RCMs and HMs, and into Residuals variance ($SS_{Residuals}$):

$$SST = SS_{RCP} + SS_{GCM} + SS_{RCM} + SS_{HM} + SS_{Residuals} \quad (4)$$

Then for each uncertainty source Y, its contribution (η_Y^2) to the overall uncertainty of X is calculated as follows:

$$\eta_Y^2 = \frac{SS_Y}{SST} \quad (5)$$

These indices range in value from 0 (no effect) to 1 (maximal effect) because they are proportions of variance.

To test the significance of each uncertainty source (RCPs, GCMs, RCMs and HMs) to the total uncertainty, we use the F-test [71]. This is a statistical test used in hypothesis testing to examine whether the variances of two groups are equal or not. The null hypothesis states that the population means for each group of the independent variable are equal, while the alternative hypothesis is that at least two of the group means differ. The ANOVA test statistic called F_{score} is calculated as:

$$F_{score} = \frac{MeanSquares_{BetweenGroups}}{MeanSquares_{WithinGroups(Residual)}} \quad (6)$$

where the $MeanSquares_{BetweenGroups}$ term, is an indirect measure of differences in group means, while the $MeanSquares_{WithinGroups(Residual)}$ term, is considered to represent statistical noise/error since this variance is not explained by the effect of the independent variable on the dependent variable. Thus, for independent groups, high F_{scores} result from large differences between group means and/or small variances within groups. In addition, higher F_{scores} corresponds to lower p-values, with the p-value also influenced by the sample size and the number of groups, each of which are distinct types of "degrees of freedom" [71].

4. Results and discussion

4.1. Hydrological models evaluation results

The comparison between observed and modeled hydrographs in this watershed during the model calibration and validation are shown in Figs. 4 and 5, while the values of efficiency are given in Table 3.

We noticed that the two models reproduced the dynamic (timing and magnitude of measured discharge) well of the catchment. The models also capture the various parts of the hydrograph well. However, low flows are more accurately simulated than high flows, which are comparatively underestimated in magnitude throughout the watershed. The results also exhibit the strong relationship between the modeled and measured discharge during the calibration and validation period (with $R^2 \geq 0.88$) indicating good model performance. This result is reinforced by the NSE and KGE greater than 0.75 obtained during the model optimization and validation. Consistent with [69], this model is classed as very good within the HBRB. This result is consolidated by the narrow band of model uncertainty prediction for the behavioral parameter sets (Figs. 4 and 5) with the R-factors <1.5 obtained during the calibration and validation period of the two models. According to Ref. [72], this result is satisfactory. We also noticed that the best simulation with respect to the measured streamflow lies inside this narrow uncertainty band with *P-factors* $\geq$ 40%. This highlights that modeled discharge agrees with the observations perfectly, indicating the two hydrological models perform well and therefore can be used for impact studies.

4.2. Projected change in precipitation, temperature, and PET under different GWLs

Fig. 6 shows the projected change in monthly, seasonal and annual precipitation, temperature and PET averaged over the whole basin area under 1.5 °C and 2.0 °C GWLs, as well as the AI caused by additional 0.5 °C warming based on the CORDEX simulations.

An analysis of mean monthly precipitation indicates that there is no change signal during the dry months (except April), while there is a mixed change signal during the rainy season from both GWLs and RCPs scenario which is associated with a large band of uncertainty compared to dry months. At GWLs of 1.5 °C (2.0 °C) under RCP4.5 scenario, the rainiest months (July and August) exhibit an increase of rainfall with an ensemble median of 4.98%(9.17%) and 5.67%(9.29%) while the other rainy months (May, June, September and October) exhibit a slightly decrease of rainfall with an ensemble median ranges from −3 to −1% and −4.5 to −2% under 1.5 °C and 2.0 °C GWLs respectively for RCP4.5. Under RCP8.5, we note a slight difference. Except for October, all the rainy months exhibit an increase of rainfall with an ensemble median ranging from 2.5 to 6.2% and 0.5–13.5% under 1.5 °C and 2.0 °C GWLs respectively. For both GWLs and RCPs scenario, August, the month of maximum rainfall in the HBRB, exhibits the highest change signal. The results also reveal that rainfall will increase at the end of the dry season (April), while there will be a decrease at the end of the rainy season

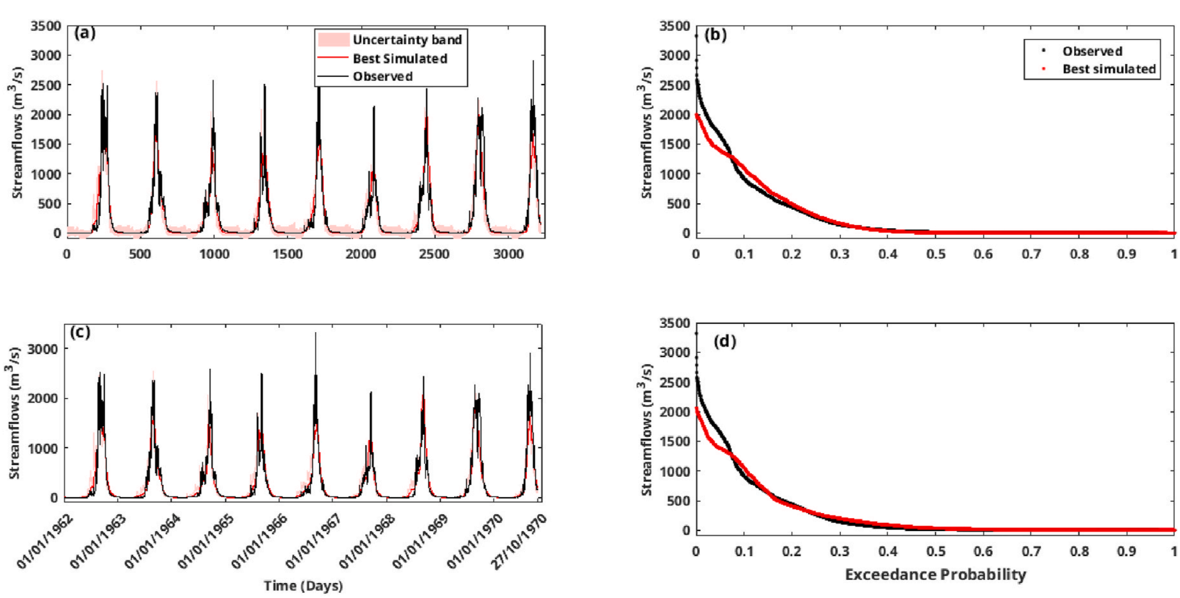

Fig. 4. Calibration of HBV-Light and HYMOD models: (a) time series plot for HBV-Light calibration, (b) flow duration curves for HBV-Light calibration, (c) time series plot for HYMOD calibration, and (d) flow duration curves for HYMOD calibration. Uncertainty band for acceptable simulations.

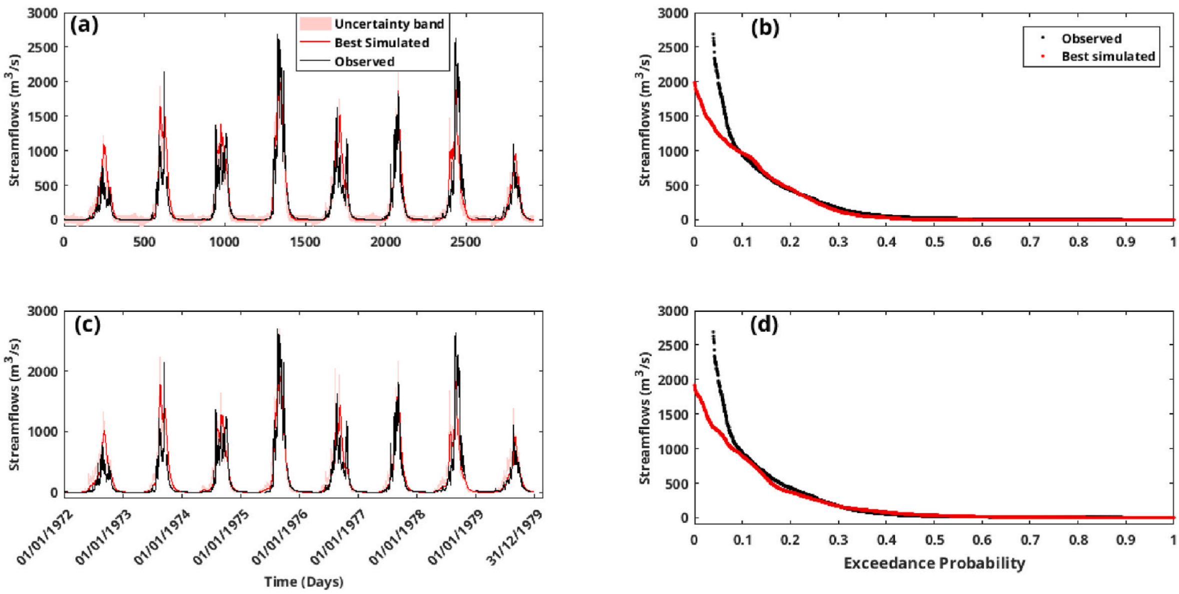

Fig. 5. Same as Fig. 4 but during the validation period.

Table 3
Statistical summary of the model's performance for the calibration and validation periods in the UBRB.

Models		KGE	NSE	RSR	PBIAS (%)	R^2	P-factor	R-factor
HBV-Light	Calibration	0.88	0.86	0.38	−1.96	0.93	0.83	1.49
	Validation	0.83	0.78	0.48	18.06	0.90	0.78	1.30
HYMOD	Calibration	0.85	0.84	0.40	−2.31	0.92	0.41	−0.14
	Validation	0.83	0.76	0.49	16.8	0.88	0.43	−0.16

(October). This means that under each GWL, RCMs projected an earlier rainfall onset and retreat dates in the HBRB.

Seasonally, June-July-August (JJA) season, which is the wettest season in this region, exhibits an increase of rainfall with an ensemble median of 0.61%(3.41%) and 5.88%(6.22%) under RCP4.5(RCP8.5) for 1.5 °C and 2.0 °C GWLs respectively. This result is similar to those of [59], who found that the total amount of precipitation above the 95th percentile increases significantly during the monsoon months. September-October-November (SON) season exhibits an increase of rainfall under RCP8.5 for both 1.5 °C and 2.0 °C GWLs. This result is slightly different under RCP4.5 which exhibits a small decrease with an ensemble mean of 0.5% for the two considering GWLs. December-January-February (DJF) season doesn't exhibit a change signal contrary to March-April-May (MAM) season there is a mixed signal. Annually, rainfall will slightly increase under both GWLs and RCPs scenario with the maximum increase (with an ensemble median of 2.06%) obtained under RCP8.5 scenarios and 2.0 °C GWL. This result is consistent with those of [73,74] who found that this region will experience increases in rainfall intensity and water related disasters - floods and droughts which will most affect the agricultural production. It is also clear from this figure that the additional 0.5 °C warming will affect the rainfall. We not the seasonal results do not reflect the earlier onset and retreat projection that the monthly analysis above reveals.

The changes in temperature and PET show similar patterns with potential increases under both scenarios and GWLs. Monthly, seasonal and annual PET is expected to increase with an increase in GWLs. This result was expected given that temperature and PET are strongly correlated [23]. We also notice that during dry months/seasons, climate models exhibit a large band of uncertainty in temperature and PET changes compared to rainy months/seasons.

4.3. Projected change in water recharge under different GWLs

The water recharge here is the amount of precipitation that directly contributes to runoff or the amount of water available for runoff and is particularly important for hydropower generation. Monthly, seasonal and annual projected impacts of climate change in water recharge are displayed in Fig. 7.

The dry months (November to April) don't exhibit a change signal thanks to the absence of rainfall during this period. However, during rainy months (May to October), mean water recharge is projected to decrease with an increased GWLs under different RCPs scenario. The maximum decrease in water recharge is obtained during September under GWLs and RCPs. Seasonally, JJA and SON seasons exhibit a strong decrease change signal. Annual water recharge is projected to decrease with an ensemble median of −8.12% (−5.67%) and −12.14% (−9.40%) under RCPs4.5 (8.5) at 1.5 °C and 2.0 °C GWLs respectively. Under RCP4.5, the decrease of the water recharge is higher than that under RCP8.5 for all GWLs.

4.4. Projected change in hydropower potential under different GWLs

Monthly, seasonal and annual projected impacts of climate change on hydropower potential under both RCPs scenarios and GWLs are displayed in Fig. 8.

This figure clearly shows that the dry months (November to April) did not exhibit a change signal. This is due to the absence of precipitation during this period, which is the natural mechanism responsible for the water supply in the watershed. During the rainy months (From May to October), there is a clear consensus about climate and hydrological models that hydropower potential will decrease under both GWLs and RCPs with a greater reduction under RCP4.5. The JJA and SON seasons exhibit a higher change signal compared to DJF and MAM seasons.

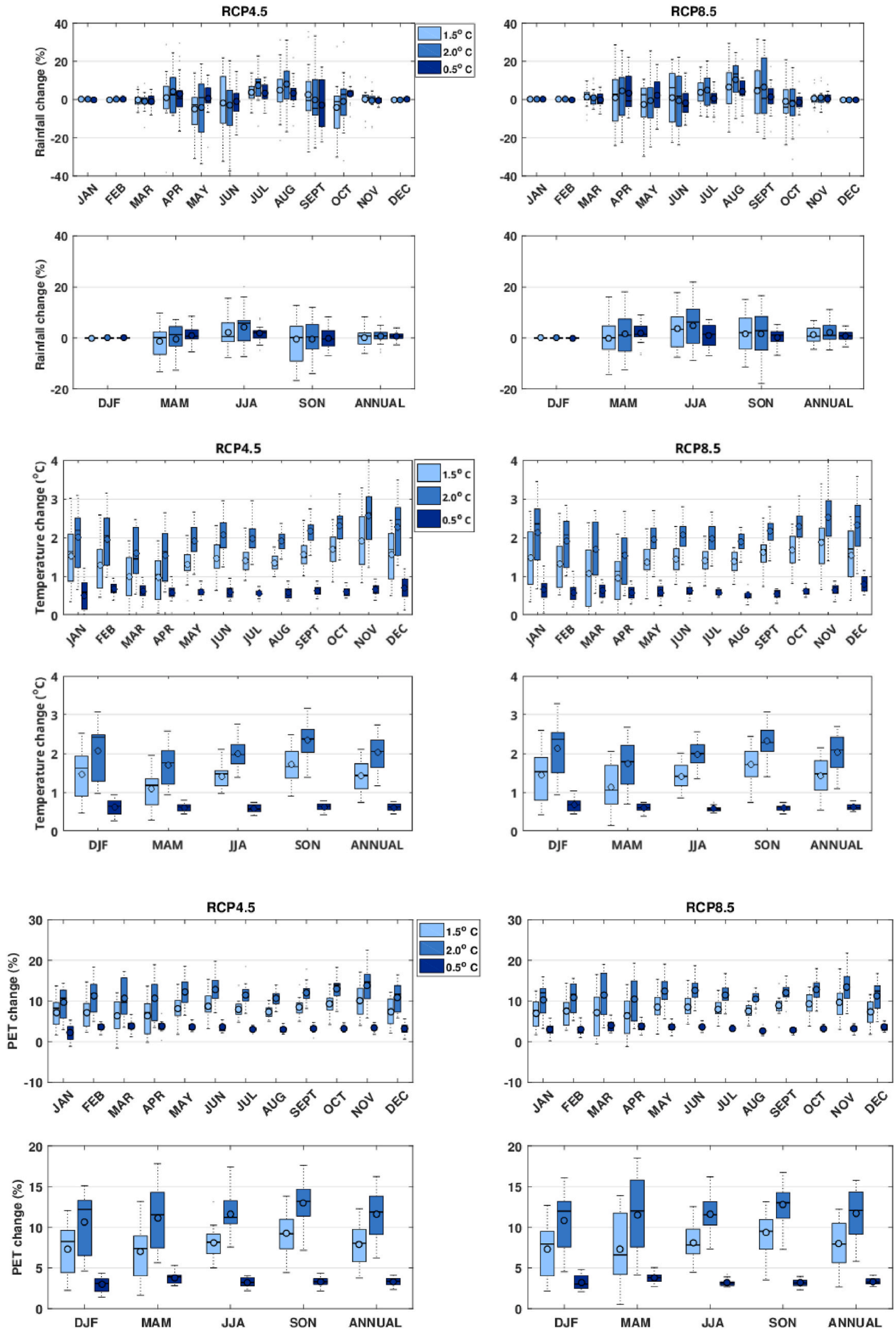

Fig. 6. Projected change in monthly, seasonal and annual Rainfall, 2-m air temperature and Potential Evapotranspiration (PET) at 1.5 °C and 2.0 °C GWLs as well as change associated with the additional 0.5 °C warming. In all the box and-whisker plots, the whiskers represent the minimum and maximum of the change signal. The outer edges of the boxes and the horizontal lines within the boxes represent the 25th, 75th, and 50th (median) percentiles of the change signal. The filled circle represents the average value of the change signal.

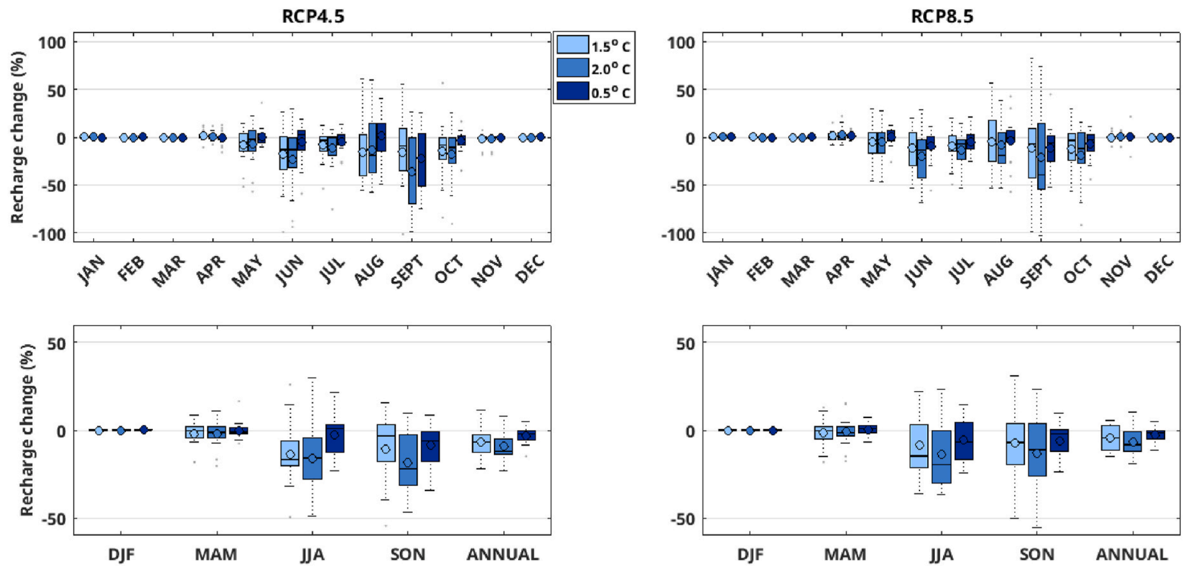

Fig. 7. Projected change in monthly, seasonal and annual water recharge at 1.5 °C and 2.0 °C GWLs as well as change associated with the additional 0.5 °C warming.

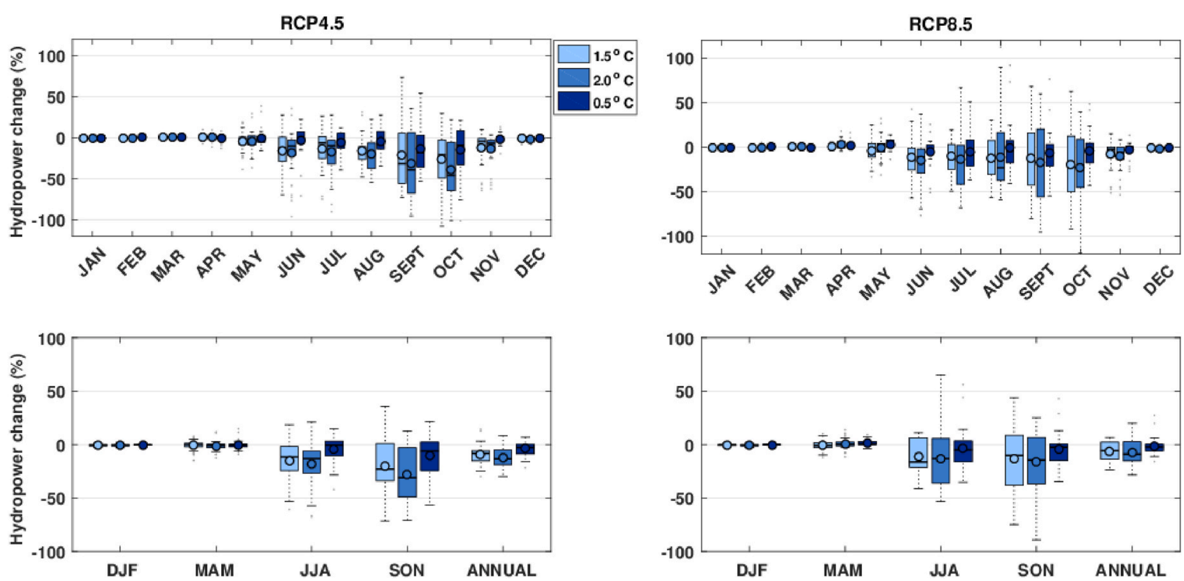

Fig. 8. Projected change in monthly, seasonal and annual hydropower potential of the Lagdo dam located in the HBRB at 1.5 °C and 2.0 °C GWLs as well as change associated with the additional 0.5 °C warming.

Annual hydropower generation is also projected to decrease with an ensemble median of −8.26%(−5.60%) and −13.35%(−8.95%) under RCPs 4.5(8.5) at 1.5 °C and 2.0 °C GWLs respectively. This finding is consistent with those of [75,76] who found that hydro-energy generated at Lagdo dam in the Benue basin may suffer a significant decrease due to climate change. This feature is common with other studies previously done in sub-Saharan African catchments [13,14].

4.5. Uncertainty estimation and decomposition for hydropower potential projections

ANOVA statistical test was used to decompose the uncertainty in the computed hydropower potential and to identify the contribution of five sources of uncertainties, i.e. RCPs, GCMs, RCMs, HMs, and residuals variance. Fig. 9 shows the contribution of each uncertainty source to the total uncertainty on hydropower potential projections under different GWLs, whereas Table 4 presents the results of the significance test (F-test). In general, the uncertainty is dominated by variance associated with the residuals. We note that the main four uncertainty sources' (RCPs, GCMs, RCMs, HMs) contribution to hydropower potential projections vary according to the GWLs. At 2.0 °C GWL, uncertainty is largely dominated by RCMs, follow by GCMs and RCPs scenarios with statistically significant effects at the 99.9%, 99% and 95% confidence level respectively. Whereas at 1.5 °C GWL, the contribution of GCMs is dominant followed by RCMs with statistically significant effects at the 99.9% and 99% confidence interval respectively. For the AI caused by additional 0.5 °C warming, we note that GCMs largely contributed to the total uncertainty with a statistically significant effect on hydropower projections followed by RCMs, but without with a statistically significant effect. In summary, the climate models (both GCMs and RCMs) are the dominant sources of uncertainty on hydropower projections under different GWLs. This result is consistent with many previous studies that found that climate models are the major contributor to uncertainty in future streamflow projections [27,33] but without considering the different GWLs and without evaluating the statistical significance of the findings.

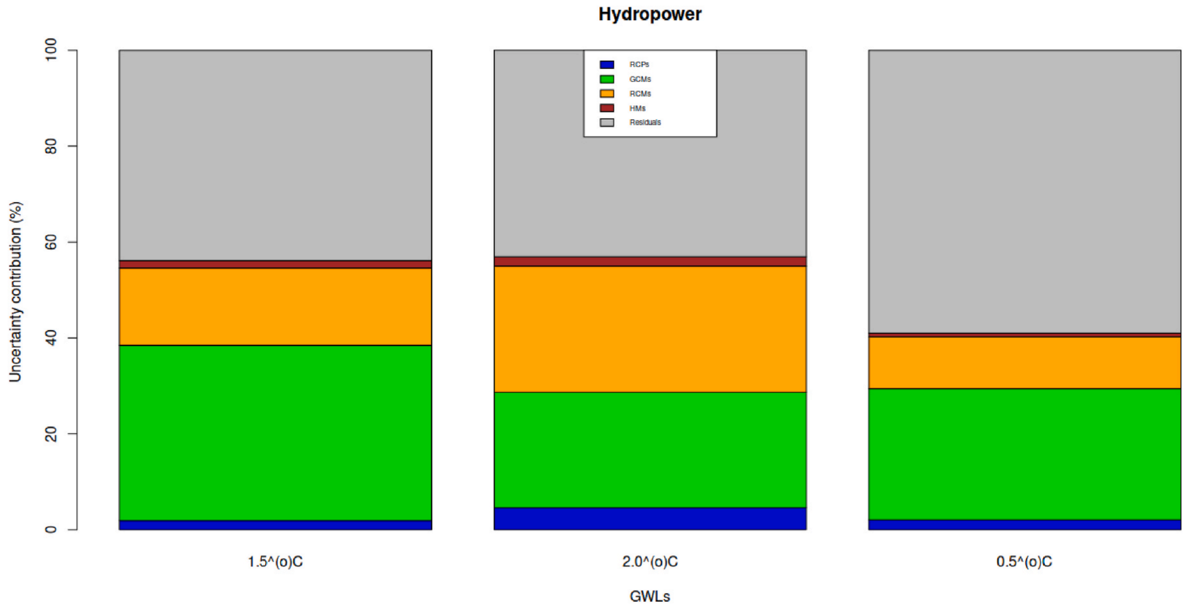

Fig. 9. Contribution of different sources to uncertainty in annual hydropower potential projections under different GWLs.

Table 4
Results of significance statistical test (F-test) (*test significant at the 95% confidence level ($\rho < 0.05$; **test significant at the 99% confidence level ($\rho < 0.01$); ***test significant at the 99.9% confidence level ($\rho < 0.001$)).

Effects	1.5 °C GWL		2.0 °C GWL		Additional 0.5 °C warming	
	F-score	P-value	F-score	P-value	F-score	P-value
RCPs	2.34	0.1322	5.67	0.0209*	1.84	0.1811
GCMs	5.52	0.000044***	3.70	0.0017**	3.07	0.0064**
RCMs	4.85	0.00208**	8.07	0.000037***	2.43	0.0591.
HMs	1.92	0.1719	2.45	0.1238	0.66	0.4208

5. Conclusions

In the region where water is the most significant factor for socio-economic development and where hydroelectricity accounts for about 70% of electricity, quantifying uncertainty within the impact modeling chain for hydrological projections is important to provide information for science-based decision making and the development of robust climate adaptation plans. The aim of this study was to assess the impacts of climate change on hydropower potential under two GWLs, their associated uncertainties and the contribution of each uncertainty source in the modeling chain. Precipitation and temperature from 17 CORDEX-Africa members under two representative concentration pathways (RCPs 4.5 and 8.5) were used to run two calibrated Lumped-conceptual hydrological models (HMs) (HBV-Light and HYMOD). An analysis of variance (ANOVA) decomposition was used to quantify the uncertainties related to each impact modeling chain step for hydrological projections and hydropower potential calculation process, namely RCP scenarios, GCMs, RCMs and HMs. The principal findings of this research are:

- The performance assessment of the two hydrological models reveals that the best simulation versus measured discharge is within the band of uncertainties in the model prediction. This highlights that modeled discharge agrees with the observations perfectly, indicating the hydrological models perform well, and that their application for supporting water resources management strategies within this basin is possible.
- Despite uncertainties, annual rainfall is projected to slightly increase while temperature and PET are projected to increase under both GWLs and RCPs scenario. This change is projected to increase/decrease with the increasing GWLS. This increase in temperature and PET will offset the projected increased rainfall considerably increase crop water and irrigation demand and the region will experience environmental drier conditions which will negatively impact agricultural production.
- The increase in PET and change in rainfall will significantly impact the water availability and quantity in the HBRB which negatively affects the water recharge, streamflow and hydropower potential of the Lagdo dam.
- The uncertainty decomposition based on ANOVA statistical test reveals that climate models (both GCMs and RCMs) are the dominant and significant sources of uncertainty in the impact modeling chain for hydropower projections under both GWLs. At the 2.0 °C GWL, uncertainty is largely dominated by RCMs, whereas in 1.5 °C GWL, contribution of GCMs is greater.
- The additional warming of 0.5 °C will change the hydrological cycle and water availability in the HBRB, with potential to cause challenges to water resource management, hydro-power production, agriculture, sanitation and ecosystems. GCMs are found to be the largest and significant contributor of uncertainty in the modeling chain.

Findings from this research should alert the water resources planners and the decision-makers about the sensitivity of the water resources and hydro-energy under GWLs in this region. This research will also help towards the development of early warning systems and risk assessment in the Cameroonian catchments to develop capabilities to mitigate the effects of climate uncertainty. It will also help to develop the new vision of water resources management, long term strategy for electricity production and planning of water needs. This is an urgent issue as the 1.5 GWL may be breached as soon as the early 2030s [77].

One limitation of this research is that we used uncorrected climate data for hydrological simulations which could be the main causes of the importance of the residuals errors in the total uncertainty. In addition, the uncertainty from hydrological model parameters were not considered. In further studies, we plan to use different bias-correction techniques to avoid systematic bias and consider hydrological parameter uncertainty to better assess the contribution of each source to the total uncertainty.

Data availability

The climate model outputs are freely available through the Earth System Grid Federation's (ESGF) platforms "https://esgf-data.dkrz.de/projects/esgf-dkrz/". The Meteorological and hydrological data are the properties of the Department of the National Meteorology of Cameroon (DNM) and the SIEREM/HSM database respectively.

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CRediT authorship contribution statement

Rodric M. Nonki: Conceptualization, Data curation, Formal analysis, Funding acquisition, Methodology, Software, Writing – original draft. **Ernest Amoussou:** Conceptualization, Formal analysis, Funding acquisition, Methodology, Writing – review & editing. **Christopher J. Lennard:** Resources, Data curation, Validation, Writing – review & editing. **André Lenouo:** Conceptualization, Funding acquisition, Methodology, Validation, Writing – review & editing. **Raphael M. Tshimanga:** Formal analysis, Methodology, Validation, Visualization, Writing – review & editing. **Constant Houndenou:** Project administration, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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