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Sensitivity and identifiability analysis of a conceptual-lumped model in the headwaters of the Benue River Basin, Cameroon: implications for uncertainty quantification and parameter optimization

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ABSTRACT

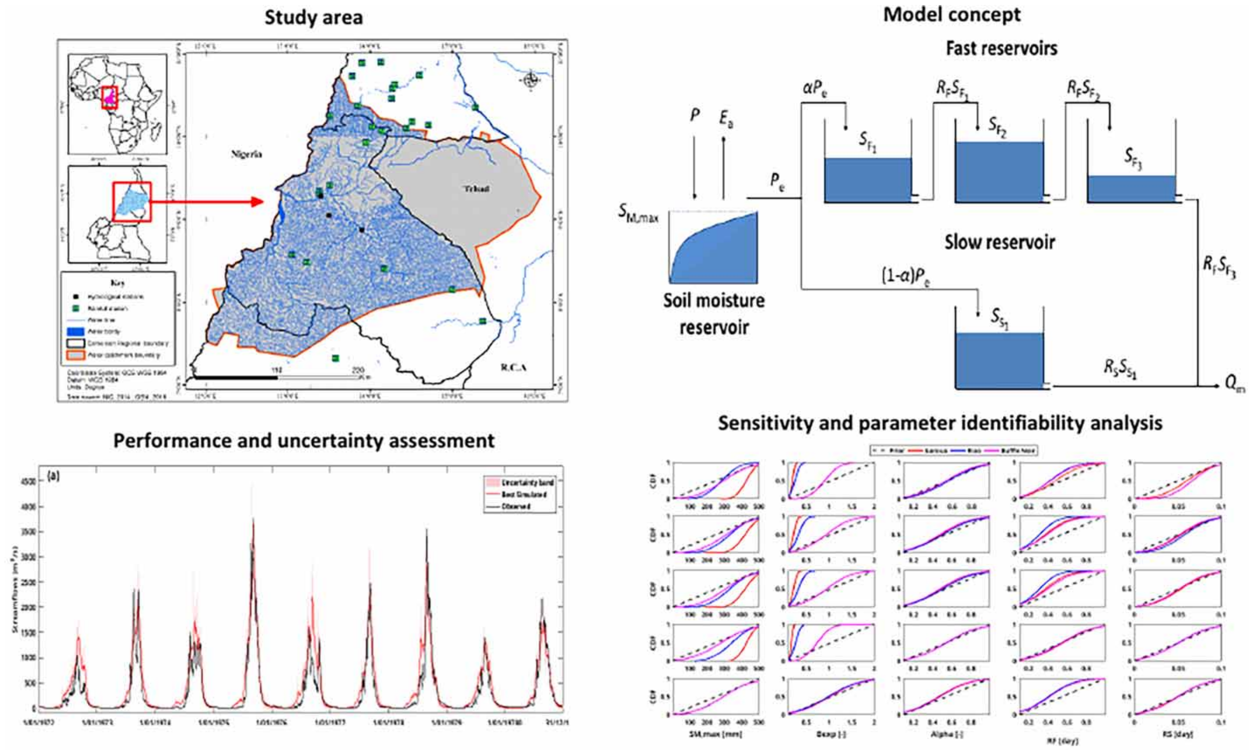
Many hydrological applications employ conceptual-lumped models to support water resource management techniques. This study aims to evaluate the workability of applying a daily time-step conceptual-lumped model, HYdrological MODel (HYMOD), to the Headwaters Benue River Basin (HBRB) for future water resource management. This study combines both local and global sensitivity analysis (SA) approaches to focus on which model parameters most influence the model output. It also identifies how well the model parameters are defined in the model structure using six performance criteria to predict model uncertainty and improve model performance. The results showed that both SA approaches gave similar results in terms of sensitive parameters to the model output, which are also well-identified parameters in the model structure. The more precisely the model parameters are constrained in the small range, the smaller the model uncertainties, and therefore the better the model performance. The best simulation with regard to the measured streamflow lies within the narrow band of model uncertainty prediction for the behavioral parameter sets. This highlights that the simulated discharges agree with the observations satisfactorily, indicating the good performance of the hydrological model and the feasibility of using the HYMOD to estimate long time-series of river discharges in the study area.

Key words: conceptual-lumped model, model optimization, parameter sensitivity, parameter uncertainty, uncertainty prediction

HIGHLIGHTS

- Local and global sensitivity analysis (SA) approaches were used for SA and parameter identifiability.
- Both approaches gave similar results in terms of sensitive parameters for the model output.
- A group of sensitive parameters depends on the selected objective criterion.
- Precisely identified parameters reduce the model uncertainties and enhance the model performance.
- Sensitive, well-defined parameters and model performance increase with catchment size.

GRAPHICAL ABSTRACT



1. INTRODUCTION

Hydrological models are considered useful and valuable tools in several aspects of water resource management. They are increasingly being employed for simulating hydrological processes (Budhathoki *et al.* 2023; Velásquez *et al.* 2023), forecasting extreme events like floods and droughts (Ich *et al.* 2022; Moore & Cole 2022), analyzing future climate change and land use scenarios on available water resources and hydropower potential (Nonki *et al.* 2019, 2021b; Obahoundje *et al.* 2021; Rahvareh *et al.* 2023). For the larger number of existing hydrological models that vary from physical-based to conceptual models, the choice between the distributed, semi-distributed, and lumped-conceptual is very important for catchment hydrology. Given the expense of semi-distributed and distributed models in terms of input data and computational resources, many hydrological applications employ conceptual-lumped rainfall-runoff models to support water resource management techniques. Their ability to work with minimal data and provide enough credible information means they are a useful tool in many data-poor domains (Tegegne *et al.* 2017; Nonki *et al.* 2021c). All models are an imperfect simplification of the physical process and therefore have an inherent uncertainty associated with them. In data-scarce regions, where accurate input data are rarely available, the model uncertainty is compounded by input data uncertainties. Therefore, for science-based decision-making, an evaluation of uncertainty sources in the model is necessary for improving the structure of the models and lowering uncertainties (Refsgaard *et al.* 2006, 2007). This research topic was one of the three major objectives of the International Association of Hydrological Sciences (IAHS) Panta Rhei Science Decade 2013–2022 (Montanari *et al.* 2013) and constitutes one of the unsolved problems in hydrology (Bloschl *et al.* 2019).

Sensitivity and identifiability analyses are now invaluable strategies for model parameterization, calibration, and optimization, as well as uncertainty quantification and reduction (Saltelli *et al.* 2006; Guse *et al.* 2020; Nonki *et al.* 2021c). The former shows how errors in input data can affect model simulations (Saltelli 2002), even as the latter expresses how well the parameter is defined in the model structure (Abebe *et al.* 2010). Although several studies have addressed this issue (search for Shin *et al.* (2015); Song *et al.* (2015); Pianosi *et al.* (2016) and Devak & Dhanya (2017) for a complete review) and new applications including data science and machine learning are being developed (Saltelli *et al.* 2021), there are still some research challenges in this area (Razavi *et al.* 2021). Clarifying the relationship and position of SA in quantifying uncertainty as well as enhancing the use of SA to assist decision-making are two of the six most important challenges highlighted through Razavi *et al.* (2021). In addition, the majority of SA studies are based on one or two objective functions. According to Guse *et al.* (2020), the use of multiple objective functions in SA and parameter identifiability studies is of paramount importance because this helps to identify the group of parameters that most influence each part of the hydrograph (e.g. low and high flows) as well as the entire hydrograph (Boyle *et al.* 2000; Wagener *et al.* 2003).

Several studies have addressed this information gap (Li *et al.* 2021; Liang *et al.* 2021; Singh & Jha 2021; Tibangayuka *et al.* 2022). Singh & Jha (2021) investigated the impact of catchment size and simulation time steps in performing SA. They observed that the sensitivity of some parameters does not depend on watershed size and simulation time step, while other parameters are sensitive for small- and medium-sized watersheds but not for large watersheds at a daily time step. Li *et al.* (2021) investigated the impact of SA on parameter optimization. The case study was conducted in four watersheds in China by using the Soil and Water Assessment Tool (SWAT) model and Sensitive Parameter Combinations (SPCs). They found that no more than 10 sensitive parameters could be identified out of 27 modifiable parameters for each watershed, suggesting that sensitivity parameter optimization can greatly reduce the computational cost of SWAT streamflow simulations while ensuring their accuracy. Liang *et al.* (2021) explored the effect of sensitivity and uncertainty evaluation for discharge prediction in the Yalong River Basin (YLRB) of Southwest China using the SWAT model and three optimization algorithms. Their results indicated that some parameters could significantly affect the discharge in the study catchment, while complex parameter combinations reacted differently under the above-mentioned three optimization algorithms. Tibangayuka *et al.* (2022) quantified the implications of Hydrologiska Byrans Vattenavdelning (HBV) model parameter uncertainties through sensitivity and identifiability analyses in the Wami Ruvu Basin, Tanzania. They found that the parameter identifiability of the HBV model varies spatially in the basin, while parameter uncertainties significantly influence the model output. All these studies have proven and strongly recommended that a comprehensive parameter sensitivity and uncertainty analysis is a vital step in setting up any hydrological model to reduce the number of parameters while still addressing all relevant hydrological processes.

These studies are all context-specific; each catchment study has a relatively unique aggregate of geographical, climatic, geological and hydrological conditions. Therefore, the predictive ability of a rainfall-runoff model depends on its structure, the quality of the input data, both in terms of spatial and temporal resolution, and the experiment design and execution. The purpose of this work is to assess the applicability of a daily conceptual time-step rainfall-runoff model, HYdrological MODel (HYMOD), to the Headwaters Benue River Basin (HBRB) for future water resource management and policy. The study proposes using two approaches of SA to identify which model parameters most influence the model output and quantify how well the parameters are defined in the model structure using six performance criteria. In doing so, we (i) provide a plausible comparison between the two approaches (local and global) commonly used in the SA studies, (ii) contribute to understanding the impact of selected performance criteria in the sensitivity and identifiability analysis, and (iii) assess the role of the sensitivity and identifiability analysis on the uncertainty quantification, parameter optimization, and model performance. This paper is structured as follows: Section 2 describes the Materials and Methods; Section 3 presents the Results and Discussions, and Section 4 provides that a summary from conclusions is drawn.

2. MATERIALS AND METHODS

2.1. Study area and data

2.1.1. The study area

The study is performed in the HBRB, the second-largest river in Cameroon, which is situated in northern Cameroon among latitudes 7°N and 11°N, and longitudes 12°E and 16°E, with a drainage area of 64,000 km^2 at the stream gauging station (Figure 1). It rises at an altitude of 1,300 m at the Adamawa Plateau and is the primary tributary of the Niger River Basin. The HBRB is the only perennial river in northern Cameroon, whereas many rivers are seasonal and dry up a few months after the end of the wet season. Its resources are used in many contexts including hydropower, irrigation, navigation, industry, domestic use, and breeding. Given its capability to sustain socio-economic activities, numerous development projects had been set up, which include business farms for irrigated sugar cane, rice, cotton, and greens, along the traditional farms of maize, sorghum, and millet. Furthermore, in 2007, the world bank accepted the second phase of the undertaking, known as the 'Niger Basin Water resources improvement and Sustainable Ecosystems management project'. The undertaking intends to increase the hydroelectric and irrigation capacity of the Lagdo Dam to deliver electricity from the dam to neighboring countries (IRAP 2015).

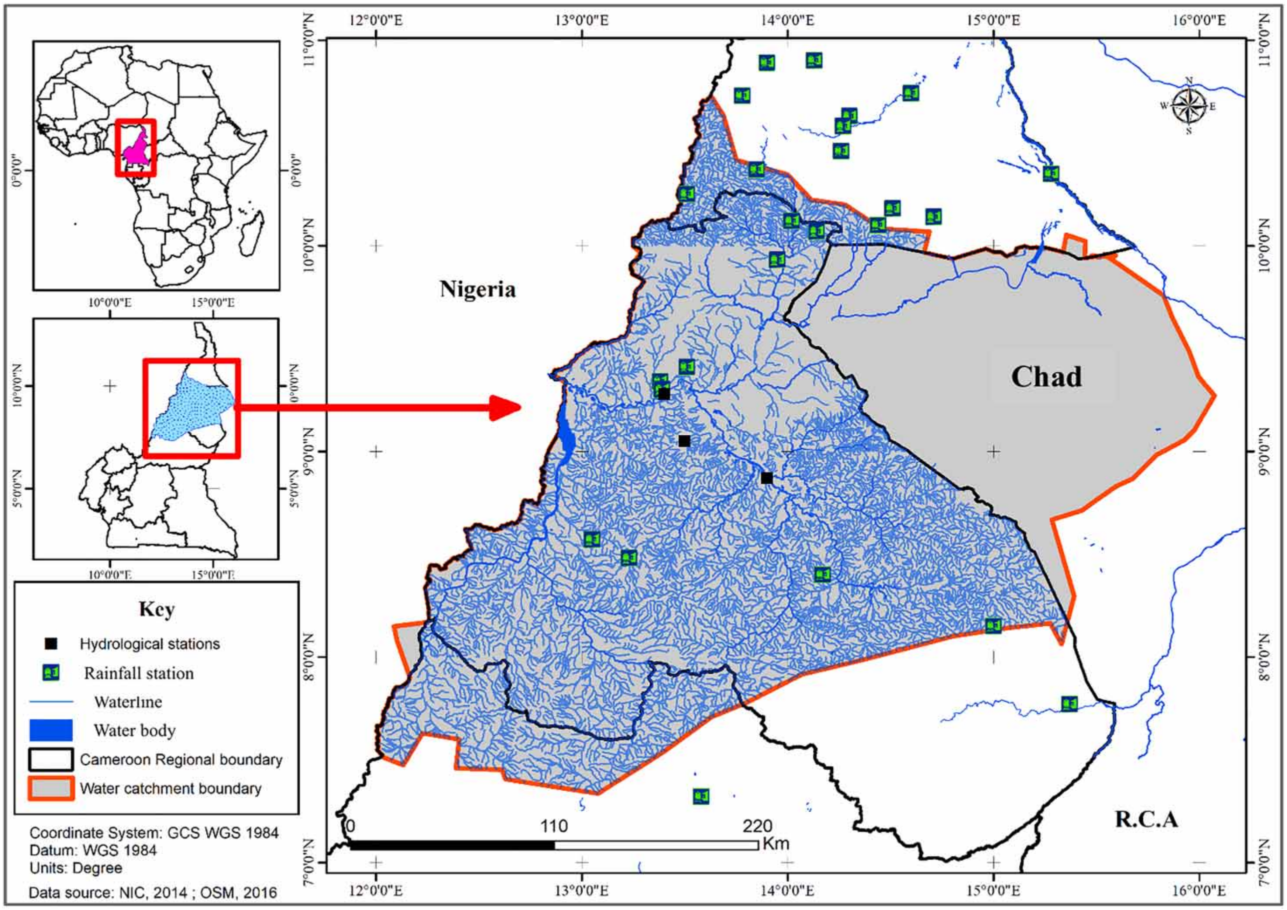


Figure 1 | Basin localization, drainage area, and rainfall as well as hydrometric stations.

The basin enjoys a Sudan-Sahelian climate (tropical humid climate), which is characterized by two distinct seasons: a dry season from November to April and a wet season from May to October. This is a unimodal rainfall zone with annual rainfall between 900 and 1,500 mm (Dassou *et al.* 2016), which gradually decreases from the south (Adamawa Plateau Highlands) to the north of the basin (Chad Plains). In contrast to rainfall, the temperature inside the basin increases gradually from south to north, with an average annual basin temperature of 28 °C. Vegetation of the area is dominated by savanna (59%), wooded savanna (38%), and highland meadow (3%). The Benue River watershed is defined by different classes of soil type: *silty clay loam*, *silty clay*, *silty loam*, *silt*, and *sandy*. The elevation varies from 220 to 2,260 m and is characterized by the Adamawa Plateau, and Alantika and Mandara mountains (Dassou *et al.* 2016).

2.1.2. Hydrometeorological data

Daily rainfall and potential evapotranspiration (PET) data were used as inputs to the hydrological model, while measured daily streamflow time-series were utilized for model calibration and validation. Daily rainfall registered at 25 weather meteorological stations (corresponding to 1 station/2,500 km^2) in the catchment and neighboring areas and daily PET computed with the Penman formula were provided by the Direction of the National Meteorology of Cameroon (DNM). Figure 1 shows the geographical location of the meteorological stations, whereas Table 1 provides the station names, coordinates, altitudes, recording period, and data quality assessment.

Daily measured streamflow data for three gauging stations (Garoua, Riao, and Buffle Noir) that are located in the basin were obtained from the environmental information system for the water resource (SIEREM) database (Boyer *et al.* 2008; http://hydrosciences.fr/sierem). These three gauging stations are considered here as sub-catchments, and Table 2 shows the physiographic and hydrological characteristics of these gauging stations.

Table 1 | Temporal and spatial characteristics of the 25 rainfall stations used

Station no.	Station name	Latitude (°N)	Longitude (°E)	Altitude (m)	Record period	Missing (%)
1	Mada	10.9	14.13	750	1950–2004	0.15
2	Guetale	10.89	13.90	490	1948–2003	0.39
3	Bogo	10.74	14.6	340	1953–2003	0.20
4	Mokolo	10.73	13.78	795	1950–2003	0.04
5	Maroua AGRO	10.63	14.30	402	1946–1990	3.50
6	Maroua station	10.58	14.27	428	1927–2003	0.00
7	Maroua Salak	10.46	14.26	423	1950–2004	0.33
8	Hina-Marbak	10.37	13.85	544	1950–2003	0.10
9	Yagoua AGRI	10.35	15.28	325	1948–2003	0.01
10	Bourrah	10.25	13.51	775	1954–2003	0.64
11	Lara	10.18	14.51	416	1950–2003	0.01
12	Guidiguis	10.14	14.71	362	1961–2003	0.10
13	Doukoula	10.12	14.02	340	1955–2001	0.40
14	Kaele	10.10	14.44	388	1944–2003	0.02
15	Lam	10.07	14.14	430	1953–2003	0.85
16	Guider	9.93	13.95	356	1948–2003	0.00
17	Pitoa	9.41	13.51	274	1961–2003	0.01
18	Garoua AERO	9.34	13.38	242	1950–2004	0.59
19	Garoua ville	9.30	13.39	213	1950–2003	0.41
20	Fignole	8.57	13.05	523	1961–2003	0.00
21	Poli	8.48	13.23	436	1950–1995	0.03
22	Madingrin	8.45	15.00	430	1961–2003	0.00
23	Tcholire	8.40	14.17	392	1950–2003	0.02
24	Touboro	7.77	15.37	500	1950–2003	0.00
25	Ngaoundere	7.32	13.58	1,138	1950–2001	0.15

Table 2 | Physiographic and hydrological characteristics of the available streamflow gauging sites in the HBRB

Characteristics	Garoua	Riao	Buffle Noir
Latitude (°N)	9.3	9.05	8.12
Longitude (°E)	13.38	13.68	13.83
Mean elevation (m a.s.l)	174	185	350
Catchment size (km^2)	64,000	30,650	3,220
Mean annual precipitation (mm/year)	1,130	1,285	1,500
Mean annual discharge (m^3/s)	451.58	260.89	37.33
Extreme discharge (m^3/s)	5,820	3,320	738
Daily streamflow data available			
Record period	1930 – 1995	1950 – 1999	1955 – 1995
Number of months	776	591	480
Missing months (%)	26.80	08.97	14.79

2.2. Methods

2.2.1. Hydrological model

The HYdrological MODel (HYMOD; Wagener *et al.* 2001) was used in this study. It is a conceptual-lumped rainfall-runoff model that operates at the daily time-step and simulates discharge using rainfall and PET as inputs. This model was selected based on its simple model structure and fewer model parameters (five parameters, see Table 3) compared to the existing models (Yin *et al.* 2018). The model has also proven to be useful for streamflow simulation, flood forecasting, and future water scenario management around the world (Gharari *et al.* 2013; Quan *et al.* 2015; Wi *et al.* 2015; Kim *et al.* 2021; Nonki *et al.* 2021a). The model is composed of two main routines, including soil moisture and evapotranspiration routine, represented by a nonlinear soil moisture reservoir and a response routine represented by three fast-flowing reservoirs and one slow-flowing reservoir. The HYMOD is based on the probability-distribution theory proposed by Moore (1985), which assumes that the soil moisture reservoirs within a catchment have variable depths. The distribution function of the reservoir depths is represented by a Pareto distribution given by the following equation:

$$F(SM) = 1 - \left(1 - \frac{SM}{SM,\ \max}\right)^{B\exp} \tag{1}$$

where *SM* is the water storage capacity; *SM,max* and *Bexp* are two parameters describing the basin maximum water storage capacity (mm) and the degree of spatial variability within the basin, respectively.

The excess rainfall that directly contributes to the runoff is partitioned into fast- and slow-flow components based on the model distribution parameter (*Alpha*). A schematic representation of the different hydrological processes in the HYMOD is shown in Figure 2.

Table 3 | Description of the different parameters in the HYMOD, unit, and initial ranges (Gharari *et al.* 2013)

Main hydrological processes	Parameter name	Definition	Unit	Initial range
Soil moisture and evaporation routine	*SM,max*	Maximum soil storage capacity of a catchment	mm	1–500
	Bexp	Degree of the spatial variability of soil moisture capacity	–	0.1–2
Response routine	*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 reservoirs	day^{-1}	0.001–0.1

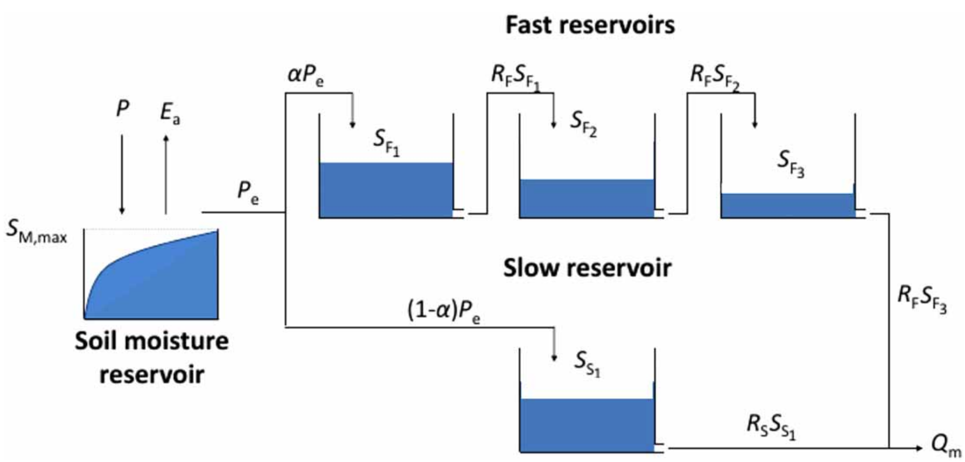


Figure 2 | HYMOD structure (adopted from Gharari *et al.* (2013)).

2.2.2. Sensitivity and parameter identifiability analyses

Two SA approaches were used in this research: the local SA (LSA) approach, which helped to identify the parameters that individually most influence the model outputs, and the global SA (GSA) approach, which considers the interactions between the model parameters and helps to refine the behavioral/non-behavioral ranges for a parameter and perform the identifiability analysis.

For the individual SA, a widely applied and recommended one-factor-at-time (OAT) method is used (Abebe *et al.* 2010; Pianosi *et al.* 2016). The optimum model parameter set was first obtained during the initial model calibration using multiple objective functions. For each model parameter that varies for its initial range (see Table 2), 2,000 values were generated using the uniform distribution function, and the model was therefore run while keeping other parameters at their optimized values. For each simulation, six performance criteria, namely Nash and Sutcliffe efficiency (NSE; Nash & Sutcliffe 1970), percent bias (PBIAS; Zhang *et al.* 2011), Pearson correlation coefficient (*r*; Moriasi *et al.* 2007), standardized root mean square error (RSR; Moriasi *et al.* 2007), Kling–Gupta efficiency (KGE; Gupta *et al.* 2009), and composite function of KGE and inverse of KGE (OF; Lemaitre-Basset *et al.* 2021) were computed. These criteria were selected based on the connection between them and part of the hydrograph, as well as the hydrological components that they consider (see Table 3 for the names, formulations, and the threshold value of these criteria for behavioral simulations). The parameter is identified as influencing or not influencing the model outputs if changes in its value influence the performance criteria or not.

For the GSA and parameter identifiability analysis, we implemented the Monte Carlo approach. It is a GSA method widely used in SA studies (Sobol' 2001; Saltelli 2002; Abebe *et al.* 2010) and implemented in many algorithms of SA (Beven & Freer 2001; Sobol' & Myshetskaya 2008; Azzini *et al.* 2021). This method has the advantage of implicitly accounting for the interactions between model parameters. It is based on running many simulations of the model using a large random sample of input variables. Considering the initial ranges of different parameters, we generated 50,000 model parameter sets. The model was run for each model parameter set with the model parameters sampled simultaneously. The simulations, as well as model parameters, were split into behavioral and non-behavioral simulations/parameters based on the threshold value of each performance criterion mentioned above. The parameter is then said to be more precisely identified in the model structure, or more sensitive to the model output if the range of behavioral parameters is smaller than the initial range. This is assessed by comparing the posterior distribution of the behavioral parameter with the prior distribution of the same parameter, which is assumed here to be uniform (Quan *et al.* 2015). If the two distributions (prior and posterior) deviate significantly, the parameter is considered a sensitive parameter (Sun *et al.* 2012; Quan *et al.* 2015).

2.2.3. Model optimization, performance assessment, and uncertainty prediction

At this stage, the Monte Carlo optimization algorithm and the split-sample test (Klemeš 1986) were applied. The data time-series were divided into two sub-periods (calibration and validation) and the first year of each sub-period was considered as a warm-up period. The lower and upper bounds of each parameter obtained from the behavioral simulations were used to evaluate the descriptive capabilities of the model in the calibration phase using the multi-objective functions mentioned above, keeping constant the values of the parameters identified as not influencing the model output and poorly defined within the model structure. This can help to reduce the parameter range and space and thus equifinality (Cibin *et al.* 2014). The optimum model parameter sets obtained from 50,000 model runs were then used to check the predictive capacities of the model in the validation period. The performance of the model was then evaluated using graphical analysis (visual hydrograph comparison as well as flow duration curves) and statistical criteria listed in Table 4. The behavioral parameter sets obtained by constraining the model parameters into a small range with respect to the KGE were used to simulate the discharge during the validation period and the uncertainty in the model prediction was assessed by plotting the uncertainty band. The *P*-factor and the *R*-factor were also used to quantify the proportion of the measured discharge that falls inside the uncertainty band and to represent the average width of the given uncertainty limits divided by the standard deviation of the observations, respectively. Ideally, most of the measured discharge should fall within the uncertainty band (*P*-factor $\rightarrow 1$) while having the narrowest band (*R*-factor $\rightarrow 0$) (Abbaspour *et al.* 2009).

3. RESULTS AND DISCUSSION

3.1. Individual sensitivity analysis

Figure 3 shows the individual sensitivity analysis of each parameter with regard to different performance criteria in the considered three sub-catchments. The results reveal that the parameters influencing the model output vary depending on the

Table 4 | Mathematical formulation and optimal as well as threshold values of each objective measure for acceptable simulations

Objective criteria	Formulation	Optimal value	Threshold for behavioral simulations
NSE (Q)	$1-\frac{\sum_{i=1}^{n}(Q_{\mathrm{obs},i}-Q_{\mathrm{sim},i})^2}{\sum_{i=1}^{n}(Q_{\mathrm{obs},i}-\overline{Q_{\mathrm{obs}}})^2}$	1	≥ 0.65
RSR	$\frac{\sqrt{\sum_{i=1}^{n}(Q_{\mathrm{obs},i}-Q_{\mathrm{sim},i})^2}}{\sqrt{\sum_{i=1}^{n}(Q_{\mathrm{obs},i}-\overline{Q_{\mathrm{obs}}})^2}}$	0	≤ 0.5
PBIAS	$\frac{\sum_{i=1}^{n}(Q_{\mathrm{obs},i}-Q_{\mathrm{sim},i})}{\sum_{i=1}^{n}Q_{\mathrm{obs},i}}\times 100$	0	$\leq \pm 15$
r	$\frac{\sum_{i=1}^{n}[(Q_{\mathrm{obs},i}-\overline{Q_{\mathrm{obs}}})(Q_{\mathrm{sim},i}-\overline{Q_{\mathrm{sim},i}})]}{\sqrt{\sum_{i=1}^{n}(Q_{\mathrm{obs},i}-\overline{Q_{\mathrm{obs}}})^2\times\sum_{i=1}^{n}(Q_{\mathrm{sim},i}-\overline{Q_{\mathrm{sim}}})^2}}$	1	≥ 0.8
KGE (Q)	$1-\sqrt{(r-1)^2+(\alpha-1)^2+(\beta-1)^2}$	1	≥ 0.75
OF	$\frac{\mathrm{KGE}(Q)+\mathrm{KGE}(1/Q)}{2}$	1	≥ 0.5

$Q_{\mathrm{obs},i}$ and $Q_{\mathrm{sim},i}$ represent, respectively, the measured and modeled streamflow in the time step i; $\overline{Q_{\mathrm{obs}}}$ and $\overline{Q_{\mathrm{sim}}}$ represent their mean values, and n is the total number of time steps of simulation. α is the ratio between the standard deviations of modeled and measured streamflow, while β is the ratio between their mean values.

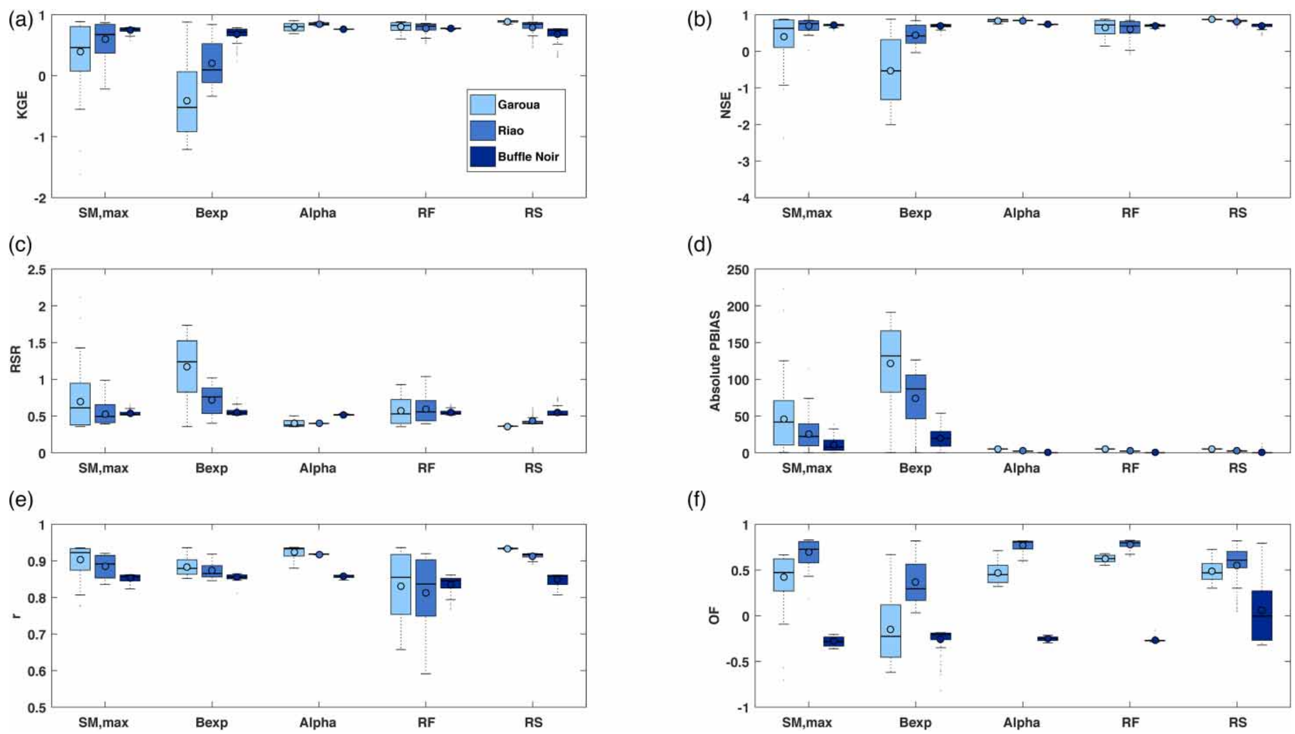


Figure 3 | Individual parameter sensitivity box plots with respect to KGE (a), NSE (b), RSR (c), absolute PBIAS (d), r (e), and OF (f) objective measures in the three gauging stations.

selected criterion and the sub-catchments. The soil moisture and evaporation routine parameters (*SM,max* and *Bexp*) are the most sensitive with respect to all selected criteria and catchments. This result is not surprising because these are the parameters that control all the processes that govern the water balance in the catchment scale, i.e., precipitation, infiltration, evapotranspiration, and runoff, and therefore should affect the entire part of the hydrograph. This result is similar to those of Nonki *et al.* (2021c) and Abebe *et al.* (2010) who found that the soil and evaporation routine parameters in the HBV model are sensitive to all the hydrological components. The results also show that the parameters related to base-flow (*Alpha* and *RS*) are little or insensitive with regard to all the selected performance criteria, except the composite criterion (OF). This result was somewhat expected given that Garcia *et al.* (2017) found OF to be the best choice for low-flow simulations.

We also notice that the residence time of the quick-flow reservoir parameter (*RF*) is sensitive with regard to RSR and *r* criteria since this parameter controls both the timing and shape of the hydrograph and therefore has little effect on high-flow series (NSE) and no influence on the volume error (PBIAS). This result underscores the importance of using several objective functions for the SA, as the group of sensitive parameters is related to the selected objective function. This finding is consistent with other research (Abebe *et al.* 2010; Zelelew & Alfredsen 2012; Guse *et al.* 2020). The results also reveal that the parameter sensitivity increases with the increasing catchment size.

3.2. Global sensitivity and identifiability analysis

Figure 4 shows the posterior distributions of behavioral values of each parameter when all the parameters were sampled simultaneously with respect to the different objective measures in different sub-catchments (Garoua, Riao, and Buffle Noir) and the assumed prior uniform distribution. In general, the sensitive parameters and the well-defined or badly defined parameters in the model structure vary according to the objective functions and sub-catchments. This result is not surprising because each criterion has a different focus and therefore captures different hydrological processes and conditions (Wagener *et al.* 2003;

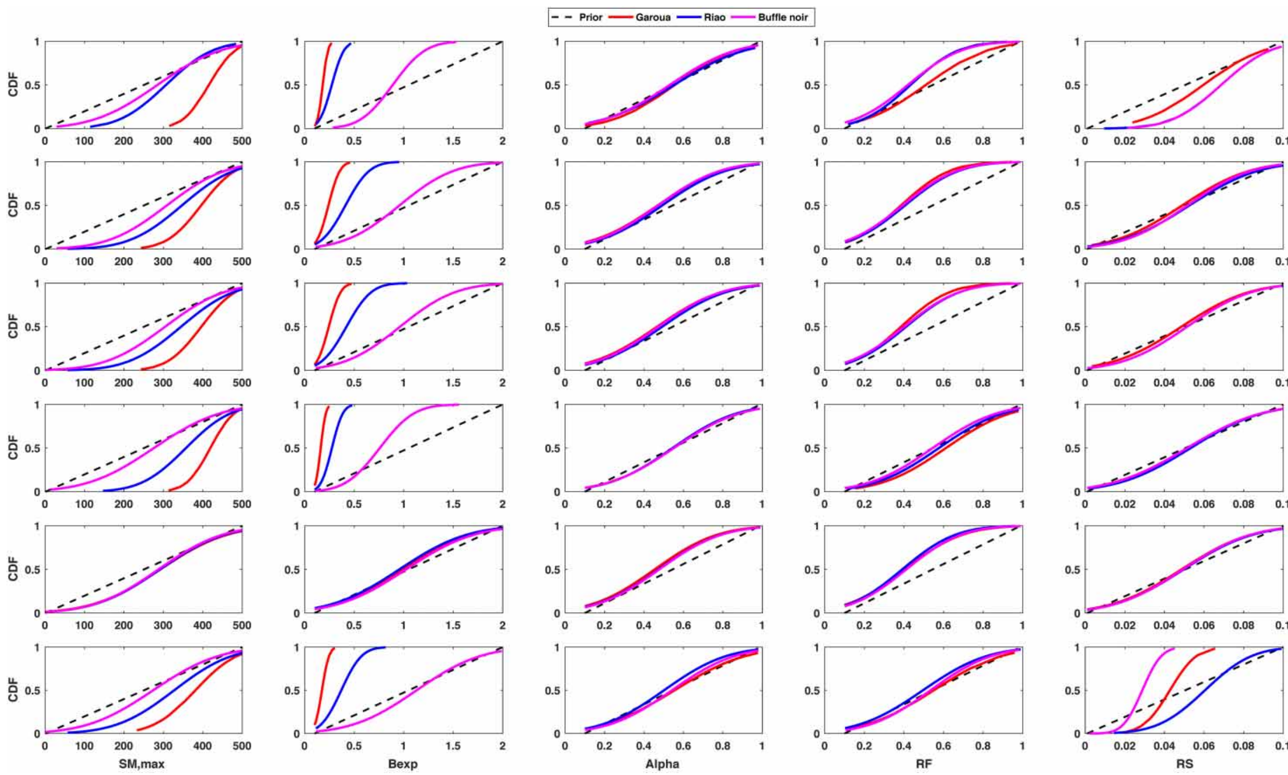


Figure 4 | Posterior distributions of likelihood for the behavioral parameter sets with respect to the different objective measures such as KGE (first line of the panel), NSE (second line), RSR (third line), absolute PBIAS (fourth line), *r* (fifth line), and OF (sixth line of the panel) in different sub-catchments (Garoua (red), Riao (blue), and Buffle Noir (magenta)) and the prior uniform distribution (dotted lines). Please refer to the online version of this paper to see this figure in colour: https://dx.doi.org/10.2166/nh.2023.243.

Fenicia *et al.* 2008; Reusser *et al.* 2009; Pfannerstill *et al.* 2014). In addition, the results show that, for all the objective measures used except the *r* criterion, posterior distributions of *SM,max* and *Bexp* are quite different from prior distribution, with the ranges smaller than the initial ranges, indicating that these parameters are the most sensitive and more precisely well-identified in the model structure than the other three (*Alpha*, *RS*, and *RF*). This result is reinforced by the narrow band of uncertainty of the behavioral parameters compared to their initial range (see Figure 5). This highlights the fact that the soil moisture and evaporation processes are accurately simulated by the model.

For all three parameters (*Alpha*, *RS*, and *RF*), the parameter related to slow reservoirs (*KS*) has the highest sensitivity, followed by the parameter associated with fast flow (*KF*), and then the parameter related to water partitioning between fast and slow reservoirs (*Alpha*) as measured by KGE and OF criteria. The above shows that in the HYMOD, slow response processes become more important than fast-flow generation processes (Parra *et al.* 2018). This is consistent with the results of the identifiability analysis in which, for the parameter *Alpha*, there is no improvement of parameter range by contrasting the majority of performance criteria compared to *RF* and *RS*, which was precisely constrained by contrasting some performance criteria (see Figure 5). The parameter sensitivity and identifiability increase with increasing catchment size as found with LSA. This means that lumped-conceptual models are better suited to large catchments than to small ones. This can be explained by the fact that the functional behavior of catchments differs considerably depending on the scale of the catchment, and that catchment size is one of the five most important explanatory variables influencing runoff simulations (Poncelet *et al.* 2017). Consequently, for large catchments with smooth hydrological behavior, it is easier for models to reproduce different hydrological processes.

Comparing the results of local SA with those of global SA shows that both give similar results in terms of parameter impact on the model output with regard to both objective functions and catchment size. However, we assess the GSA to have advantages over LSA as GSA not only provides the influential or non-influential model parameters to the model output, it is also used to constrain the model parameters in a small range that helps to reduce the equifinality and therefore quantify and reduce the uncertainties in the model output.

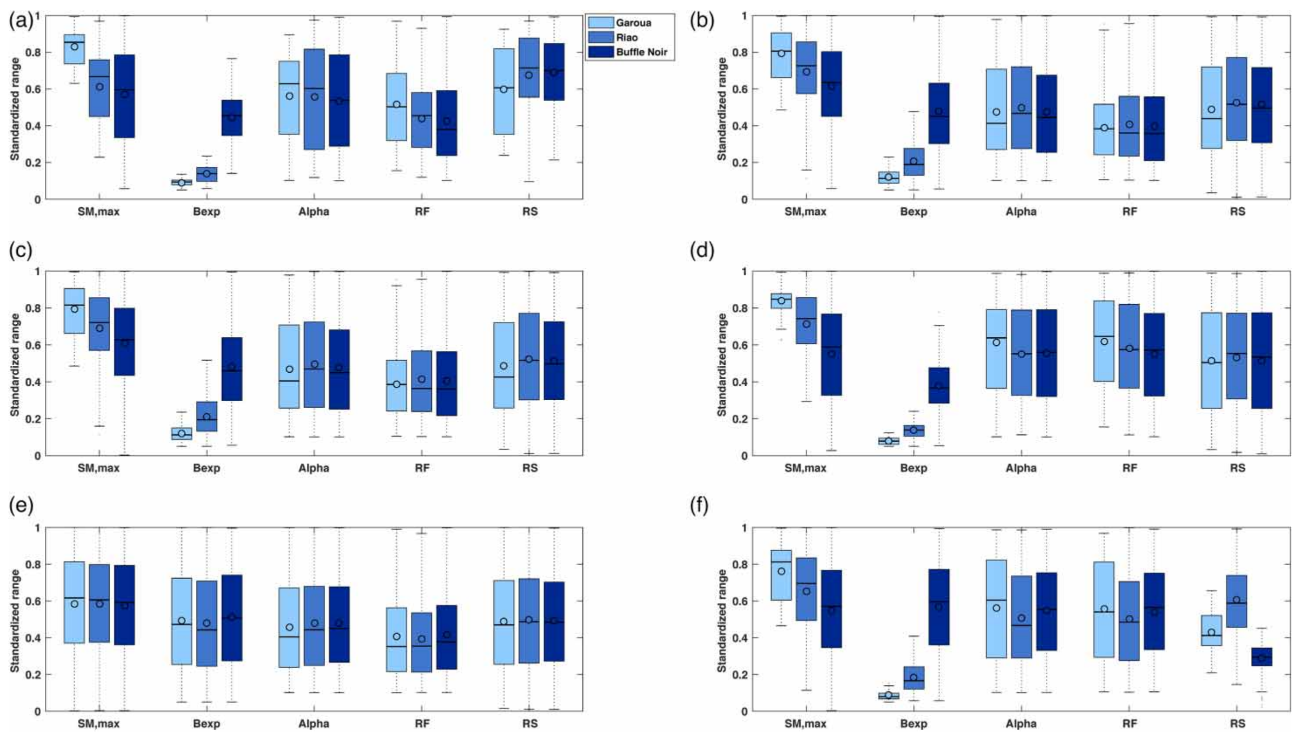


Figure 5 | Box plots on parameter identifiability analysis with respect to different statistical metrics and sub-catchments. KGE (a), NSE (b), RSR (c), absolute PBIAS (d), *r* (e), and OF (f).

3.3. Implications of sensitivity and identifiability analysis on the model uncertainty quantification

For the behavioral simulations, the non-constraint of the model parameters to small ranges by contrasting the *r* criterion (refer to Figures 4 and 5) results in a high uncertainty band (with the *P*-factor and *R*-factor equal to 0.67 and 1.35, respectively) compared to the KGE criterion, for example, that shows a narrow band on uncertainty (*P*-factor and *R*-factor equal to 0.46 and -0.02, respectively) as the model parameters were precisely constrained by contrasting this criterion (see Figure 6). This result is similar to Guse *et al.* (2020) who found that the higher the model parameters are constrained, the lower the uncertainty band of the behavioral simulations is. It also clarifies the relationship and role of SA to uncertainty quantification and improves the use of SA in support of decision-making. This can be considered as a significant contribution to the SA future challenges and outlooks identified by Razavi *et al.* (2021).

3.4. Performance assessment and uncertainty prediction

Figures 7 and 8 show the comparison between measured and modeled hydrographs in the three gauging stations as well as the cumulative frequency curves during the model recalibration and validation periods while the values of efficiency are given in Table 5. The model reproduced the timing and magnitude of the measured discharge well in the different gauge stations and also captures various parts of the hydrograph well. However, low flows are more correctly simulated than high flows, which are comparatively underestimated in magnitude throughout the sub-catchments. The results also exhibit a strong relationship between the modeled and measured discharge during the calibration and evaluation periods (with *r* greater than 0.80; Figure 9), indicating good model performance. This result is supported by the NSE and the KGE greater than 0.65 obtained

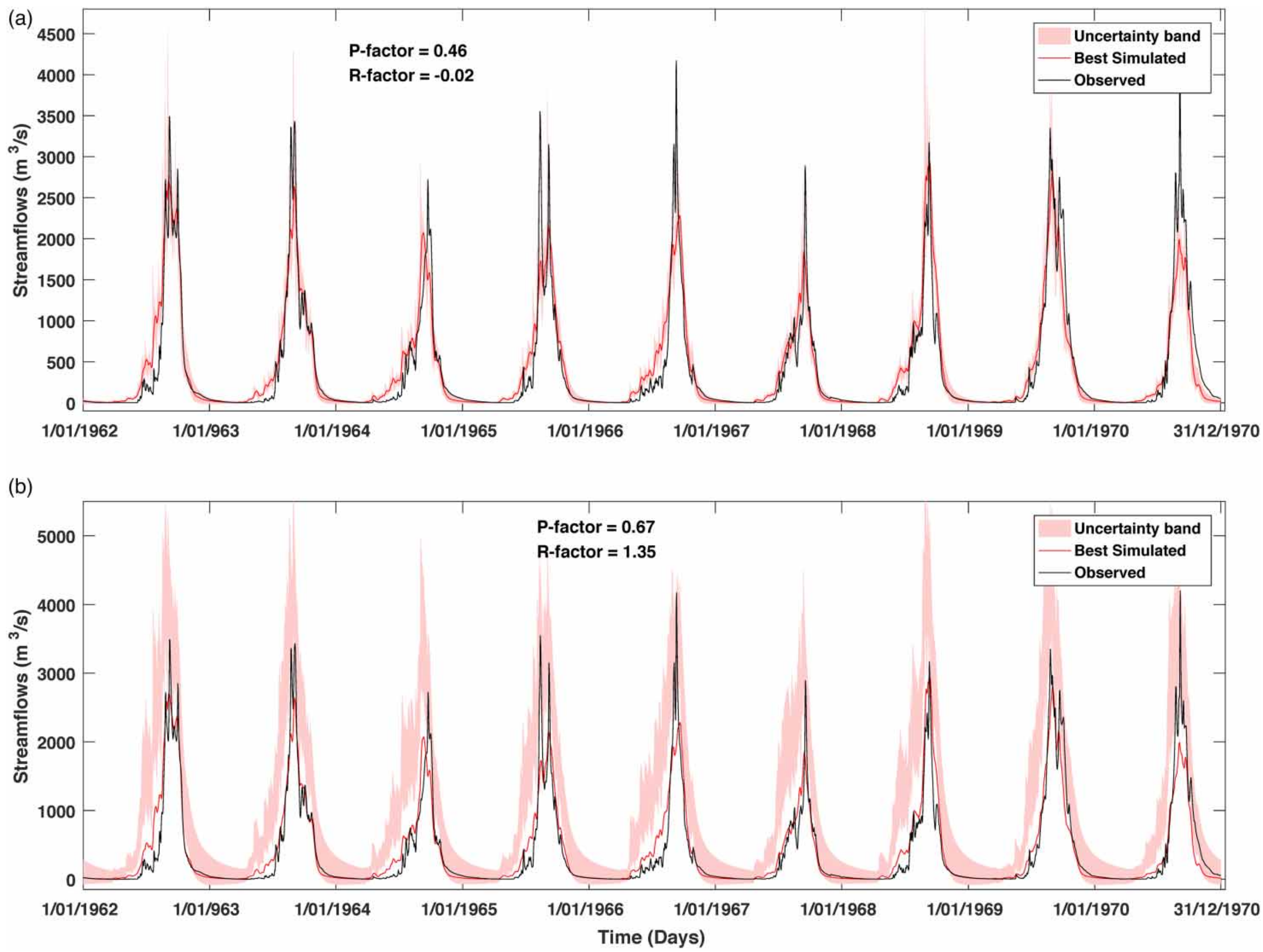


Figure 6 | Uncertainty band of model predictions for behavioral parameter sets, best simulation and measured streamflow in the Garoua sub-catchment with regard to different objective criteria. KGE (a) and *r* (b).

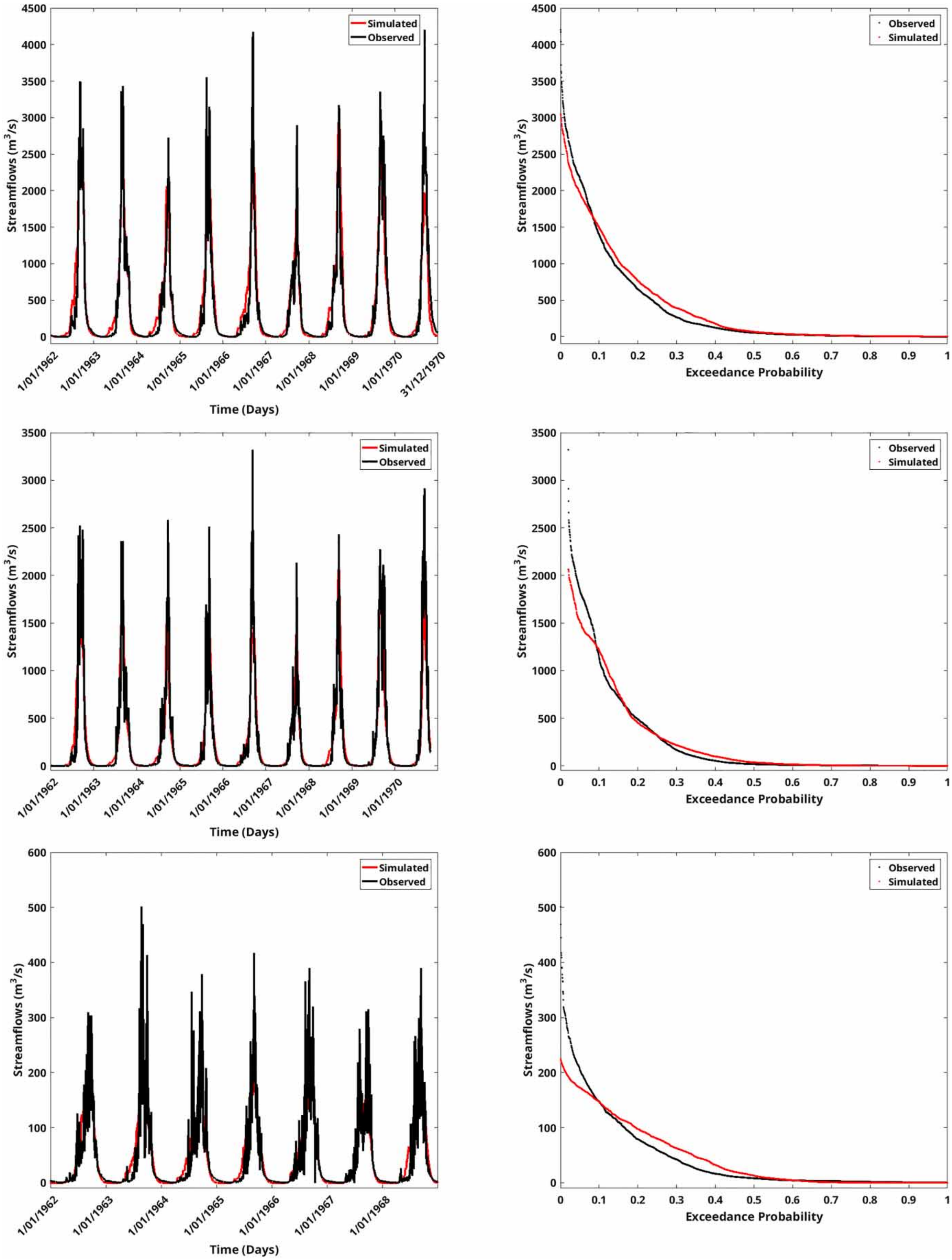


Figure 7 | Comparison between measured and modeled hydrographs as well as flow duration curves in the three sub-catchments during the model recalibration: Garoua (top), Riao (middle), and Buffle Noir (bottom).

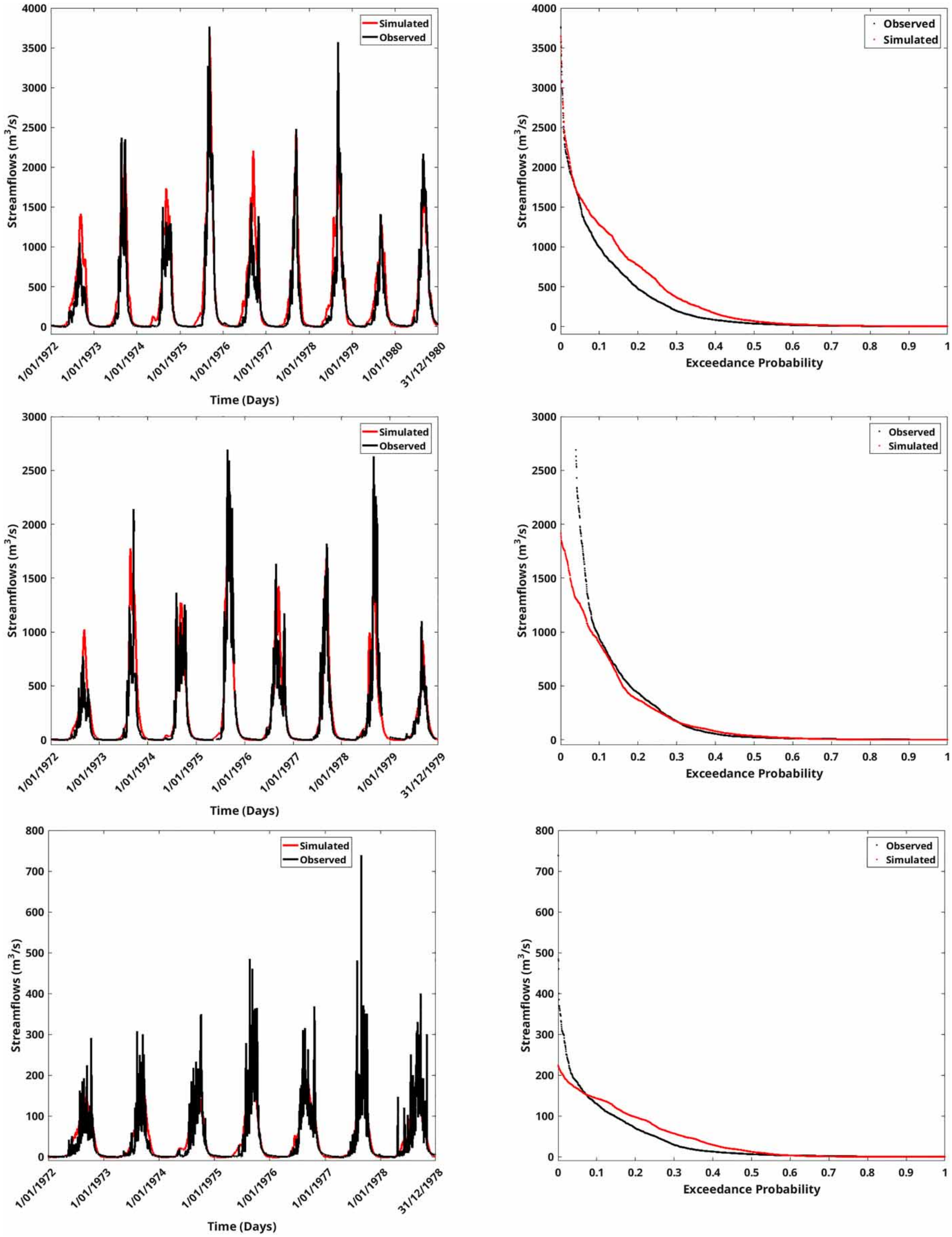


Figure 8 | Same as Figure 7 but during the validation.

Table 5 | Statistical performance results during the calibration and validation periods

Outlet		Period	KGE	NSE	RSR	PBIAS	*r*
Garoua	Calibration	1961–1970	0.89	0.88	0.35	5.1	0.94
	Validation	1971–1980	0.67	0.82	0.42	30.2	0.94
Riao	Calibration	1961–1970	0.85	0.84	0.4	–2.31	0.92
	Validation	1971–1979	0.83	0.76	0.49	16.8	0.88
Buffle Noir	Calibration	1961–1968	0.77	0.74	0.51	2.19	0.86
	Validation	1971–1978	0.73	0.67	0.58	12.9	0.82
Mean model efficiencies	Calibration	–	0.84	0.82	0.42	3.2	0.91
	Validation	–	0.74	0.75	0.50	19.97	0.88

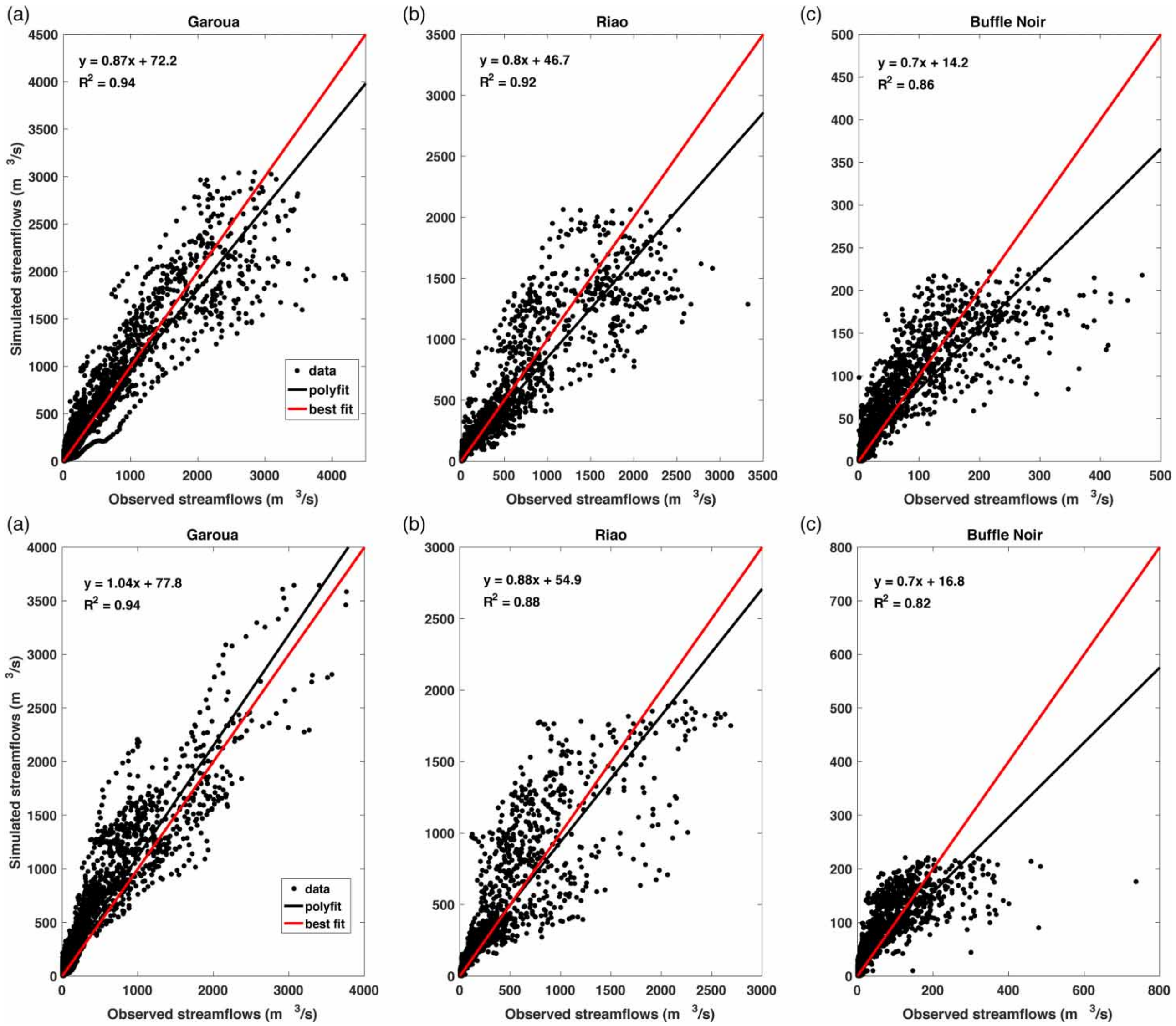


Figure 9 | Correlation between daily measured and modeled discharge during the calibration (first line of the panel) and the validation (second line) periods at the three sub-catchments: (a) Garoua, (b) Riao, (c) Buffle Noir.

during the model optimization and validation. Consistent with Moriasi *et al.* (2007), this model is classed as very good within the Garoua and Riao sub-catchments and good within the Buffle Noir. This result is consolidated by the narrow band of model uncertainty prediction for the behavioral parameter sets (Figure 10) with the R-factors of −0.01, −0.16 and −0.30 obtained at Garoua, Riao, and Buffle Noir, respectively. 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 the modeled discharges agree

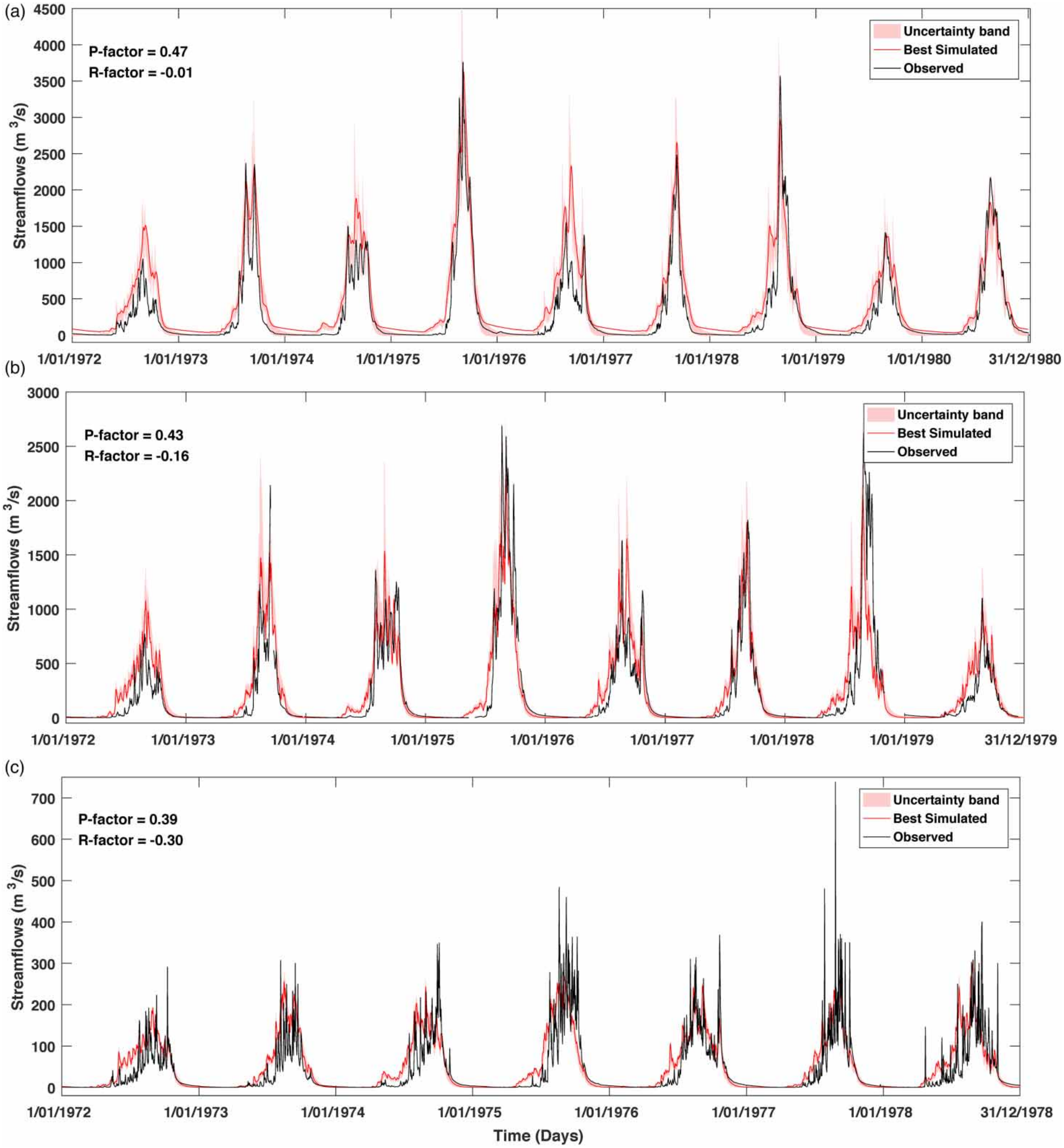


Figure 10 | Measured streamflow (black line), best-modeled streamflow (red line), and the uncertainty band for the acceptable simulations during the validation period at the different gauging stations of the watershed. (a) Garoua, (b) Riao, and (c) Buffle Noir. Please refer to the online version of this paper to see this figure in colour: https://dx.doi.org/10.2166/nh.2023.243.

with the observations satisfactorily, indicating the good performance of the hydrological model and the feasibility of using the HYMOD to estimate long time-series of river discharge in the study area.

For the three sub-catchments considered, the calibration efficiency is higher than the validation efficiency with a loss in the model efficiency of 0.1, 0.07, 0.08, and 0.03 for the KGE, NSE, RSR, and *r* criteria, respectively (see the mean model efficiencies of the three sub-catchments in Table 5). This result is somewhat expected as the models are generally assumed to represent calibration data better than validation data. In addition, the model is calibrated to better represent the hydrological conditions of the catchment during the calibration period, which are never exactly the same during the model validation period (Merz *et al.* 2009).

The statistical evaluation of the model performance also shows that the model performance increases with increasing catchment size. This can be explained by the fact that the SA and the parameter identifiability analyses show that the precisely identified model parameters increase with the catchment size and, consistent with Guse *et al.* (2020), the precisely identified model parameters improve the model robustness and performance. This result is consistent with those of Merz *et al.* (2009) and Nonki *et al.* (2021c), who found that the performance of the conceptual rainfall-runoff model increases with catchment size. Catchment size is one of the five most important explanatory variables influencing runoff simulations (Poncelet *et al.* 2017). Therefore, it is expected that for large catchments with smooth hydrological behavior, it is easier for the models to breed streamflow. In addition, consistent with Poncelet *et al.* (2017), model performance decreases with precipitation and streamflow variability. For example, within the Buffle Noir outlet, the streamflow variability is more pronounced with a discharge coefficient of 39% compared to Riao (22%) and Garoua (15%) sub-catchments (see Figure 10). This may be due to the fact that this sub-catchment has a clear torrential character and each heavy rainfall will end in a definite peak flow.

The relative error-based statistical analysis (PBIAS) shows that the model underestimates the total discharge during the calibration and validation periods at the different gauging stations (see Table 5). This underestimation is more pronounced during the validation period than during the model calibration period because the model adjusts its parameters to the over- or underestimation of the input data during the calibration period (Nonki *et al.* 2021a). We also find that the model bias increases with the size of the catchment. This may be a consequence of the density and distribution of the rainfall stations considered for the calculation of mean areal rainfall (1/2,500 km^2). Xu *et al.* (2013) found that increasing the number of rain gauges for the calculation of mean areal rainfall gradually reduces the range of simulated hydrographs and absolute errors, with a higher probability of over- or underestimation of peak flows when the number of rain gauges considered is smaller compared to a threshold number. Similar results have also been reported by Merz *et al.* (2009) and Xiaojun *et al.* (2021).

4. SUMMARY AND CONCLUSIONS

Conceptual rainfall-runoff models are widely used in many hydrological applications to support water resource management practices. They provide an advantage in data-poor regions due to their ability to use limited data and generate sufficiently reliable information. The main challenge with this type of hydrological model remains the flexibility to determine an optimal set of model parameters due to several sources of uncertainty. This study is being carried out in the HBRB in Cameroon and has the aim of developing a rainfall-runoff model that is appropriate in the context of the hydro-climatic characteristics of the basin. Local and global SA approaches were applied to identify which model parameters have the greatest impact on model output and how well model parameters are defined within the model structure using six performance criteria to reduce and predict model uncertainty and improve model performance. The results showed that the group of parameters sensitive to different hydrological components depended on the selected objective function using both local and global SA approaches. However, soil and evapotranspiration routine parameters (*SM,max* and *Bexp*) are sensitive to all the selected objective measures. We also found that the more precisely the model parameters are constrained within a small range, the smaller the model uncertainties and therefore the better the model performance. In addition, the best simulation versus measured discharge is within the narrow band of model prediction uncertainties and shows that the simulated discharge is in good agreement with the observations, indicating that the hydrological model performs well in this basin. The parameter sensitivity and identifiability, as well as the model performance, increase with the catchment size.

In summary, we have demonstrated the role and relationship between SA and uncertainty quantification and highlighted the importance of SA and parameter identifiability in uncertainty prediction and parameter optimization. Within this context, we conclude that the application of HYMOD to support various water management initiatives in this catchment is possible.

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DATA AVAILABILITY STATEMENT

Data cannot be made publicly available; readers should contact the corresponding author for details.

CONFLICT OF INTEREST

The authors declare there is no conflict.

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