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Satellite-based rainfall estimates to simulate daily streamflow using a hydrological model over Gambia watershed

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ABSTRACT

Satellite rainfall products (SRPs) have the potential to overcome the limitations of ground-based rainfall observations and provide an alternative to inadequately or ungauged watersheds. However, due to the relatively poor accuracy and associated uncertainties to SRPs, it is necessary to evaluate their quality and applicability for each investigated watershed. This paper evaluates the usefulness of SRPs as forcing data for hydrological modeling under different scenarios and assesses their applicability for the Kedougou, Mako and Simenti sub-basins of the Gambia River. To achieve this, *the "Génie Rural à 4 paramètres Journalier model" (GR4J)* hydrological model was employed to simulate the streamflow considering four different scenarios: *i)* non-calibrated GR4J model run with uncorrected SRPs (Scenario 1); ii) non-calibrated model run with corrected SRPs (Scenario 2); GR4J model was calibrated and validated using uncorrected SRPs, and then they were utilized to drive the model (Scenario 3); GR4J model was calibrated and validated and then run using forcing inputs from corrected SRPs (Scenario 4). Results revealed that under Scenario 1 the SRPs performed poorly over the three sub-basins, while under scenario 2, the simulated daily streamflows showed relative improvement when run using corrected SRPs with 6 or 10 rainfall stations. Under the scenarios 3 and 4, the calibrated model provides significant improvement of the simulated streamflow with both the corrected and non-corrected SRPs. Finally, the SRPs demonstrate potential for use in watersheds where there are no rain gauges. The performance loss from scenario 4 (considered as the reference) to scenario 3 does not exceed 20%. Similarly, the performance loss from scenario 4 to scenario 2 does not exceed 50% when the SRPs are corrected using 3 and 6 rainfall stations (e.g., in the Kedougou sub-basin). Thus, they can be considered acceptable for hydrological simulations when the hydrological model is calibrated with measured streamflow.

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Introduction

The planning, design, and management of water resources require good estimates of streamflows and peak discharges at certain points within a watershed. Observed meteorological and streamflow data are initially used for the understanding of the hydrological processes and thus for modeling these processes to predict the streamflow of a watershed (Arsenault, Martel, Brunet, Brissette, & Mai, 2023; Loukas & Vasiliades, 2014; Oliveira, Ramos, & Neves, 2023; Zhang, Luhar, Brunner, & Parolari, 2023). It is likely that most watersheds of the world are ungauged or poorly gauged (Fasipe & Izinyon, 2021; Loukas & Vasiliades, 2014; Zhang, Luhar, Brunner, & Parolari, 2023). This is especially true in West Africa, where many watersheds are ungauged (e.g., Ibrahim, Wisser, Barry, & Fowe, 2015; Kwakye & Bárdossy, 2020). These ungauged watersheds can be categorized into: i) watersheds with only stream gauges; ii) watersheds with only ground-based rain gauges; iii) ungauged watersheds (i.e., those that have no rain gauge and no stream gauge). The main reason for the lack of observations is the inadequate funding for the installation and operation of ground-based measurement networks (Bui, Ishidaira, & Shaowei, 2019).

The lack of in-situ hydro-meteorological observations makes it extremely difficult to carry out hydrological modeling for quantification and predictions of water resources (Camera, Bruggeman, Zittis, Sofokleous, & Arnault, 2020; Naabila, Lampteyc, Arnaultd, Olufayoa, & Kunstmann, 2017). Indeed, it has been arguably nearly impossible for hydrologists to simulate the water cycles over regions with no or sparse ground-based rain gauge networks (e.g., Xue et al., 2013; Zeng et al., 2018). This lack of quantitative hydrological information constitutes to be a major challenge in terms of hydrological knowledge to support the development, design, and sizing of hydraulic

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structures such as dams and reservoirs on the one hand, water management and the management of risks related to extreme hydrometeorological events on the other hand.

In 2003, the International Association of Hydrological Sciences (IAHS) launched the Decade on Predictions in Ungauged Basins (PUB) to achieve major advances in the capacity to make reliable prediction in ungauged basins (Hrachowitz et al., 2013). Despite the remarkable results of this initiative (Adjei, Ren, Appiah-Adjei, & Odai, 2015), a great deal more still needs to be done in terms of in-situ data for hydrological predictions and studies in poorly gauged basins (Kratzert et al., 2019). The in-situ data are often unavailable or limited in numerous watersheds around the world (Bao et al., 2012; Gao et al., 2017). Predictions in ungauged watersheds have become a challenge for the hydrological community worldwide (e.g., Emmerik, Mulder, Eilander, Piet, & Savenije, 2015; Ibrahim, Wisser, Barry, & Fowe, 2015; Sivapalan et al., 2003). To achieve better predictions of water resources over sparsely gauged or ungauged watersheds, lacking sufficient in-situ measurements, hydrologists, and water resource managers need to develop and use models or techniques which do not require long time series of meteorological and hydrological measurements (Gao et al., 2017; Khan et al., 2012; Loukas & Vasiliades, 2014; Mei & Anagnostou, 2016).

The use of satellite rainfall products (SRPs) to drive hydrologic models in data-sparse or ungauged basins has been found to be an ideal choice to tackle the hydrological quantification problem in ungauged basins (Liu et al., 2017). They have also been recognized as an alternative to in-situ rainfall measurements, capable of covering large areas with adequate temporal coverage (Bui, Ishidaira, & Shaowei, 2019). Various SRPs are available which produce rainfall estimates at various spatial and temporal scales. They are also used in several operational applications (e,g, dam design, hydrological modeling, flood forecasting, crop yield forecasting, disease risk monitoring), although they are also deemed to be subject to bias which needs to be adjusted/corrected before their use in any hydrological modeling application (Faty et al., 2018). Moreover, various studies conducted in different regions worldwide, employing different SRPs, have consistently highlighted the necessity of bias correction in SRPs for diverse hydrological applications (e.g. Bhatti, Rientjes, Haile, Habib, & Verhoef, 2016; Kim, Jung, Park, Yoon, & Lee, 2016; Pratama, Buono, Hidayat, & Harsa, 2018; Ziarh, Shahid, Ismail, Asaduzzaman, & Dewan, 2020). Thiemig, Rojas, Zambrano, and Roo (2013) emphasized the importance of applying bias-corrections to satellite products prior to model calibration from the use of a specific satellite precipitation source.

The Gambia River Basin is one of the main river basins in West Africa and provides important water resources for the local communities. Unlike the other major river basins in West Africa, the Gambia River rain gauge network has an acceptable coverage compared to other basins (44 rain gauges in 77,100 km^2). In addition, streamflows are routinely measured at more than 10 stream gauge stations. Therefore, the Gambia River provides the opportunity to evaluate the quality of different SRPs for hydrological modeling of river streamflows. This will allow us to test and recommend SRPs for hydrological modeling of other river basins in West Africa where the rain gauges coverage are not sufficient for model calibration and validation.

In this paper, various approaches have been tested to simulate streamflows based on four different scenarios: i) in scenario 1, no rainfall and streamflow data are available (ungauged watershed) and in this case, only a non-calibrated hydrological model can be run with uncorrected SRPs. In scenario 2, rainfall data are available, but no streamflow data. In this case, a non-calibrated model can be run with uncorrected and corrected SRPs and the in-situ rainfall data. In scenario 3, only streamflow data are available, which allows us to calibrate and validate a model with uncorrected SRPs. Finally, in scenario 4, both rainfall and streamflow data are available, which allows us to calibrate and validate a hydrological model that can be run using bias-corrected SRPs and in-situ rainfall data.

With the aim of assessing the quality of SRPs for various hydrological modeling applications in the Gambia watershed, this paper focuses on two main scientific questions:

- How accurately does the non-calibrated hydrological model (GR4J) simulate streamflow when run with uncorrected and corrected SRPs?
- To what extent does the calibrated hydrological model enhance streamflow simulation when run with uncorrected and corrected SRPs?

Materials and methods

Study area

The Gambia River basin, covering an area of 77,100 km2, is the sixth-largest river basin in West Africa and the second largest in Senegal. It spans across parts of three West African Sahelian countries: Gambia, Guinea Conakry, and Senegal (see Figure 1a). Geographically, the Gambia River basin and its sub-basins are situated between latitudes 11°22“to 14°40” N and longitudes 11°13“to 16°42” W. The region exhibits high topographic variation, with elevations ranging from 0 m in the far west to over 1531 m in the southeast (see Figure 1a,b), where the river source is in the Fouta Djalon Mountains of Guinea Conakry.

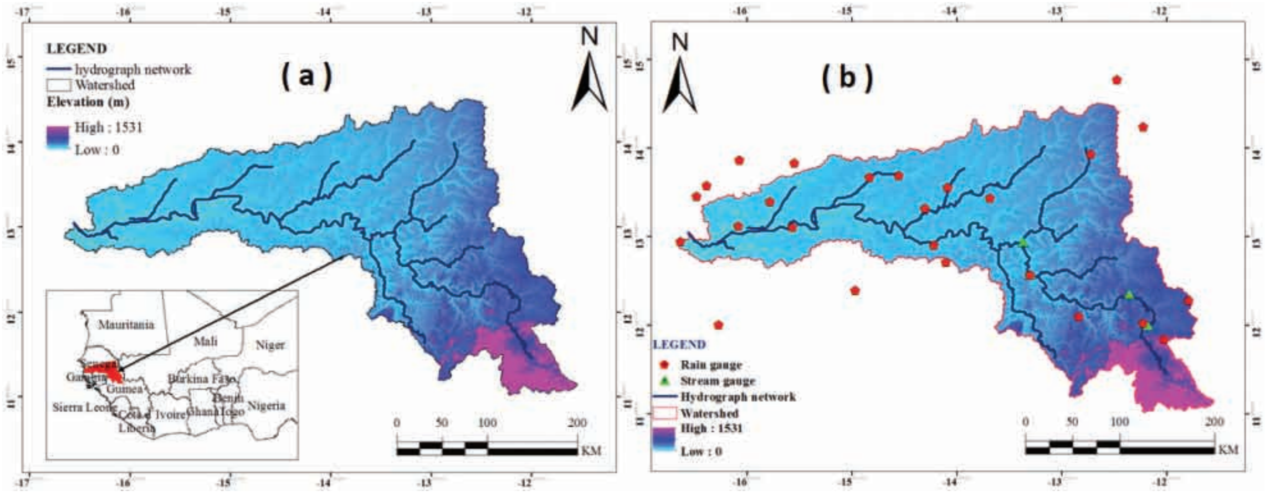

Figure 1. Location of the Gambia River basin (a), and the distribution of the stream gauges (green) and rain gauges (red) (b).

The Gambia River system stretches over 1130 km and experiences a Sudano-Sahelian climate.

The *Direction de la Gestion et de la Planification des Ressources en Eau* (DGPRE) of the Ministry of Water and Sanitation in Senegal monitors discharge at several stream gauges throughout the Gambia River basin. The drainage areas represented by Kedougou, Mako, and Simenti sub-basins are about 7550 km^2, 10450 km^2 and 20,500 km^2, respectively. The average runoff from the Kedougou, Mako and Simenti sub-basins is about 73.5 m^3/s; 86.4 m^3/s and 123.0 m^3/s over the period 1971–2000, respectively. The rainfall regime is driven by the West African monsoon. This implies (i) a strong seasonal cycle of rainfall with two distinct seasons (namely the dry and the rainy season – more than 80% of the annual precipitation occurring in the period from May to October); and a the strong latitudinal gradient of the annual rainfall over the basin which ranges from 600 mm (in the Northern part) to 1600 mm (in the South-eastern parts). All in all, the basin mean annual rainfall reaches 1300 mm.

Gauge observed rainfall and discharge data

Daily rainfall data from 25 stations over the entire Gambia River basin for 1998 to 2010 were provided by the *Agence Nationale de l'Aviation Civile et de la Météorologie du Sénégal* (ANACIM) and the Water Resources Department (WRD) of the Republic of Gambia. The distribution of the rain gauges in the Gambia River basin is shown in Figure 1b. The daily rainfall datasets recorded by the 25 stations are considered as Reference Rainfall Product (hereinafter, RRP). In addition, the maximum and minimum daily temperatures were also provided by the meteorological services listed above and were also used to calculate the daily potential evapotranspiration values using Oudin (2004) approach. Data of daily river discharge recorded at Kedougou, Mako, and Simenti from 1998 to 2009 were also obtained from *Direction de la Gestion et de la Planification des Ressources en Eau du Sénégal* (DGPRE).

Satellite rainfall products

Three different SRPs used in this paper are the widely used Climate Hazards Group Infrared Precipitation with Stations (CHIRPS) (Funk et al., 2014), the Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks-Climate Data Record (PCDR) (Miao, Ashouri, Hsu, Sorooshian, & Duan, 2015), and the Tropical Rainfall Measuring Mission version 7 (TRMM) (Huffman & Bolvin, 2013). The main specifications and related characteristics of the three satellite products are also summarized in Table 1.

Evaluation of satellite rainfall products

To quantify the potential uncertainties associated with the SRP across the three sub-basins, various metrics were selected and calculated for all three SRPs in comparison to ground-based daily rainfall measurements. For this purpose, the geostatistical approach based on the ordinary Kriging interpolation method was used. Kriging is widely recognized

Table 1. Main characteristics of satellite-based precipitation products used in this study.

Product	Temporal Resolution	Spatial Resolution	Period covered	Zonal Coverage
TRMM	03 h	.25° x .25°	1998 – 2019	50N–50S
PCDR	24 h	.25° x .25°	1983- present	60N–60S
CHIRPS	24 h	.25° x .25°	1981- present	50N–50S

as one of the most relevant spatial interpolation methods for rain gauge data in the Sahel (see, Ali, Amani, Diedhiou, & Lebel, 2005; Ali, Lebel, & Amani, 2005). The SRPs performances were then quantitatively assessed using the three following widely used statistical metrics: i) percentage bias (PBIAS); ii) mean absolute error (MAE); and iii) root mean square error (RMSE). The percent bias (PBIAS) (see equation 1) represents the systematic bias of satellite-based precipitation. A positive PBIAS indicates an overestimation of satellite precipitation, whereas a negative value implies an underestimation. The Mean Absolute Error (MAE) (see equation 2) is a measure of the average size of the errors in a collection of predictions, without considering their direction. It is calculated as the average absolute difference between the predicted values and the actual values, and it is widely used to evaluate the performance hydrological models. Finally, The Root Mean Square Error (RMSE) (see equation 3) measures the average magnitude of errors in satellite precipitation estimates. It considers the squared differences between the predicted values and the actual values. It also assigns greater weight to larger errors, providing a more comprehensive assessment of the model's accuracy. A smaller RMSE indicates that the satellite precipitation estimates are closer to the observations.

$$PBIAS(\%) = \frac{\sum_{i=1}^{n}(P_{Si} - P_{Gi})}{\sum_{i=1}^{n} P_{Gi}} x100 \tag{1}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|(P_{si} - P_{Gi}| \tag{2}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{n=1}^{n}(P_{Si} - P_{Gi})^2} \tag{3}$$

The results presented in Table 2 provide an overview of the biases associated with the various SRPs used. These biases can have varying effects on the performance of the model simulations when employed as inputs.

Satellite rainfall products bias correction

As mentioned earlier, the systematic errors (i.e., bias) found in the SRPs, as indicated in Table 2, have the potential to introduce uncertainty in the hydrological modeling simulation. These biases can subsequently impact the simulated discharges, leading to inaccuracies in the results (Goshime, Absi, & Ledésert, 2019). However, the SRPs were not only used uncorrected, but also bias-corrected before using as input into a hydrological model for streamflow simulation. To do so, the SRPs were bias-corrected using the Cumulative Distribution Function-Transform (CDF-t) method (Michelangeli, Vrac, & Loukos, 2009). This approach is based on the distribution function of the SRPs from the distribution function of the ground-based rainfall. This is a probability-based method that corrects the systematic biases in satellite estimations based on a cumulative distribution function (CDF). Here, the method assumes that the satellite or gauged pixels within each 0.25° × 0.25° grid box share the same CDF for precipitation. According to Yang et al. (2017) that is reasonable because the probability distributions for multiple years of precipitation events generally exhibit spatial homogeneity in the local area. Thus, the CDF pairs over a specific grid box were calculated using mixed precipitation estimates from the included gauges and collocated satellite pixels. For those 0.25° × 0.25° grid boxes with no gauge stations, the gauge and satellite estimates from nearby 0.25° × 0.25° grid boxes were collected to estimate the CDFs for that grid box. Based on these CDFs, the satellite precipitation estimation over a given pixel was primarily corrected using the CDF from neighboring grid boxes. Values were then generated according to precipitation in chronological agreement with satellite-based rainfall estimates.

GR4J hydrological model

The GR4J model (Perrin, Michel, & Andréassian, 2003) was used to evaluate the utility of SRPs in

Table 2. Comparison between SRPs and ground-based daily rainfall over three sub-basins of the Gambia watershed during the 1999–2009 period.

		Sub-basin		
Performance metric	SRP	Kédougou	Mako	Simenti
PBIAS (%)	CHIRPS	50.2	45	27.3
	PCDR	−31.4	−31.7	−39.6
	TRMM	29.0	28.0	20.9
RMSE (mm)	CHIRPS	11.46	11.13	10.08
	PCDR	9.03	8.89	8.88
	TRMM	12.21	12.55	12.56
MAE (mm)	CHIRPS	7.97	7.68	6.88
	PCDR	6.29	6.19	6.17
	TRMM	7.83	7.81	7.66

streamflow simulation over three sub-basins on the Gambia River. GR4J is a daily, lumped, four-parameter rainfall-runoff model (Perrin, Michel, & Andréassian, 2003). It consists of a production reservoir, two unit-hydrographs, a routing reservoir, and an underground exchange function. The GR4J has a function for compensating precipitation by evapotranspiration. The model is based on two functions: 1) the production function that determines the effective precipitation that supplies the production reservoir, and 2) the routing function that is based on the unit hydrograph. For more details of the GR4J model, see Perrin, Michel, and Andréassian (2003). The GR4J model version used in this study was from the *airGR* package in R (Coron et al., 2021; Coron, Thirel, Delaigue, Perrin, & Andréassian, 2017). The four parameters of the GR4J model are : i) X1 which is maximum capacity of the production store (mm) ii) X2 is groundwater exchange coefficient (mm/d) iii) X3 1 day ahead maximum capacity of the routing store (mm) and iv) X4 is time base of unit hydrograph UH1 (days). In the case the GR4J model is not calibrated before application, the following parameter values of X1-X4 are recommended for the Gambia basin: $X1 = 257.238$; $X2 = 1.012$; $X3 = 88.235$; $X4 = 2.208$ (see, Coron, Thirel, Delaigue, Perrin, & Andréassian, 2017, for more details).

Model calibration and validation

Appropriate model calibration can reduce the parametric uncertainty and improve streamflow simulations (Gan et al., 2018). In this study, the GR4J model was calibrated and validated for an independent period using different rainfall datasets. These were ground-based rainfall, uncorrected SRPs, and bias-corrected SRPs using 1, 3, 6, 10, and 25 rainfall stations. For each rainfall product, the GR4J model parameters were optimized by comparing the simulated discharge measurements against the observed discharge measurement at Kedougou, Mako, and Simenti streamflow gauges. According to Thiemig, Rojas, Zambrano, and Roo (2013), model performance can be said to be good when $KGE \geq 0.75$, an efficient medium if it is between 0.75 and 0.5 and mediocre if it is less than 0.5.

The method used to calibrate the streamflow consists of the "Pas-à-Pas" method (Michel, 1989; Nascimento, 1995). This method was developed by the Hydrology Division of the National Research Institute for Agriculture, Food, and the Environment (INRAE) in Antony (formerly Cemagref). "The hydrological model calibration method used in this study is the "Pas-à-Pas" method (Michel, 1989; Nascimento, 1995), developed at the Hydrology Division of the National Research Institute for Agriculture, Food, and the Environment (INRAE) in Antony (formerly Cemagref). This method is integrated into the airGR (Coron et al., 2021; Coron, Thirel, Delaigue, Perrin, & Andréassian, 2017) package of R software. It is a local method that performs an optimization (maximization or minimization) of an objective function (independently of the method). In this paper, we adopt a maximization of the Kling Gupta Efficiency criterion (2009) computed on the non-transformed streamflows noted here KGE. The optimization process is iterative. The method adopts a moving strategy, mostly along the axes of the parameter space, with a search step that can vary from one iteration to another. The amplitude of the search step being here the same for all parameters, prior mathematical transformations (**e.g.**, logarithmic or square root transformations) can be applied to guarantee roughly equivalent sensitivities to this search step for all parameters. These transformations on the parameters are chosen taking into account the way the parameters are involved in the model, and are specific to the model (Perrin, 2000). The search starts from an initial vector of parameters. We then calculate the corresponding value of the objective function. We then vary successively each value of the parameters of the initial deviation (Perrin, 2000).

The available observed data for calibration including daily precipitation, daily mean discharge and evapotranspiration were divided into two 5-year periods (1999 to 2004 and 2005 to 2009). The years 1998 and 2004 were used as warm-up for initializing the model reservoirs. Thus, the model calibrations were done for Kedougou, Mako and Simenti watersheds during the period from 1999 to 2004. Then, the model was validated for an independent period from 2005 to 2009 for three sub-basins.

The simulated discharge values from the four rainfall datasets, over the calibration and validation periods, were compared to the observed discharge measurements to evaluate the model performance for discharge simulations. Beyond the percentage bias (PBIAS), the Mean Absolute Error (MAE) and the Root Mean Square Error (RMSE) metrics, as mentioned above, several other statistical criteria were also used to evaluate the simulated streamflow performances. In other words, the streamflow simulations was also assessed using the normalized root-mean-square error (NrMSE) and Kling Gupta Efficiency (KGE) methods. Note that KGE evaluates simultaneously the mean bias, the standard deviation, and the correlation between the observations and the simulation. These performance metrics are also defined as follows:

$$NRMSE = \frac{RMSE}{\overline{P_{Gi}}} x100 \tag{4}$$

$$KGE = 1 - \sqrt{\left(\frac{\sigma_{Q_{Sim}}}{\sigma_{Q_{Obs}}}\right)^2 + \left(\frac{1}{Bias}\right)^2 + (r-1)^2} \quad (5)$$

In equation 1–5, n is the number of measurements, P_{Si} the daily value estimated or simulated, P_{Gi} the daily value of reference or observed, $RMSE$ is the root mean square error, $\bar{P}_{Gi}$ the average of the reference or observed values, $\bar{P}_{Si}$ the average of the simulated values, $\sigma_{Q_{Obs}}$ is the standard deviation of the observed flow rates, $\sigma_{Q_{Sim}}$ the standard deviation of the simulated daily flows, r is the Pearson correlation coefficient between the observation and the simulation, and the *Bias* represents the mean bias in average volume.

Simulation scenarios

To evaluate the quality of SRPs for hydrological modeling, the following procedure was used by creating four simulation scenarios. In the first scenario, the non-calibrated GR4J model was run with uncorrected SRPs for simulating discharges. This scenario represents the case of an ungauged watershed which lacks both rainfall and streamflow measurements. In the second scenario, the non-calibrated GR4J model was run with bias-corrected SRPs and the in-situ rainfall data. Here, the SRPs were corrected by 1, 3, 6, and 10 in-situ rainfall stations, which were selected in such a way that maximum coverage was achieved. The purpose of this approach is evaluate the potential spatial subsampling effects that may arise from using a small number of stations to correct the biases in SRPs. This approach is inspired by Sy et al (2021). The utility of this scenario is to evaluate the discharge measurement simulation utility of the three SRPs in watersheds that lack streamflow and contain some rainfall measurements. In the third scenario, the GR4J model was calibrated and validated using uncorrected SRPs. The validation results were compared with the actual measured streamflow data. This scenario was exclusively used to investigate the feasibility of hydrological modeling over the watersheds wherein only discharge measurements exist. In the last and fourth scenario, the GR4J model was calibrated and validated using corrected SRPs with in-situ rainfall data. The corrected SRPs were similar as under scenario 2, meaning that 1, 3, 6, and 10 rain gauges were used for bias correction. This scenario corresponds to watersheds where both rainfall and discharge measurement data exist.

Results

Evaluation of satellite rainfall products against gauged rainfall product

When the bias-corrected SRPs using 1, 3, 6, and 10 stations were compared with the RRP constructed from the 25 stations by kriging, the difference between the daily mean of the satellite products and that of the ground-based rainfall is almost zero (Table 3). Generally, the PCDR product

Table 3. Comparison between the daily averages of the rainfall estimated by SRP and daily rainfall data obtained considering the different sampling of stations (i.e., 1, 3, 6, 10, and 25 stations). NC refers to un-corrected SRP, while C refers to the corrected-SRP using 1 station (C1), 3 stations (C3), 6 stations (C6), 10 Stations (C10) and 25 stations (C25). Rain-gauge refers to the daily averages of the recorded rainfall datasets.

Number of Stations considered.	Product	Kédougou mm	Mako mm	Simenti mm
Raw SRPs	CHIRPS (NC)	3.832	3.673	3.230
	PCDR (NC)	1.696	1.687	1.479
	TRMM (NC)	3.273	3.212	3.012
1	CHIRPS (C1)	3.510	3.519	3.516
	PCDR (C1)	3.488	3.486	3.519
	TRMM (C1)	3.645	3.632	3.569
	Rain-gauge	3.406	3.406	3.406
3	CHIRPS (C3)	3.266	3.251	3.230
	PCDR (C3)	3.247	3.243	3.236
	TRMM (C3)	3.645	3.632	3.569
	Rain-gauge	3.324	3.324	3.324
6	CHIRPS (C6)	2.924	2.900	2.874
	PCDR (C6)	2.889	2.882	2.869
	TRMM (C6)	2.892	2.867	2.821
	Rain-gauge	3.095	3.095	3.095
10	CHIRPS (C10)	2.584	2.559	2.528
	PCDR (C10)	2.543	2.537	2.518
	TRMM (C10)	2.549	2.522	2.474
	Rain-gauge	2.890	2.890	2.890
25	CHIRPS (C25)	2.526	2.509	2.490
	PCDR (C25)	2.497	2.489	2.488
	TRMM (C25)	2.501	2.526	2.496
	RRP−25	2.462	2.456	2.458

showed better performance in terms of capturing the mean daily rainfall than the CHIRPS and TRMM SRPs. The mean daily rainfall of ground-based rainfall, CHIRPS, PCDR, and TRMM SRPs was estimated to be in the same order of magnitude, depending on the number of stations. Based on the daily mean values, the raw satellite products (PCDR and TRMM) underestimate the values obtained at a single station, while the raw CHIRPS overestimates rainfall at all stations except at Simenti where it slightly underestimates rainfall. Compared to the average rainfall at a 1, 3, 6, and 10 rainfall stations, the uncorrected CHIRPS product overestimates rainfall at all rainfall stations, with the exception of Simenti with a single and three rainfall stations. For the uncorrected PCDR, it is characterized by an underestimation of precipitation at all station categories (1, 3, 6, and 10 rainfall stations). The uncorrected TRMM product, it underestimates rainfall at a single and three rainfall stations, while it overestimates the rainfall at a 6 and 10 rainfall stations (Table 3).

Scenario 1: Uncalibrated GR4J model run with uncorrected SRPs

In scenario 1, the uncorrected daily CHIRPS, PCDR, and TRMM rainfall products were used to drive the GR4J uncalibrated model. The rationale behind this scenario was to test the hydrological usability of these SRPs for ungauged watersheds. The performance metrics of daily streamflow simulations using the uncalibrated model with the uncorrected SRPs are shown in Table 4. The CHIRPS and TRMM products resulted in an overestimation of the peak streamflows, whereas they resulted in a reasonable match with the

Table 4. Performance metrics of the discharge simulation with the uncorrected SRPs over the period 1999–2009 using an uncalibrated model.

		Sub-basin		
Performance metric	SRP	Kédougou	Mako	Simenti
PBIAS (%)	CHIRPS	63.2	77.6	52.7
	PCDR	−84.4	−82.1	−87.3
	TRMM	22.5	42.7	44.9
MAE (m^3/s)	CHIRPS	78.4	97.9	129.3
	PCDR	76.6	85.7	153.4
	TRMM	56.7	76.2	126.4
NRMSE (%)	CHIRPS	136.2	146.9	126.4
	PCDR	104.2	102.5	106.7
	TRMM	96.9	115.5	129.3
KGE (-)	CHIRPS	−0.09	−0.29	−0.01
	PCDR	−0.29	−0.25	−0.33
	TRMM	0.44	0.15	−0.02

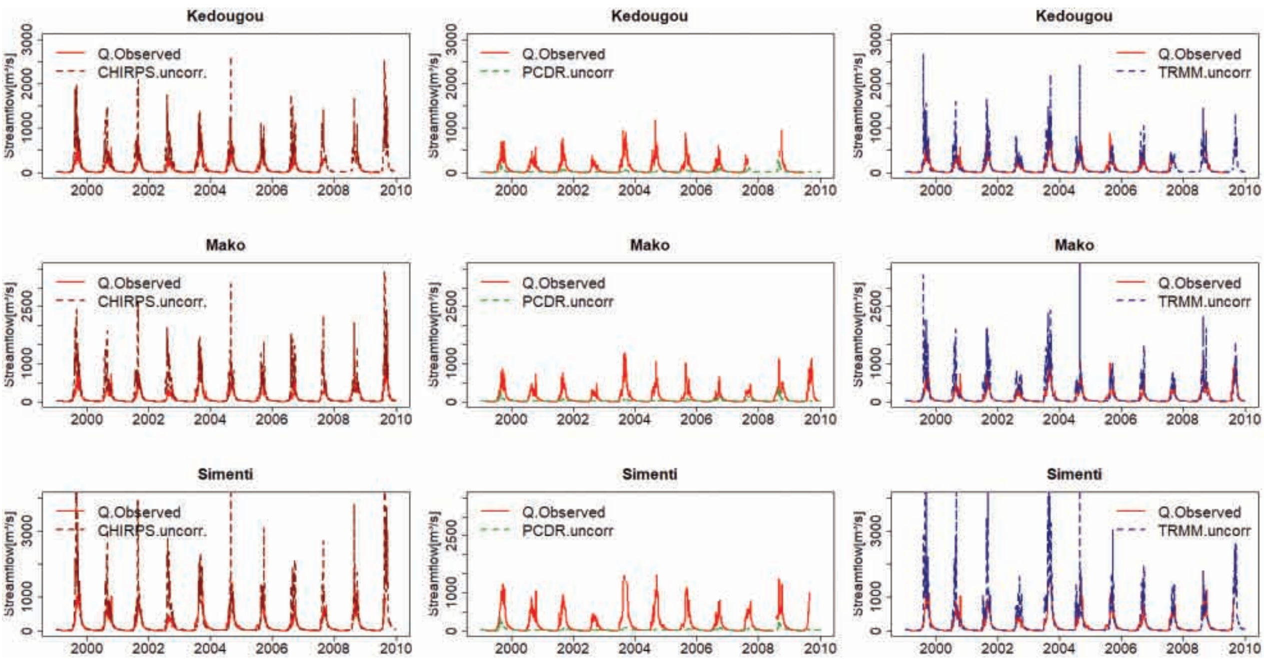

Figure 2. Observed and simulated streamflow of the Gambia sub-basins Kedougou, Mako and Simenti, using the uncalibrated GR4J model and three uncorrected SRPs as rainfall input.

low streamflows. The PCDR product resulted in an underestimation in peak streamflows, while it also resulted in a reasonable match for low streamflows.

Overall, there was a poor agreement between the observed and simulated streamflows in the Gambia sub-basins. Figure 2 shows the simulated and measured hydrographs for Kedougou, Mako and Simenti. The poor performance is also illustrated by the low KGE values for CHIRPS, PCDR, and TRMM (Table 4). The other metrics (MAE, NRMSE, and PBIAS) also indicate a poor performance of the uncalibrated GR4J model using uncorrected SRPs. The model has a tendency to substantially overestimate (CHIRPS and TRMM) or underestimate (PCDR) the high streamflows. Based on these results, it can be concluded that the streamflows of the Gambia basin cannot be simulated from uncorrected satellite data using the uncalibrated GR4J hydrological model.

Scenario 2: Uncalibrated GR4J model run with corrected SRPs

Note that because of the results obtained in both Simenti and Mako sub-basins are similar to those from Kedougou sub-basin, only results from Kedougou sub-basin are shown. The aim of this scenario is to evaluate the utility of three bias-corrected SRPs (TRMM, CHIRPS, and PCDR) for simulating streamflow in the sub-basins assuming that no discharge measurements exist. The performance metrics of daily streamflow simulations are shown in Table 5. The results indicate that all SRPs corrected with 1 or 3 rainfall stations overestimate the streamflows. However, when corrected with 6, 10, or 25 rainfall stations, they underestimate streamflows. The performance of the discharge simulation with the SRPs corrected with either 3 or 6 rainfall stations [3 in

Table 5. Performance metrics of the discharge simulation (peak streamflow) for three sub-basins in the Gambia basin using the uncalibrated GR4J model and the corrected SRPs over the period 1999–2009.

Nr. of rainfall stations used	Product	PBIAS %	MAE m^3/s	NRMSE %	KGE-
Kedougou					
1	CHIRPS	68.4	96.8	206.8	−0.70
	PCDR	67.7	107.9	196.8	−0.47
	TRMM	8.1	102.4	215.2	−0.81
3	CHIRPS	.4	46.4	72.9	0.74
	PCDR	2.4	56.6	88.0	0.64
	TRMM	.5	42.7	66.0	0.79
6	CHIRPS	−37.3	44.9	65.6	0.44
	PCDR	−35.3	5.2	75.1	0.41
	TRMM	−36.9	43.5	64.9	0.44
10	CHIRPS	−66.7	62.4	88.5	0.0
	PCDR	−65.6	62.9	89.6	0.0
	TRMM	−66.2	61.7	87.3	0.02
25	CHIRPS	−5.1	52.9	75.4	0.29
	PCDR	−49.8	58.7	84.4	0.23
	TRMM	−51.2	52.3	75.2	0.27
Mako					
1	CHIRPS	95.4	126.5	250.2	−1.17
	PCDR	105.0	152.8	261.3	−1.20
	TRMM	11.5	137.5	249.5	−1.24
3	CHIRPS	18.7	57.8	88.8	0.54
	PCDR	25.2	72.4	113.6	0.37
	TRMM	18.0	5.7	72.7	0.61
6	CHIRPS	−27.3	45.8	60.7	0.58
	PCDR	−21.5	52.9	72.9	0.59
	TRMM	−26.0	43.1	57.7	0.60
10	CHIRPS	−61.5	65.7	83.4	0.08
	PCDR	−58.0	64.7	83.3	0.12
	TRMM	−6.1	64.2	81.6	0.11
25	CHIRPS	−44.7	56.5	72.8	0.36
	PCDR	−39.9	62.2	89.0	0.37
	TRMM	−42.3	53.1	68.9	0.40
Simenti					
1	CHIRPS	134.9	241.5	344.7	−2.18
	PCDR	163.0	3.5	334.7	−2.26
	TRMM	137.9	234.4	308.6	−1.92
3	CHIRPS	38.5	99.1	118.9	0.15
	PCDR	58.2	133.9	147.6	−0.12
	TRMM	35.9	86.3	91.0	0.32
6	CHIRPS	−16.2	69.9	62.5	0.73
	PCDR	−2.3	77.5	71.6	0.75
	TRMM	−17.4	6.2	51.1	0.75
10	CHIRPS	−57.1	96.3	81.7	0.14
	PCDR	−48.7	87.9	73.1	0.27
	TRMM	−56.6	94.8	77.4	0.18
25	CHIRPS	−36.5	85.1	74.4	0.49
	PCDR	−24.1	86.1	88.4	0.55
	TRMM	−36.3	76.8	64.9	0.52

Kedougou sub-basin (7550 km^2) and 6 rainfall stations in Simenti sub-basin (20500 km^2)] was relatively improved (see the reported KGE values). This performance can be surprising with an uncalibrated model. But it could be explained, perhaps, by the fact that the spatial pattern of rainfall is good for those corrected for SRPs .

The results in Table 5 show that the underestimation bias decreases from the smallest basin (Kedougou) to the largest basin (Simenti). Except for these two cases, the performance of the uncalibrated model run with the corrected SRPs is not so poor overall. This is reflected in the KGE value of the corrected SRPs with 1, 3, 6, 10, and 25 rainfall stations (Table 5). In addition, this performance of the simulation, in terms of statistical metrics, is mainly because the peak values are not correctly simulated (Figure 3). Apart from that, the patterns of streamflows are good given that the model was not calibrated in this scenario.

In terms of bias, the underestimation becomes more important when we increase the number of rainfall stations from 6 to 10 stations (Figure 3). Because the value of SRPs corrected with a small number of stations is larger than that of SRPs corrected with a large number of stations (Table 3).

In addition to the bias and KGE, the other metrics (MAE and NRMSE) indicate poor performance of the corrected SRPs using the uncalibrated model (Table 5). However, the model reproduces more or less well the temporal variability of the streamflows. As seen in Figure 3, when the SRPs are corrected with 1 and 3 rainfall stations the peak flows are overestimated while when corrected with 6, 10, and 25 rainfall stations the peak flows are underestimated. Figure 3 shows also that the patterns are good, even if it can be noted that the absolute differences are large in terms of peak flows. In addition, the strong overestimation of peak flows with the SRPs corrected with 1 rainfall station are obvious. The peak flows can even reach 6000 m^3/s (Figure 3). It is concluded that the rainfall obtained from 1 and 3 stations is not sufficiently representative for the basin. This is the reason why when PCDR is bias-corrected with 1 and 3 rainfall stations, it overestimates the streamflow while it underestimated before the bias correction.

Based on the results of this scenario, it can be concluded that the daily streamflows of the Gambia

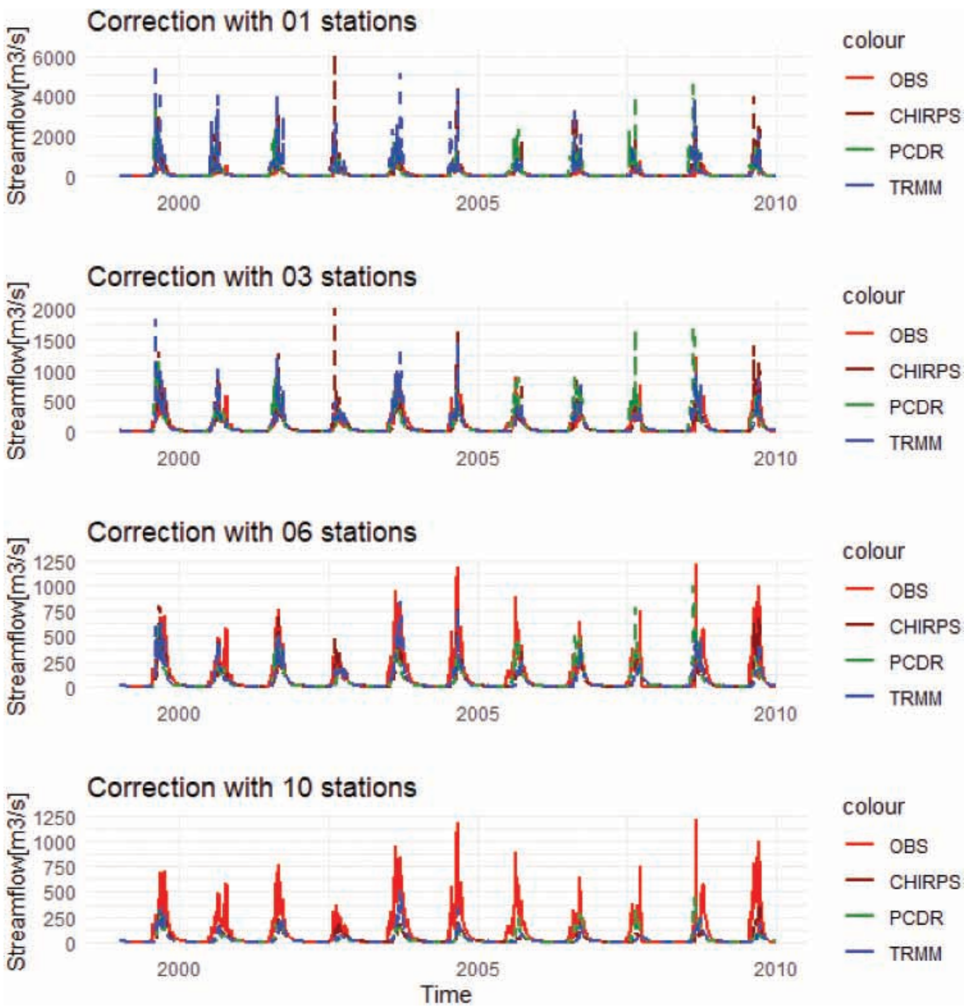

Figure 3. Observed and simulated streamflow of the Gambia sub-basins Kedougoui using the uncalibrated GR4J model and three corrected SRPs with using 1, 3, 6 and 10 rainfall stations, as rainfall input.

Table 6. Statistical performance of uncorrected SRPs in hydrological modelling during calibration and validation periods, respectively (1999-2003; 2005-2009).

Sub basins	Product	PBIAS %	MAE m^3/s	NRMSE %	KGE-
Calibration					
Kedougou	CHIRPS	-3.5	42.25	65.8	0.79
	PCDR	-2.3	50.20	71.4	0.72
	TRMM	-3.7	33.22	52.3	0.86
Mako	CHIRPS	-1.3	48.05	64.5	0.79
	PCDR	-0.6	58.84	73.9	0.71
	TRMM	-3.1	40.79	52.7	0.85
Simenti	CHIRPS	0.8	86.60	79.8	0.66
	PCDR	4.8	91.35	77.7	0.71
	TRMM	-6.2	62.13	53.5	0.83
Validation					
Kedougou	CHIRPS	-21.4	40.77	60.9	0.64
	PCDR	22.5	68.60	85.8	0.55
	TRMM	-39.7	49.16	71.5	0.35
Mako	CHIRPS	-21.6	44.83	60.3	0.67
	PCDR	20.7	73.79	84.3	0.61
	TRMM	-46.5	52.89	72.3	0.33
Simenti	CHIRPS	-20.0	62.31	65.5	0.71
	PCDR	31.0	93.76	79.6	0.56
	TRMM	-42.1	66.77	65.1	0.36

sub-basins can be simulated acceptably with the SRPs corrected with 6 or 10 rainfall stations using the uncalibrated GR4J hydrological model (Table 5 and Figure 3). The particular cases of the Kedougou and Simenti sub-basins with corrected SRPs with 3 and 6 rainfall stations cannot overturn the conventional notion that calibration is an inevitable prior step to any model application (Karthik & Patrick, 2018; Revilla-Romero et al., 2015; Thorstensen, Nguyen, Hsu, & Sorooshian, 2016). Thus, without measured streamflows, the performance of SRPs in hydrologic modeling cannot be satisfactorily evaluated since observed streamflows are essential for model calibration.

Scenario 3: Calibrated and validated GR4J model using uncorrected SRPs

This scenario was exclusively used to investigate the feasibility of hydrological modeling over the watersheds wherein only discharge measurements exist. This scenario evaluates the possibility of modeling

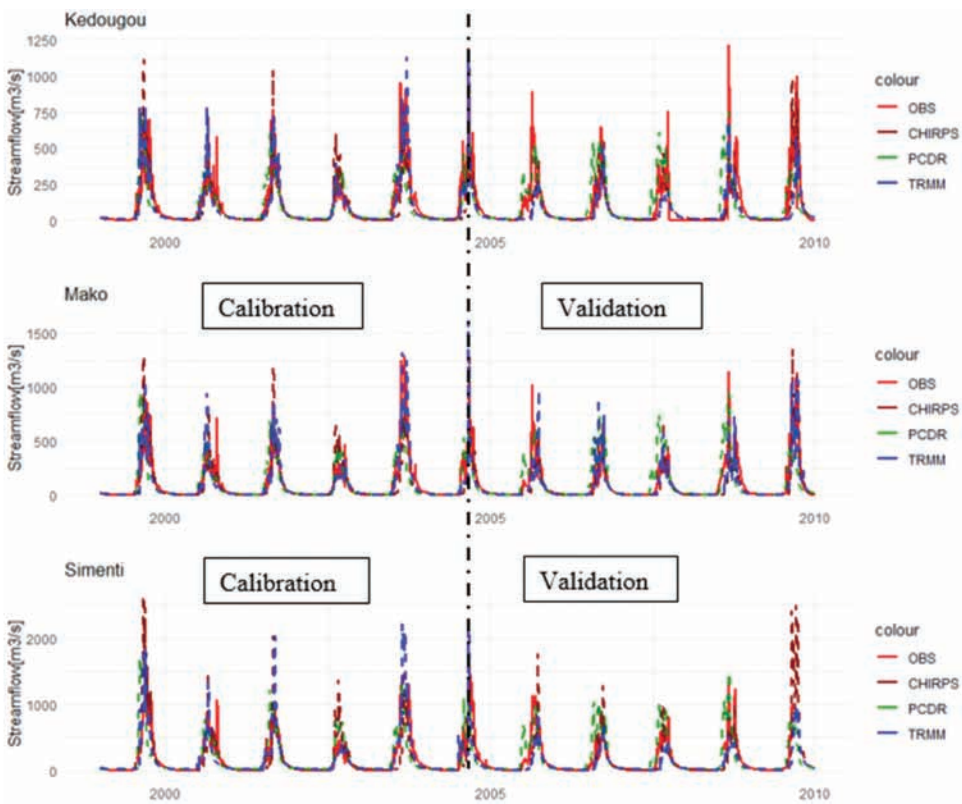

Figure 4. Comparison of observed vs. simulated streamflow during calibration and validation periods.

streamflow with a model that is calibrated using uncorrected SRPs as the rainfall input. The GR4J hydrological model was calibrated for the three Gambia sub-basins over the period of 1999–2003 and validated over the period of 2005–2009. The year 1998 was used for warming-up. The statistical metrics of the simulation results during calibration and validation are summarized in Table 6. In addition, Figure 4 shows the streamflow simulation results.

During calibration, all model simulations forced by the uncorrected SRPs match the observed streamflows relatively well. They show a capacity of the SRPs to reproduce acceptably the streamflows during the calibration period (Figure 4). The performance statistics (Table 6) indicate a good performance, in terms of KGE values, for TRMM over all sub-basins. CHIRPS also presents a good performance over Kedougou and Mako sub-basins while over Simenti sub-basin this performance is somewhat lower (KGE = 0.66). As for PCDR, it presents an efficient medium during the calibration period (Table 6). This overall good performance of the calibration using the three SRPs is also reflected in the low PBIAS values of the simulated streamflows. This shows the capability of the calibrated GR4J model using uncorrected SRPs to simulate observed streamflow. Apparently in the calibration process there is sufficient correction for the bias in total rainfall, and the pattern of the satellite-based rainfall in this case is more important.

The performance of the hydrological modeling during the calibration period is better than during the validation period (Table 6). These results agree with the findings of Belayneh, Sintayehu, Gedam, and Tirunesh (2020) in which model performance during the calibration period was better compared to the validation period. Although observed and simulated streamflow matched well for the calibration period (Figure 4), there was mostly an underestimation of the observed streamflows for all three SRPs. The agreement of peak magnitude between the observed and simulated streamflow was good for the calibration period (Figure 4). In terms of KGE, TRMM is the best product during the calibration period, followed by CHIRPS, despite its low KGE value in Simenti sub-basin. As for PCDR, it shows a constant performance in all sub-basins during calibration (Table 6).

During the validation period (2005–2009), the performance of the model using the three SRPs is overall also good. But this performance is not as good as the performance during the calibration period. Because the transition from calibration to validation leads to a significant increase in errors (Coron, 2013) particularly visible in the percent bias (Tables 6 and 7). This is acceptable since the validation is done under different climatic conditions than those used during the calibration. Also, it is during this period that the model parameters are optimized.

In addition, the performances vary for the different SRPs (Table 6). CHIRPS and TRMM show again underestimations during the calibration period, and these become more important during validation period.

It should be noted that CHIRPS and PCDR show acceptable performance in terms of KGE values during the validation period. They achieve better performance than TRMM, in terms of KGE. At the same time, the streamflow simulated with PCDR show a slight overestimation during the validation period, while those simulated with CHIRPS and TRMM are underestimated (Table 6). This indicates that the uncorrected SRPs used as input for the GR4J model is a good way to simulate the streamflow in watersheds wherein only streamflow measurements are available. The analysis of Table 6 shows also that all SRP simulations during the validation period have more bias compared to the calibration period. This suggests an increase in the uncertainty of streamflow simulations of SRPs over the validation period.

In conclusion, the overall performance of the GR4J model forced with uncorrected SRPs is good for the validation period, indicating that the GR4J model can be applied to simulate the streamflow in Gambia sub-basins beyond the calibration period, using uncorrected SRPs. This implies that the model is capable to simulate the hydrology of West African watersheds where only streamflow data is available, and no measured rainfall data.

Scenario 4: Calibrated and validated GR4J model using bias-corrected SRPs

In this scenario, the GR4J model was calibrated and validated with each of the three bias-corrected SRPs as forcing inputs. The calibration and validation periods of scenario 3 were kept unaltered within scenario 4. The performance metrics of the calibration period are shown in Table 7. All simulations using the bias-corrected SRPs resulted in KGE values above 0.7, except for the streamflows simulated with CHIRPS bias-corrected with 1 rainfall station. Despite this, all the simulations with the bias corrected SRPs show a good tendency to adequately reproduce the observed streamflows during the calibration period (Figure 5).

The TRMM-based simulations showed better results than CHIRPS and PCDR-based simulations during the calibration period, as reflected by the higher values of KGE and lower values of MAE and NRMSE. This indicates that the TRMM product had a more reliable hydrological utility than the other two products during the calibration period. Under this scenario, CHIRPS-driven model simulation performed less well, overall. It should be noted that even if the streamflow simulated with TRMM showed the best performance, but those simulated with CHIRPS

Table 7. Statistical evaluation criteria during calibration period using the bias-corrected SRPs.

Nr. of rainfall stations used	Product	PBIAS %	MAE m^3/s	NRMSE %	KGE-
Calibration					
Kedougou					
1	CHIRPS	−5.0	49.4	81.3	0.68
	PCDR	−7.8	48.2	73.8	0.72
	TRMM	−4.4	39.1	67.1	0.78
3	CHIRPS	−4.7	47.1	69.2	0.77
	PCDR	−3.7	43.9	64.6	0.84
	TRMM	−4.2	36.2	53.0	0.85
6	CHIRPS	−3.4	44.4	62.3	0.81
	PCDR	−1.6	43.4	61.4	0.81
	TRMM	−2.7	35.6	53.2	0.86
10	CHIRPS	−2.8	67.1	90.3	0.76
	PCDR	−4.3	49.7	67.5	0.73
	TRMM	−5.2	41.5	61.6	0.79
Mako					
1	CHIRPS	−3.1	60.3	83.1	0.67
	PCDR	−2.0	42.7	59.8	0.82
	TRMM	−5.0	43.8	61.0	0.80
3	CHIRPS	−4.3	53.2	68.5	0.77
	PCDR	−2.4	48.3	60.8	0.82
	TRMM	−4.2	42.6	52.7	0.85
6	CHIRPS	−2.1	50.7	61.0	0.81
	PCDR	−0.4	48.9	57.8	0.82
	TRMM	−2.6	41.5	53.6	0.85
10	CHIRPS	−1.2	49.4	60.5	0.80
	PCDR	−2.1	51.5	64.8	0.77
	TRMM	−3.3	43.2	61.1	0.80
Simenti					
1	CHIRPS	1.3	98.8	89.7	0.61
	PCDR	1.2	65.2	56.8	0.81
	TRMM	−9.2	67.4	56.5	0.82
3	CHIRPS	−4.3	101.0	74.1	0.73
	PCDR	−2.1	84.1	56.1	0.84
	TRMM	−7.2	75.8	50.9	0.83
6	CHIRPS	−1.1	84.3	60.9	0.82
	PCDR	−0.2	82.5	52.5	0.86
	TRMM	−3.9	64.3	43.4	0.89
10	CHIRPS	8.4	76.3	62.6	0.78
	PCDR	−2.5	93.2	60.3	0.80
	TRMM	−4.0	72.6	49.8	0.87

and PCDR are also good in all the sub-basins (Figure 5).

During the validation period, the streamflows simulated with TRMM present lower performance. The streamflows simulated with CHIRPS showed the best values of KGE followed by PCDR.

The statistical results obtained during the validation period for the performance of corrected SRPs used as input into GR4J over the three sub-basins are summarized in Table 8. The streamflows simulated with SRPs bias-corrected with 3, 6 and 10 rainfall stations exhibited quite excellent values of KGE but also have relatively high values of bias. The simulations using SRPs bias-corrected with 1 rainfall station provide low values of KGE, particularly for PCDR and TRMM. All simulations with SRPs bias-corrected with 6 and 10 rainfall stations performed better than the SRPs bias-corrected with 3 rainfall stations (Table 8 and Figure 5). Figure 5, which compares the simulated and observed streamflows, clearly shows the differences in performance of the corrected SRPs with 1, 3, 6, and 10 rainfall stations in each sub-basin. However, the performance of SRPs corrected with 6 and 10 rainfall stations is overall the same order of magnitude in simulating streamflows during the validation period in all sub-basins. In summary, the SRP data with bias-correction used for model calibration and validation showed good performance for the three Gambia sub-basins.

Discussion

As in previous studies, the use of satellite rainfall products does not aim to substitute ground-based rainfall observations for hydrological modeling, but rather to use them as an alternative for ungauged or poorly gauged watersheds. In addition, this paper evaluates the accuracy of streamflow simulation with a non-calibrated hydrological model using uncorrected and corrected SRPs. The findings of our paper correspond with other research carried out in the field of simulating or calibrating hydrological models using SRPs, such as hydrological modeling from several satellite products (Artan et al., 2007; Behrangi et al., 2011; Belayneh, Sintayehu, Gedam, & Tirunesh, 2020; Bitew & Gebremichael, 2011; Bâ et al., 2018; Gao et al.,

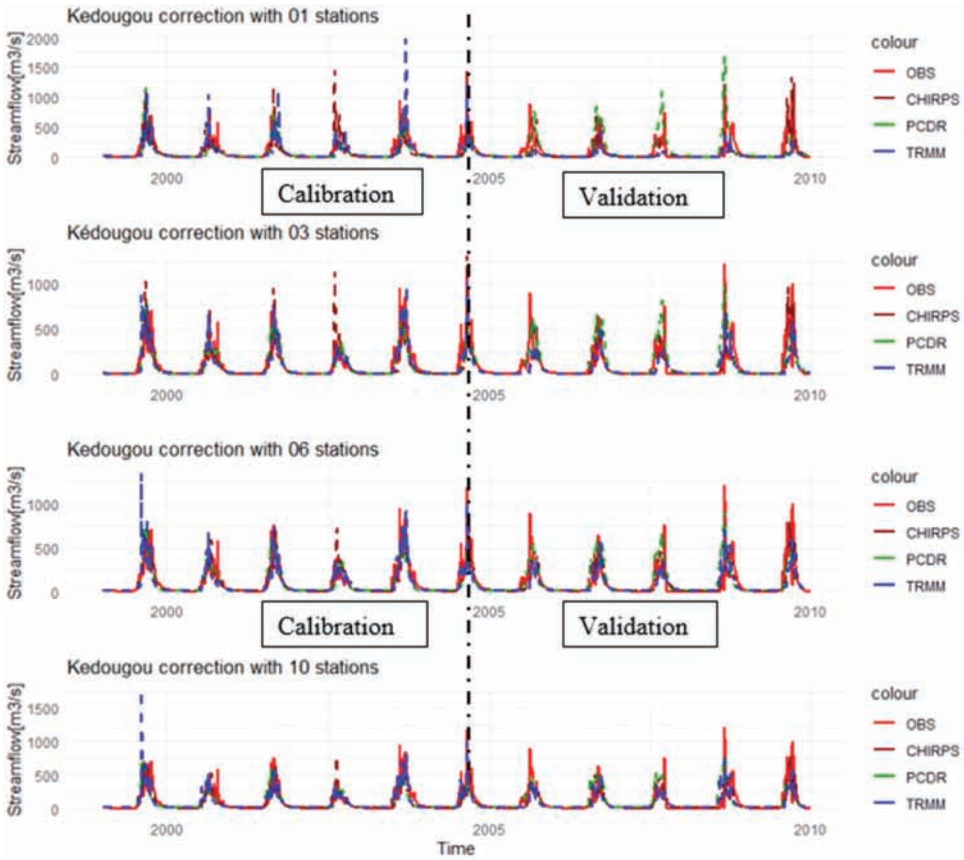

Figure 5. Comparison of observed and simulated hydrographs in the calibration period (01-01-1999 to 12-31-2003) and in the validation period (01-01-2005 to 01-31-2009).

2017; Kim, Jung, Park, Yoon, & Lee, 2016; Shrestha, Artan, Bajracharya, Gautam, & Tokar, 2011; Tang et al., 2016; Thiemig, Rojas, Zambrano, & Roo, 2013; Xue et al., 2013; Yilmaz et al., 2005; Yong et al., 2010). In these studies, the usefulness of SRPs to increase the performance and reliability of the models was highlighted. Zeweldi, Gebremichael, and Downer (2011) reported increased performance of a rainfall-runoff model when the model was calibrated using satellite data.

In our study, the results of scenario 1 showed poor performance which is illustrated by the low values of KGE for CHIRPS, PCDR, and TRMM (Table 4). The other performance evaluation criteria, such as MAE, NRMSE, and PBIAS also indicate a poor performance of the uncalibrated GR4J model using uncorrected SRPs. These findings are similar to those of Revilla-Romero et al. (2015) who compared the performance of the calibrated and the uncalibrated model simulations in terms of reproducing the in situ streamflow time series. They demonstrated that simulated streamflows from an uncalibrated model resulted in poor KGE and PBIAS scores. Indeed, in our study, as described in the Tables 6 & 7, the GR4J model gives better outcomes when it was calibrated by uncorrected and corrected SRPs. But the streamflows simulated with TRMM product are better than CHIRPS and PCDR SRPs for Gambia River sub-basins during the calibration period. This result is consistent with the findings of the study done by Belayneh, Sintayehu, Gedam, and Tirunesh (2020), which was conducted in the Upper Blue Nile Basin on TMPA_3B42v7 and CHIRPS. In that study, an evaluation of SRPs was made using the HECHMS model. The results revealed that the HEC-HMS model performance with TMPA_3B42v7 was better than when using the CHIRPS SRP during calibration periods. In addition, Tables 6 & 7 and Figs. 4 & 5 clearly indicate that the model performance statistics value has been increased when the model used bias-corrected SRPs. Thus, it can be concluded that bias-corrected SRPs showed better performance than uncorrected SRPs for streamflow simulation in the Gambia sub-basins. Behrangi et al. (2011) found that bias-correction of SRPs is critical and can yield substantial improvement in capturing both the streamflow pattern and magnitude. Even though bias correction of SRPs improves the accuracy of streamflow simulations of satellite products, the usefulness of SRPs for hydrologic modeling became most apparent when the hydrologic models were calibrated with SRPs was highlighted. These findings corroborate those of Artan et al. (2007) who concluded that that satellite-based rainfall estimates can be used to

Table 8. Statistical evaluation criteria during validation period using the bias-corrected SRPs

Nr. of rainfall stations used	Product	PBIAS %	MAE m^3/s	NRMSE %	KGE-
Validation					
Kedougou					
1	CHIRPS	-37.4	48.09	69.8	0.48
	PCDR	32.0	79.90	110.2	0.38
	TRMM	-66.7	61.11	89.1	-0.02
3	CHIRPS	-20.5	42.04	62.0	0.63
	PCDR	26.1	61.54	83.1	0.59
	TRMM	-33.1	46.93	68.4	0.43
6	CHIRPS	-12.3	43.54	64.4	0.68
	PCDR	21.2	58.77	78.5	0.64
	TRMM	-28.1	44.85	63.8	0.5
10	CHIRPS	-11.8	45.19	66.4	0.64
	PCDR	16.8	60.69	78.5	0.63
	TRMM	-24.5	47.21	64.0	0.52
Mako					
1	CHIRPS	-30.6	54.18	71.4	0.59
	PCDR	36.7	82.46	111.2	0.32
	TRMM	-67.1	67.74	88.5	0.02
3	CHIRPS	-17.2	43.16	61.9	0.74
	PCDR	27.3	69.73	90.6	0.51
	TRMM	-39.8	49.72	68.1	0.41
6	CHIRPS	-11.3	42.59	58.2	0.79
	PCDR	21.1	64.4	80.7	0.62
	TRMM	-30.1	45.87	60.1	0.55
10	CHIRPS	-7.4	49.0	64.3	0.76
	PCDR	16.4	64.87	77.9	0.67
	TRMM	-27.1	45.7	57.2	0.56
Simenti					
1	CHIRPS	-30.8	74.43	78.9	0.56
	PCDR	96.6	155.95	180.9	-0.69
	TRMM	-66.7	96.47	89.8	0.00
3	CHIRPS	-12.2	55.74	66.8	0.75
	PCDR	39.2	84.40	90.0	0.32
	TRMM	-37.6	65.88	67.3	0.45
6	CHIRPS	-7.0	60.16	58.9	0.81
	PCDR	34.0	82.07	81.3	0.43
	TRMM	-20.7	53.49	52.3	0.72
10	CHIRPS	-0.9	65.75	63.5	0.80
	PCDR	31.2	86.37	80.1	0.49
	TRMM	-18.8	55.18	48.0	0.72

drive hydrologic models for streamflow prediction if the hydrologic model is calibrated with satellite-based rainfall estimates. Bâ et al. (2018) also evaluated PCDR with the hydrological model before bias correction and after bias correction over upper Senegal River and Rani River basins. Their study demonstrated that PCDR is useful for rainfall-runoff simulation in this region.

Furthermore, when comparing all scenarios, scenario 4 appears to be a better approach than the other three scenarios, and scenario 3 is also better than scenarios 2 and 1. However, it should be noted

Table 9. Difference in performance between scenarios 1; 2 and 3 compared to the baseline scenario in Δ (%) Kedougou (1st : 1 rainfall station, 3st: 3 rainfall stations, 6st: 6 rainfall stations, 10st: 10 rainfall stations).

SCENARIOS	ΔMAE(100%)	ΔNRMSE(100%)	ΔKGE(100%)
Scenario1-CHIRP	– 77	−119	111
Scenario1-PCDR	– 76	−70	136
Scenario1-TRMM	−59	−82	49
Scenario2-1st- CHIRPS	−96	−154	203
Scenario2-1st -PCDR	−124	−167	165
Scenario2-1st -TRMM	−162	−221	204
Scenario2-3st- CHIRPS	01	−05	04
Scenario2-3st -PCDR	−29	−36	24
Scenario2-3st -TRMM	−18	−25	07
Scenario2-6st -CHIRPS	−01	−05	46
Scenario2-6st -PCDR	−16	−22	49
Scenario2-6st -TRMM	−22	−22	49
Scenario2-10stCHIRPS	07	02	100
Scenario2-10st -PCDR	−27	−33	100
Scenario2-10st -TRMM	−49	−42	97
Scenario3 -CHIRPS	05	−06	02
Scenario3 -PCDR	−16	– 16	11
Scenario3 -TRMM	07	02	00

Table 10. Difference in performance between scenarios 1; 2; and 3 compared to the baseline scenario in Δ (%) Mako.

SCENARIOS	ΔMAE(100%)	ΔNRMSE(100%)	ΔKGE(100%)
Scenario1-CHIRP	−93	−141	136
Scenario1-PCDR	−75	−77	130
Scenario1-TRMM	−84	−115	82
Scenario2-1st- CHIRPS	−110	−201	275
Scenario2-1st -PCDR	−258	−337	246
Scenario2-1st -TRMM	−214	−309	255
Scenario2-3st- CHIRPS	−09	−30	30
Scenario2-3st -PCDR	−50	−87	55
Scenario2-3st -TRMM	−19	−38	28
Scenario2-6st -CHIRPS	10	00	28
Scenario2-6st -PCDR	−08	−26	28
Scenario2-6st -TRMM	−04	−08	29
Scenario2-10stCHIRPS	−33	−38	90
Scenario2-10st -PCDR	−26	−29	84
Scenario2-10st -TRMM	−49	−34	86
Scenario3 -CHIRPS	05	−06	02
Scenario3 -PCDR	−20	−28	13
Scenario3 -TRMM	02	02	00

that scenario 4 is only better than scenario 3 when the products are corrected with 6 and 10 rainfall stations. The only exception was the use of PCDR in the validation period while it was corrected with 10 rainfall stations. The streamflows simulated under scenario 4 have the highest KGE values and the lowest estimation errors in both calibration and validation. However, only the SRPs corrected with 6 rainfall stations have higher values of KGE than the KGEs obtained under Scenario 4, in all sub-basins. Sometimes, the KGE values obtained under scenario 3 are higher than those under scenario 4 when the SRPs are corrected with 1, 3 , and 10 rainfall stations. This can be explained by the fact that 6 rainfall stations are more representative than 1, 3, and 10 rainfall stations. These can be considered as lack of spatial representativeness of the sparse gauges that were used for the bias correction.

In conclusion, instead of 1 or 3 rainfall stations, it is preferable to use uncorrected satellite data in the Gambia sub-basins for hydrological modeling. The study also shows that if the rainfall stations are not well distributed in the basin (e.g., . 10 stations), no matter how many there are, they are no better than uncorrected satellite data.

Analysis of the add-value of scenarios

This section assesses the add-value and usefulness of scenarios 1, 2, and 3 (based on partial information) compared the scenario 4 considered as reference (which uses the full available information). For this purpose, the level of the loss of performance from scenario 4 to scenarios 1, 2 and 3 is quantified by the percentage of the difference between the performance criteria of the reference scenario and those of the evaluated scenarios. The following performance criteria are considered: MAE, NRMSE, and KGE. However, the analysis is focused only on KGE criterion to simplify the text. The results are summarized in Tables (9, 10, 11) where only the results for the Kedougou sub-basin are shown. Statistical results for Mako and Simenti sub-basins are similar to those for Kedougou and are not shown.

Table 11. Difference in performance between scenarios 1; 2; and 3 compared to the baseline scenario in Δ (%) Simenti.

SCENARIOS	ΔMAE(100%)	ΔNRMSE(100%)	ΔKGE(100%)
Scenario1-CHIRP	−53	−108	101
Scenario1-PCDR	−86	−103	138
Scenario1-TRMM	−97	−198	102
Scenario2-1st- CHIRPS	−144	−284	457
Scenario2-1st -PCDR	−361	−489	379
Scenario2-1st -TRMM	−248	−446	334
Scenario2-3st- CHIRPS	02	−60	79
Scenario2-3st -PCDR	−59	−163	114
Scenario2-3st -TRMM	−14	−79	61
Scenario2-6st -CHIRPS	17	−03	11
Scenario2-6st -PCDR	06	−36	13
Scenario2-6st -TRMM	06	−18	16
Scenario2-10stCHIRPS	−26	−31	82
Scenario2-10st -PCDR	06	−21	66
Scenario2-10st -TRMM	−31	−55	79
Scenario3 -CHIRPS	−03	−31	20
Scenario3 -PCDR	−11	−48	17
Scenario3 -TRMM	03	−23	07

Thus, it appears from the analysis of Table 9 that, although the reference scenario (scenario 4) is better, the loss of performance from this scenario to scenario 3 does not exceed 20%. Also, the loss of performance from scenario 4 to scenario 2 does not reach 50% when the SRPs are corrected with 3 and 6 rainfall stations in Kedougou sub-basin. In the Mako sub-basin also (Table 10), except for PCDR corrected with 3 rainfall stations which reached 55%, the loss of performance of this scenario when the SRPs are corrected with 3 and 6 rainfall stations is not as huge as that. So, we can conclude that, in addition to the scenario 4, the scenario 3 can be used. The scenario 2 also can be used when the SRPs are corrected with 3 and 6 rainfall stations because the loss of information is not as important as that (Table 11).

Conclusion

This paper quantitatively evaluated the accuracy and error of the three SRPs (CHIRPS; PCDR and TRMM) by comparing them with the ground-based observations of the Kedougou, Mako and Simenti sub-basins during 1998–2010. For further validation, the hydrological simulations were performed with those SRPs in the Gambia sub-basins, using the GR4J model during 1999–2009 under four scenarios: uncalibrated GR4J model run with uncorrected SRPs for simulating the streamflows; the uncalibrated GR4J model run with uncorrected and corrected SRPs (scenario 2) ; GR4J model calibrated and validated using uncorrected SRPs and then utilized them to drive the model (scenario 2) and GR4J model calibrated and validated and then run again using forcing inputs from corrected SRPs (scenario 4). For the hydrological validation under scenario 1, the SRPs performed unsatisfactory over all sub-basins. Under scenario 2, except the simulations with 1 and 3 rainfall stations, hydrological simulation is characterized by underestimation of streamflows. Under scenario 3, during the validation period (2005–2009), the performance of the model using the three uncorrected SRPs is overall also good, with satisfactory KGE and better estimation of streamflow discharge distribution. Therefore, the SRPs demonstrate potential for use in watersheds where there are no or limited rain gauges. Under scenario 4, hydrological validation performance of the SRPs corrected with 3, 6, and 10 rainfall stations is acceptable, with KGE values globally higher than 0.5, which means that the model is capable of reproducing the streamflow not observed during the calibration period. and better estimation on streamflow discharge during validation period. Hence, SRPs can be acceptably used for a hydrological simulation when the hydrological model is calibrated with SRPs over the sub-basin. This paper provides a reference for the use of SRPs in ungauged basins. Globally, the SRPs present satisfactory performance in both statistical evaluation and hydrological simulation when using a calibrated model and indicating their potential to be used as the hydrological modeling input and water resources management. Hence, the SRPs can be recommended for use in the watersheds wherein there is no ground-based observation.

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