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Hydrological evaluation of gridded rainfall products for streamflow simulation in West Africa

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ABSTRACT

Study region: Casamance, Gambia and Senegal rivers basins in West Africa
Study focus: The challenges in accessing reliable rainfall and hydrometric gauge data in Africa, gridded precipitation products (satellite, reanalysis, and in situ) provide exciting opportunities for hydrological studies. However, these products are indirect measurements and this requires hydrological validation of these products in relation to ground observations in order to guarantee their relevance and reliability. This study assesses the ability of twenty-three gridded precipitation products to develop monthly (GR2M) and daily (GR4J) rainfall-runoff models to simulate streamflows in the Senegal, Gambia, and Casamance river basins. The Kling-Gupta Efficiency (KGE) and Percentage Bias (PBIAS) metrics were used to evaluate catchment rainfall and discharge derived from the 23 products against in situ observations of rainfall and streamflow.
New hydrological insights for the region: Multi-source datasets, integrating satellite, reanalysis, and in situ observations, provide better performance for streamflow simulation at both monthly and daily time steps. Among the evaluated products, IMERGDF emerges as the most reliable, followed by MSWEP, GPCP, and TAMSAT. Conversely, CPC, which relies on interpolated ground data, exhibited unexpectedly poor performance. These findings highlight the remarkable performance of certain datasets including at a daily time step, establishing their ability to simulate runoff in poorly gauged catchments. In the event of inaccessibility or unavailability of observed data, the best products of this study can be used for hydrological applications in Senegal's main hydrosystems.

1. Introduction

In the context of climate variability and change, long-term hydro-climatic datasets are essential to characterise water resources (Van De Giesen et al., 2014; Nkiaka et al., 2017; Brocca et al., 2020; Qquenta et al., 2023) and support adequate management and

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allocation of surface waters (Dörfliger and Perrin, 2011). According to the World Meteorological Organization (WMO), in 2019, only 22 % of rainfall stations in Africa met the requirements of the Global Climate Observing System (GCOS), compared to 57 % in 2011 (State of the Climate in Africa, 2019). Furthermore, in Senegal, the hydrometric network is outdated and provides limited spatial coverage (Faye, 2017). The deterioration of the observation network results in reduced data availability, while existing time series are short, fragmented, and difficult to exploit in hydrological studies (Bodian et al., 2016; Faye, 2017). These constraints are further compounded by difficulties in accessing daily rainfall in situ data, which are managed by meteorological services and remain costly for the academic community (Panthou et al., 2014; Bodian et al., 2016; Faty et al., 2018; Tramblay et al., 2021; Kouakou et al., 2023).

To overcome the challenges related to the availability and accessibility of ground-based observations, gridded precipitation products offer new opportunities for hydrological studies (Thiemig et al., 2013; Ashouri et al., 2015). However, precipitation estimates derived from satellites, reanalysis, and in situ datasets (interpolated observed data) are indirect measurements subject to spatial and temporal uncertainties (Maggioni et al., 2016; Maggioni and Massari, 2018; Satgé et al., 2020). Consequently, these gridded datasets require rigorous evaluation against observed data if they are to be applied in operational circumstances. Two main evaluation approaches exist: comparisons with in situ rainfall and hydrological assessments.

Several studies (Dembélé and Zwart, 2016; Satgé et al., 2020; Goudiaby et al., 2024) have directly compared gridded rainfall datasets with observed ground-based measurements in West Africa. For instance, Dembélé and Zwart (2016) assessed the reliability of 7 products (ARC 2.0, CHIRPS, PERSIANN, RFE 2.0, TAMSAT, TARCAT, and TRMM) in Burkina Faso. Similarly, Satgé et al. (2020) evaluated the performance of 23 gridded precipitation products in West Africa, including ARC-2, CHIRPS v.2, CMORPH, GSMaP, MSWEP, PERSIANN, TAMSAT, TMPA, WFDEI, MERRA-2, and ERA-Interim. The work of Goudiaby et al. (2024) focused on a direct comparison of 23 gridded precipitation products against field data, specifically for the Casamance, Gambia, and Senegal river basins. In general, these authors have shown that the reliability of satellite rainfall varies in time and space due to the complexity of the West African rainfall regime. Product performance depends on the analysis time step, the density and quality of reference stations, local climatic and topographical conditions, and the estimation methods and correction algorithms used. Products tend to overestimate light rainfall and underestimate extreme events, partly due to time differences between the times when ground measurements are tacken and the times when the observation satellites pass overhead.

For hydrological validation, various authors (Stisen and Sandholt, 2010; Gosset et al., 2013; Casse et al., 2015; Bodian et al., 2016; Gascon, 2016; Poméon et al., 2017; Bâ et al., 2018; Dembélé et al., 2020; Faty et al., 2018; Kouakou et al., 2023) have used

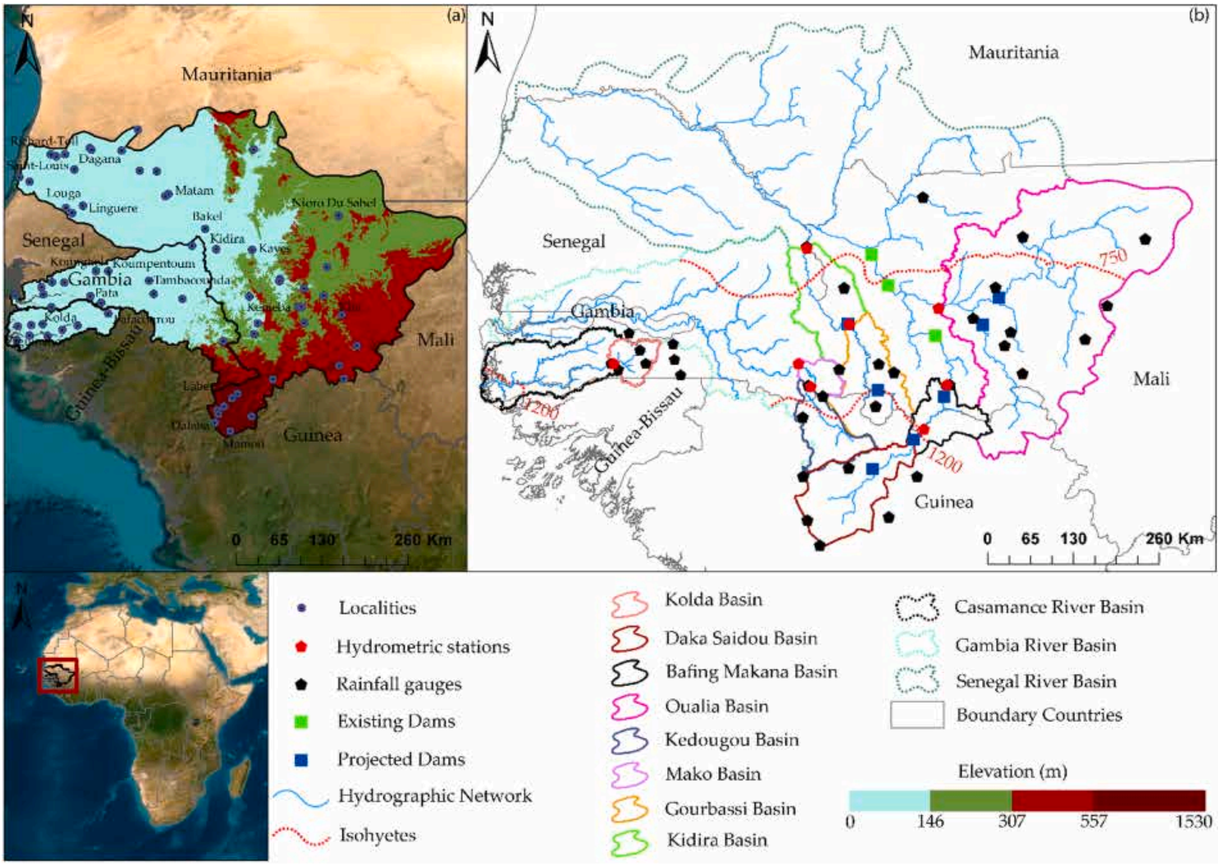


Fig. 1. Location of the Casamance, Gambia and Senegal river basins: (a) localities and spatial altitude distributions; and (b) sub-basins studied, hydrometric and rain gauge stations used, and main infrastructures.

hydrological models to assess the ability of gridded precipitation products to simulate streamflows, including in West African river basins. For example, Gosset et al. (2013) evaluated the ability of 9 products (PERSIANN, CMORPH, TRMM, TMPA 3B42, GSMaP, RFE, CPC, EPSAT, and GPCP-1DD) to simulate streamflows in Niger and Benin using the SCS (Soil Conservation Service) method and GR4J model, respectively. Similarly, Casse et al. (2015) analyzed the potential of 6 products (CPC, RFE2, TRMM 3B42v7, TRMM 3B42RT, CMORPH, and PERSIANN) for flood forecasting in Niamey (Niger) using the ISBA model. These 2 studies show that the products can satisfactorily simulate daily flows in some West African basins, reproducing daily flow dynamics using hydrological models such as SCS, GR4J and ISBA, confirming their usefulness for hydrological modelling in the region.

In Senegal river basin, Stisen and Sandholt (2010) applied the MIKE SHE model to evaluate 5 products (CMORPH, CCD, CPC-FEW v2, TRMM 3B46 v6, and PERSIANN) for flow simulations in the Bafing Makana, Gourbassi, and Oualia catchments. Bodian et al. (2016) also used TRMM with the GR4J model to simulate flows in Bafing Makana. Similarly, Faty et al. (2018) used CHIRPS, TRMM 3B42v7, and PERSIANN-CDR as input data for GR4J to analyze the rainfall-runoff relationship in the Gambia basin.

Studies on rainfall validation have generally shown good agreement between gridded and observed precipitation data. Similarly, hydrological validation studies have demonstrated that gridded precipitation products can reasonably reproduce streamflow dynamics in West Africa. Furthermore, many studies assess only a limited number of gridded rainfall products and these must be compared against field observations across catchments and climatic zones.

To address these gaps, this study investigates the 23 most promising gridded precipitation products against 8 hydrometric stations across West Africa catchments. The hydrological evaluation of gridded precipitation data is performed at daily and monthly time steps with the GR2M and GR4J global conceptual models, in order to simulate streamflows in eight sub-catchments of the Senegal, Gambia, and Casamance river basins.

2. Data, tools and methods

2.1. Study area

This study focuses on eight catchments within the three major hydrosystems of Senegal (Fig. 1b; Table 2). In the Senegal River basin, five hydrometric stations are exploited: Bafing Makana, Daka Saïdou, Kidira, Gourbassi, and Oualia. On the Gambia River basin two stations are considered, Mako and Kédougou, and one station, Kolda in the Casamance River basin. These hydrometric stations are not influenced by dams (Fig. 1b), ensuring natural hydrological conditions for analysis.

The watershed boundaries were delineated using Shuttle Radar Topography Mission (SRTM) data with a 30 m spatial resolution, provided by NASA (Farr et al., 2007). From a climatic perspective, the study area spans three biogeographical zones: the Sahelian (<750 mm/year), Sudanian (750–<1200 mm/year), and Guinean (≥ 1200 mm/year) zones (Fig. 1). The rainfall regime varies according to these climatic domains, with a rainy season lasting between three and six months and a dry season lasting between six and nine months (Descroix et al., 2015; Faye, 2018; Ndiaye, 2021).

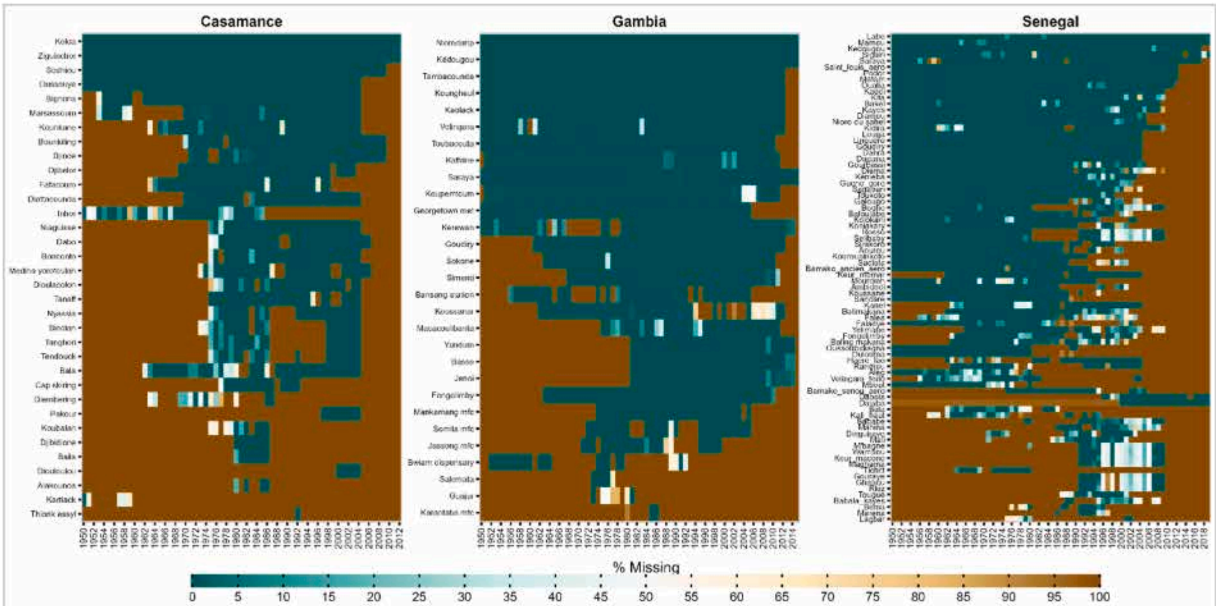


Fig. 2. Inventory of daily rainfall data collected from the three hydrosystems. The color of each tile represents the percentage of missing data, with a gradient ranging from dark green (no gaps) to dark brown (total data unavailability).

2.2. Hydroclimatic data time series

This study relies on daily records of observed rainfall, gridded precipitation datasets, observed streamflow data, and gridded maximum and minimum temperature records, which are used to calculate potential evapotranspiration.

2.2.1. Observed rainfall data

The daily rainfall data used in this study were collected from the national meteorological services of Senegal, Mali, Guinea, and

Table 1
Characteristics of the twenty-three selected gridded precipitation products.

Data sets	Full product name	Data sources	Types	Available period	Spatial resolution	Temporal resolution	References
ARC v2.0	Africa Rainfall Estimate Climatology v2.0	IS, S	Satellite	1983-P	0.1°x0.1°	Daily	(Novella and Thiaw, 2013)
CHIRP v2.0	Climate Hazards Group InfraRed v2.0	S, R	Satellite	1981-P	0.05°	Daily	(Funk et al., 2015)
CHIRPS v2.0	Climate Hazard group InfraRed Precipitation with Stations v2.0	IS, S, R	Satellite	1981-P	0.05°	Daily	(Funk et al., 2015)
MSWEP v2.2	Multi-Source Weighted-Ensemble Precipitation V2.2	IS, S, R	Satellite	1979-P	0.1°x0.1°	3 h	(Beck, Wood, et al., 2019; Beck, Pan, et al., 2019)
TAMSAT v3.0	Tropical Applications of Meteorology using SATellite and ground-based observations v.3	IS, S	Satellite	1983-P	0.0375°x0.0375°	Daily	(Tarnavsky et al., 2014; Maidment et al., 2017))
GPCP-1DD v1.2	Global Precipitation Climatology Project 1-Degree Daily Combination v1.2	IS, S	Satellite	1997-P	1°x1°	Daily	(Huffman et al., 2001)
PERSIANN	Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks	S	Satellite	2000-P	0.25°x0.25°	6 h	(Hsu et al., 1997; Sorooshian et al., 2000)
PERSIANN-CDR v1r1	Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks Climate Data Record	IS, S	Satellite	1983-P	0.25°x0.25°	Daily	(Ashouri et al., 2015)
PERSIANN-CCS	PERSIANN-Cloud Classification System	S	Satellite	2003-P	0.4°x0.4°	Daily	(Hong et al., 2004)
PERSIANN-PDIR-NOW	PERSIANN-Dynamic Infrared Rain Rate near real-time		Satellite	2000-P	0.4°x0.4°	Daily	(Nguyen et al., 2020)
PERSIANN-CCS-CDR	PERSIANN-Cloud Classification System- Climate Data Record	IS, S	Satellite	1983-P	0.4°x0.4°	Daily	(Sadeghi et al., 2021)
CMORPH-CRT v1.0	Climate Prediction Center MORPHing technique bias corrected v1.0	IS, S	Satellite	1998–2019	0.25°x0.25°	Daily	(Joyce et al., 2004; Xie et al., 2007)
RFE v2.0	Climate Prediction Center African Rainfall Estimate	IS, S	Satellite	2001-P	0.1°x0.1°	Daily	(Xie and Arkin, 1996; Herman et al., 1997)
IMERGDE v06	Integrated Multi-satellitE Retrievals for GPM (IMERG) Early	IS, S	Satellite	2000-P	0.1°x0.1°	Daily	(Huffman et al., 2020)
IMERGDL v06	Integrated Multi-satellitE Retrievals for GPM (IMERG) Late	IS, S	Satellite	2000-P	0.1°x0.1°	Daily	(Huffman et al., 2020)
IMERGDF v06	Integrated Multi-satellitE Retrievals for GPM (IMERG) Final	IS, S	Satellite	2000-P	0.1°x0.1°	Daily	(Huffman et al., 2020)
MERRA-2	Modern-Era Retrospective Analysis ForResearch and Applications 2	IS, S, R	Reanalysis	1980-P	0.5°x0.5°	Hourly	(Gelaro et al., 2017; Reichle et al., 2017)
ERA5	European Centre for Mediumrange Weather Forecasts ReAnalysis 5 (ERA5)	R	Reanalysis	1979-P	0.25°x0.25°	Hourly	(Hersbach et al., 2018)
EWEMBI v1.1	EartH2Observe, WFDEI and ERA-Interim data Merged and Bias-corrected for ISIMIP (EWEMBI)	IS, R	Reanalysis	1979–2016	0.5°x0.5°	Daily	(Lange, 2016)
PGF v3	Princeton University Global Meteorological Forcing	IS, R	Reanalysis	1979–2016	0.25°x0.25°	Daily	(Sheffield et al., 2006)
WFDEI-CRU	WATCH Forcing Data ERAInterim (WFDEI) corrected using Climatic Research Unit (CRU)	IS, R	Reanalysis	1979–2018	0.5°x0.5°	3 h/Day	(Weedon et al., 2014)
WFDEI-GPCC	WATCH Forcing Data ERAInterim (WFDEI) corrected using Global Precipitation Climatology Centre	IS, R	Reanalysis	1979–2016	0.5°x0.5°	3 h/Day	(Weedon et al., 2014)
CPC v.1	Climate Prediction Center unified v.1	IS	In situ	1979-P	0.5°x0.5°	Daily	(Xie et al., 2007; Chen et al., 2008)

In the data source column, IS refers to In situ, S to Satellite, and R to Reanalysis. In the available period column, P indicates Present.

Gambia. These data are stored in the databases of the Organization for the Development of the Senegal River (in French, Organisation pour la Mise en Valeur du fleuve Sénégal (OMVS)) and the Organization for the Development of the Gambia River (in French, Organisation pour la Mise en Valeur du fleuve Gambie (OMVG)).

Fig. 2 provides an inventory of the collected data, which includes 137 stations, distributed as follows: 34 stations in the Casamance basin, 29 in the Gambia basin, and 74 in the Senegal basin. The quality and duration of these datasets vary between basins, with noticeable inconsistencies in data availability. Additionally, many stations exhibit significant data gaps in recent years due to challenges in updating the databases maintained by OMVS and OMVG.

2.2.2. Gridded precipitation data

The characteristics of the gridded precipitation datasets used in this study, along with their corresponding references, are presented in Table 1. These same datasets have already undergone point-to-pixel evaluation against rainfall gauges in the study by Goudiaby et al. (2024).

2.2.3. Observed hydrological data

In Senegal's major basins, flow measurements at hydrometric stations are carried out by national hydrological services. Water levels are measured by means of limnimetric scales or automatic recorders, such as limnigraphs, thalimeters, pressure or float sensors. The gauging required to establish rating curves (head-flow relationships) is often carried out using acoustic current meters (ADCP). These curves are regularly updated to estimate continuous flow series. However, as Faye (2017) points out, measurements often have gaps and uncertainties due to equipment malfunctions, the low frequency of gauging and the logistical constraints of station maintenance.

In this study, daily discharge data for the various catchments were obtained from the Directorate of Water Resources Management and Planning (in French, Direction de la Gestion et de la Planification des Ressources en Eau (DGPRE)) for the Gambia and Casamance basins and from the OMVS for the hydrometric stations in the Senegal basin. The available time series cover different periods depending on the station, between 1952 and 2015. Fig. 3 provides an inventory of the collected streamflow data by gauging stations. It highlights the incomplete and discontinuous nature of the datasets, particularly at some stations before the 1960s and extending into the late 2010s.

2.2.4. Potential evapotranspiration data

Potential evapotranspiration (PET) is calculated using maximum and minimum temperature data from the National Centers for Environmental Prediction (NCEP) reanalysis (NCEP; https://downloads.psl.noaa.gov/Datasets/ncep.reanalysis/Dailies/surface_gauss/, last accessed June 17, 2023) provided by the National Oceanic and Atmospheric Administration (NOAA).

The daily NCEP reanalysis dataset extends from 1948 to the present, providing a long-term dataset for climate studies. The temporal depth of NCEP data allows the calculation of evapotranspiration for the studied basins since the 1950s, ensuring consistency with the observed rainfall time series and enabling the simulation of basin streamflows over extended periods. Temperature data were selected because they generally exhibit stronger correlations with observed measurements, unlike other variables produced by

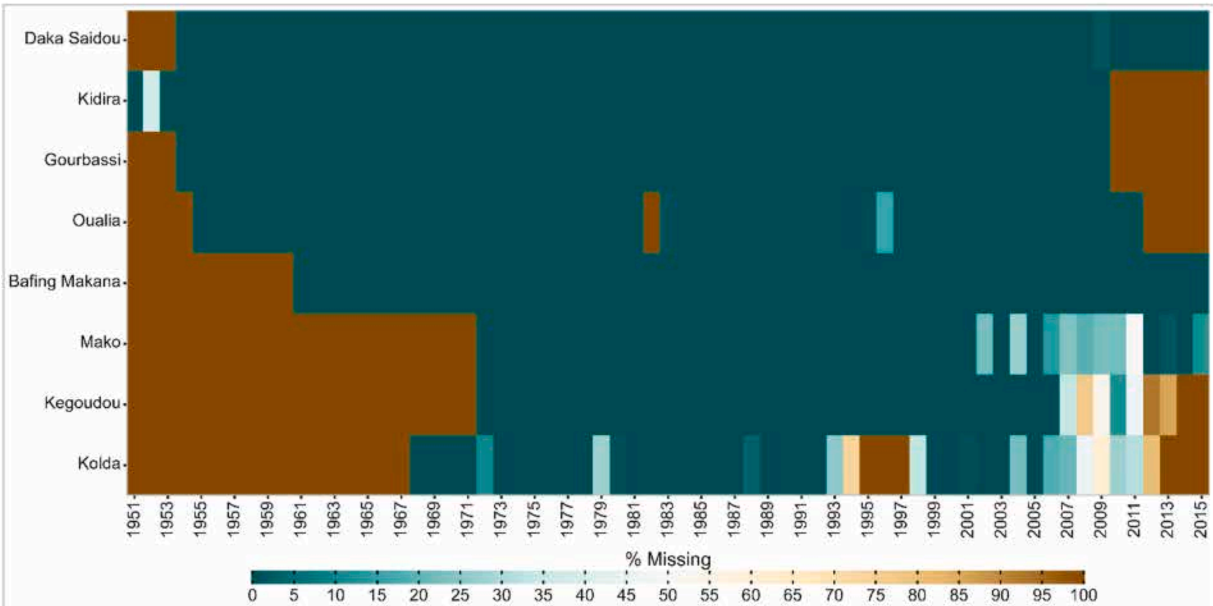


Fig. 3. Inventory of daily hydrological data collected from the eight stations used. The color of each tile represents the percentage of missing data, with a gradient ranging from dark green (no gaps) to dark brown (total data unavailability).

reanalysis (Ndiaye et al., 2021). The coordinates of the stations shown in Fig. 1b were used to extract maximum and minimum temperature data, which were then used to compute PET.

The temperature-based method of (Droogers and Allen, 2002) is used to calculate potential evapotranspiration (PET) using maximum and minimum temperature data extracted from the rain station coordinates (Fig. 1b). This method was selected for its simplicity and proven performance in estimating PET in the Senegal basin (Ndiaye et al., 2021). Additionally, the hydrologic models used in this study are less sensitive to PET errors (Andréassian et al., 2004; Oudin, 2004). In this context, a simple method based on temperature or solar radiation can produce simulation results comparable to those of a more complex method requiring multiple climatic variables (Oudin, 2004; Ndiaye et al., 2024). The mathematical formulation of this method is expressed as follows:

$$\mathrm{PET} = 0.0025 \times (\mathrm{T} + 16.8) \times (\mathrm{Tmax} - \mathrm{Tmin})^{0.5} \times \mathrm{Ra}$$

where T is the mean temperature, Tmax is the maximum temperature, Tmin is the minimum temperature, and Ra is the extraterrestrial radiation, determined based on the station's positional parameters (latitude and altitude).

2.2.5. Hydrologic models

Several types of hydrological models—physical, distributed, semi-distributed, and conceptual—are available in the literature. The choice of an appropriate model depends on the study context, input variables, data availability, and model performance (Flores et al., 2021). Physical models require multiple input variables, many of which are often unavailable in the West African context, limiting their applicability. In contrast, global conceptual models require fewer data inputs, making them more suitable for this study. Consequently, we selected the Génie Rural (GR) global conceptual models, developed by the Institut National de Recherche Agronomique et de l'Environnement (INRAE). These models require only rainfall and PET as inputs and their ability to simulate runoff in West African catchments has been demonstrated in several studies (Le Lay, 2006; 2011; 2014; Amoussou et al., 2014; Nnomo, 2016; Bodian et al., 2018; Faty et al., 2018; Kodja, 2018; Koubodana et al., 2021; Ndiaye et al., 2024). A detailed description of these models (Fig. 4) can be found in Mouelhi et al. (2006) for GR2M and Perrin et al. (2003) for GR4J. GR2M is a monthly time-step model with two parameters: X1, production reservoir capacity (mm) and X2, underground exchange coefficient (mm). Whereas GR4J is a daily time-step model with four parameters: X1, production reservoir capacity (mm); X2, underground exchange coefficient (mm); X3, one-day routing reservoir capacity (mm) and X4, HU1 unit hydrograph base time (days). In this study, we used the versions of these models implemented in the AirGR package under R (Delaigue et al., 2019).

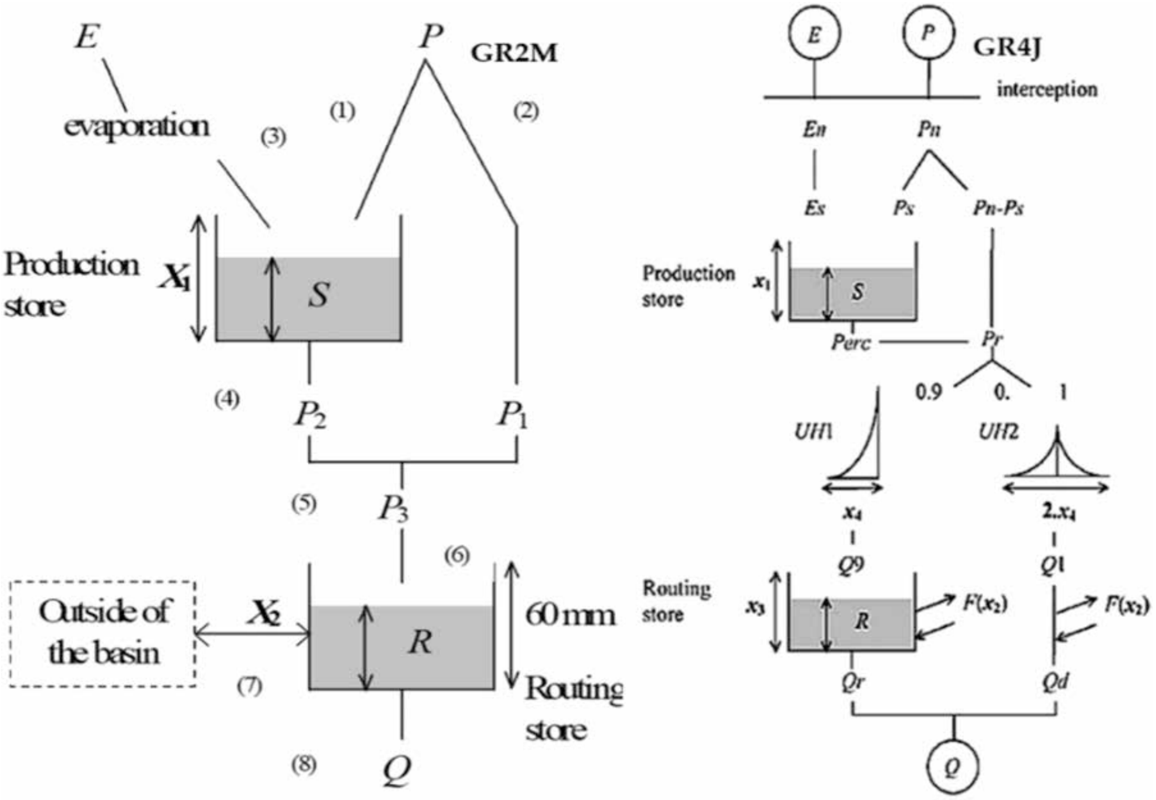


Fig. 4. Conceptual diagrams of the GR2M model (Mouelhi et al., 2006) and the GR4J model (Perrin et al., 2003).

2.3. Methods

Fig. 5 summarizes the overall methodology used in this study, which is structured into four key stages. First, observed and gridded rainfall and PET are interpolated across the 8 catchments. Secondly, the 23 gridded rainfall values per catchment are compared with observed data. Thirdly, hydrological models are calibrated and cross-validated using both ground-based and gridded rainfall data. Finally, streamflows are simulated using gridded rainfall over different periods based on the parameter sets obtained in the previous step.

Mean observed rainfall and mean PET per catchment are calculated using the Inverse Distance Weighted squared (IDW) method (Tomczak, 1998; Bodian et al., 2012, 2020). The interpolated basin rainfall is computed using the IDW method in two ways: first, by extracting values at the coordinates of rainfall gauges in Fig. 1b, and secondly, by extracting values from the centroid coordinates of the grid cells.

The spatially averaged gridded rainfall values are then compared with the average observed rainfall, and the best-performing products are selected for hydrological modeling. The GR4J and GR2M models are initially calibrated and validated with observed data, followed by calibration with gridded rainfall datasets. The optimal parameter sets obtained from cross-validation are subsequently used to simulate basin streamflows using gridded rainfall. A detailed description of each methodological step is provided in the following sections.

2.3.1. Calculation of catchment rainfall and PET

Based on the inventory of rainfall gauge data (Fig. 2), a selection of stations per catchment was made to interpolate rainfall for each basin. Seven stations for the Bafing, six for the Falémé, eleven for the Bakoye, seven for the Mako, and eight for the Casamance at Kolda were selected (Fig. 1b and Fig. 2). In total, thirty-nine stations with time series spanning 1950–2019, and data gaps ranging from 0 % to 80 % (Fig. 2), were used to calculate observed rainfall averages for the various sub-basins using the Inverse Distance Weighted (IDW) method. For gridded precipitation datasets, spatial averages were calculated using the IDW method in two ways. The first approach involved extracting values at the coordinates of rainfall gauges in Fig. 1b, here defined as Gridded Products Extracted from Ground Station Coordinates (GPEGSC) (Fig. 1b). The second approach, Gridded Products Extracted from Grid Centroid Coordinates (GPEGCC), extracted values from the centroid coordinates of the grid cells (Table 2 and Fig. 6). The choice of GPEGCC was motivated by the need to generate a evenly distributed rainfall grid at the basin scale, given the low density of ground stations. Table 2 presents the number of centroids corresponding to each spatial resolution as a function of basin size, while Fig. 6 illustrates the spatial distribution of centroids for the Oualia basin, the largest in terms of surface area. Additionally, the average PET for each basin was calculated using the IDW method.

2.3.2. Comparison of catchment rainfall from gridded datasets and observed data

To compare catchment rainfall interpolated from gridded rainfall and observed rainfall, the gridded products were classified into

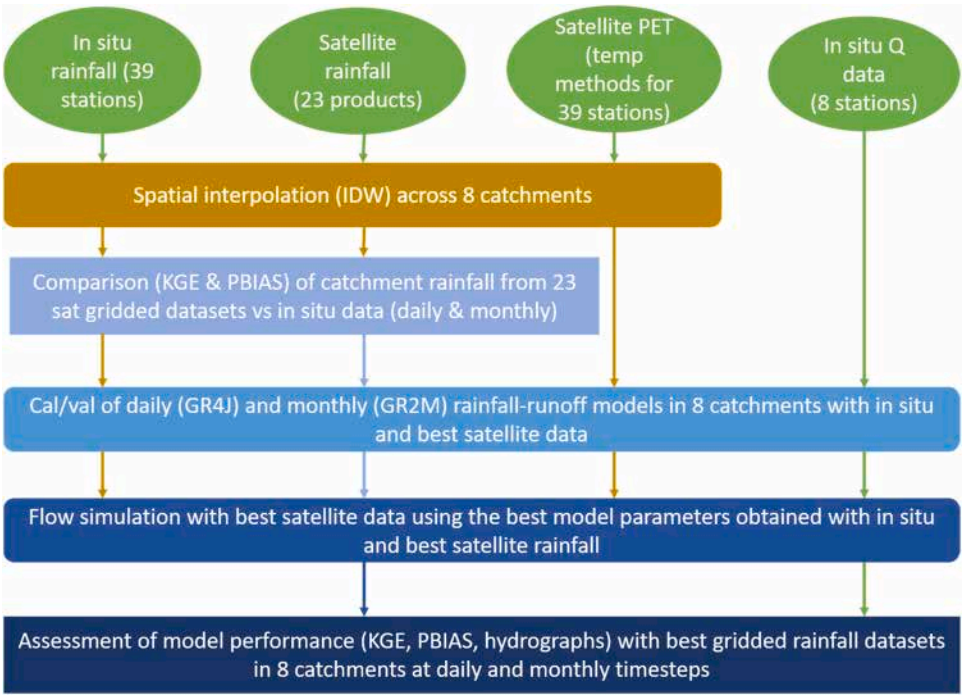


Fig. 5. Diagram illustrating the overall methodology used in this study.

Table 2
Number of centroids used per spatial resolution for each watershed.

Grids / Basins	Surface (Km^2)	0.0375°	0.04°	0.05°	0.1°	0.25°	0.5°	0.625°x0.5°	1°
Bafing Makana	22420	1516	1338	860	212	48	19	17	8
Daka Saïdou	15061	1008	889	579	146	33	12	12	5
Kidira	28516	1870	1644	1052	259	54	17	16	6
Gourbassi	15681	1065	935	610	168	33	12	11	5
Oualia	87931	5895	5173	3304	812	149	44	40	14
Mako	10569	759	666	424	121	28	9	10	4
Kédougou	7609	554	495	326	91	22	8	8	4
Kolda	3652	260	247	146	45	11	6	4	2

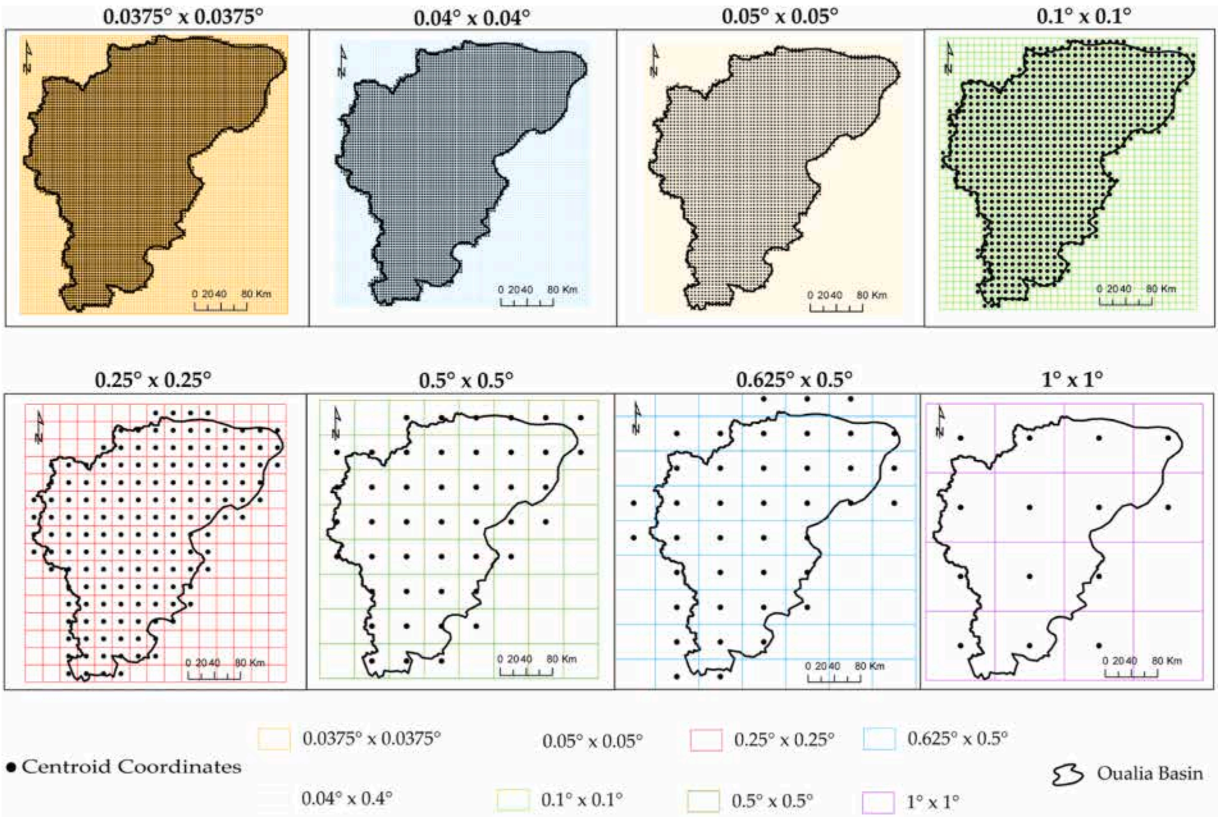


Fig. 6. Coordinates of grid centroids at different spatial resolutions for the Oualia basin.

groups based on the temporal depth of their time series. Five groups were defined in Appendix A: group 1 (1984–2019), group 2 (1998–2019), group 3 (2000–2019), group 4 (2001–2019), and group 5 (2003–2019). This temporal classification takes into account the fact that satellite data present a variety of time series, as do the flow series specific to each basin. Here, the average precipitation of the basins is compared, but the rest of the assessment is based on hydrological modelling. It was therefore necessary to work on series of the same length to ensure consistency between the two stages of the analysis. Thus, these evaluation periods (Fig. 7) vary across the basins depending on the overlap between the observed rainfall series and the corresponding gridded products.

The Kling-Gupta Efficiency (KGE, Gupta et al., 2009) and percentage bias (PBIAS) were used as evaluation criteria. These metrics were calculated using the hydroGOF package in R (Zambrano-Bigiarini, 2024). To facilitate the visualization of results in heatmaps, the optimal values of KGE (1) and PBIAS (0) were taken as reference points. Values of KGE $\leq$ -1.5 and PBIAS $\geq$ 100 or $\leq$ -100 were rounded to -1.5, 100, and -100, respectively, for consistency in representation. Additionally, the classification by Thiemig et al. (2013) was applied to interpret product performance. According to these authors, performance is considered good when KGE is greater than or equal to 0.75, average when KGE is between 0.75 and 0.5, and poor when KGE is below 0.5.

The KGE and PBIAS values calculated from catchment rainfall against observed rainfall on a daily scale are presented in Figs. 8 and 9. Using the GPEGSC approach, the best-performing products include TAMSAT, IMERGDF, PERSIANN-CDR, MSWEP, GPCP, and CHIRPS, with KGE values ranging from 0.53 to 0.65 and generally low percent biases. These same products maintain good performance

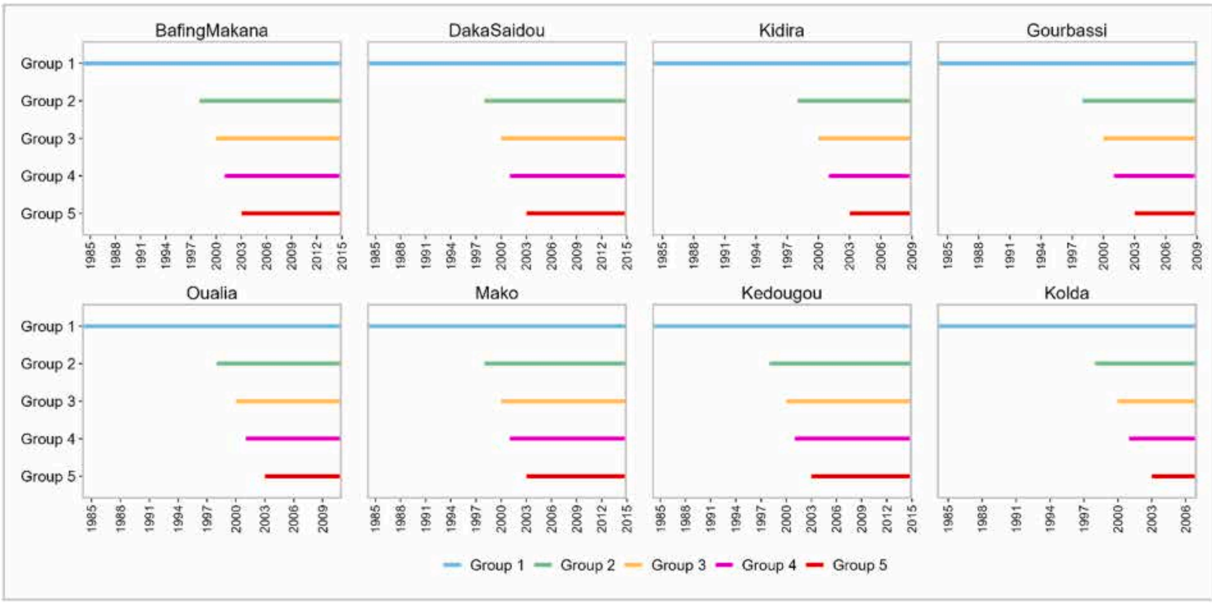


Fig. 7. Periods used to evaluate interpolated gridded rainfall against observed rainfall for each basin, for the five gridded rainfall product groups.

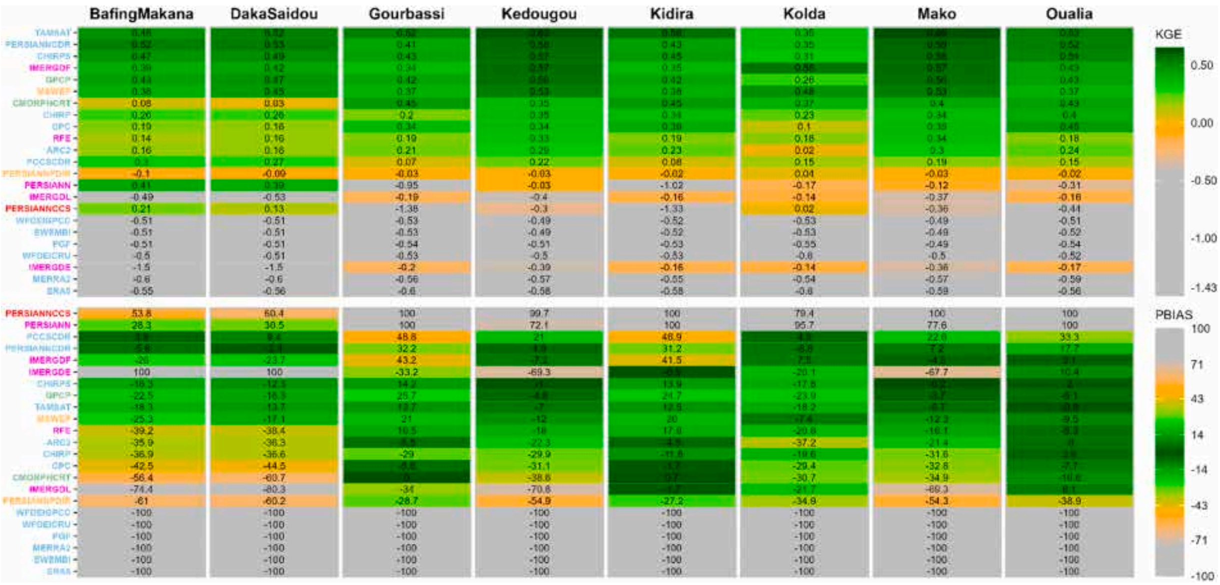


Fig. 8. Comparison of catchment rainfall at the daily time step using GPEGSC and observed data. The colors of the product names on the Y-axis correspond to the product groups defined in Fig. 7 and Appendix A.

using the GPEGCC approach, with KGE values ranging from 0.47 to 0.66 and relatively low estimation biases.

Analysis of Figs. 10 and 11 shows that the best products at the monthly time step are broadly similar to those identified at the daily scale, except for CHIRPS with GPEGCC. For GPEGSC, KGE values increase and range from 0.53 to 0.94, with relatively low estimation biases (Fig. 10). For GPEGCC, KGE values range from 0.39 to 0.94, with bias percentages indicating a slight underestimation (Fig. 11).

Given the small difference in values between both interpolation approaches, using a single grid for further analysis is justified. Considering the number of products with a monthly KGE value > 0.75 across all basins, GPEGSC is slightly superior (45 vs. 43). This is coherent with the fact that GPEGSC employs the same density of rainfall observations as observed data. However, GPEGCC performs better in four out of eight basins, with one basin showing equal performance. Importantly, GPEGCC by employing a denser network of rainfall observations is expected to provide a more accurate estimate of the catchment rainfall. Accordingly, GPEGCC was selected for hydrological modeling.

The final objective of this analysis was also to identify the most reliable gridded precipitation products for hydrological modeling.

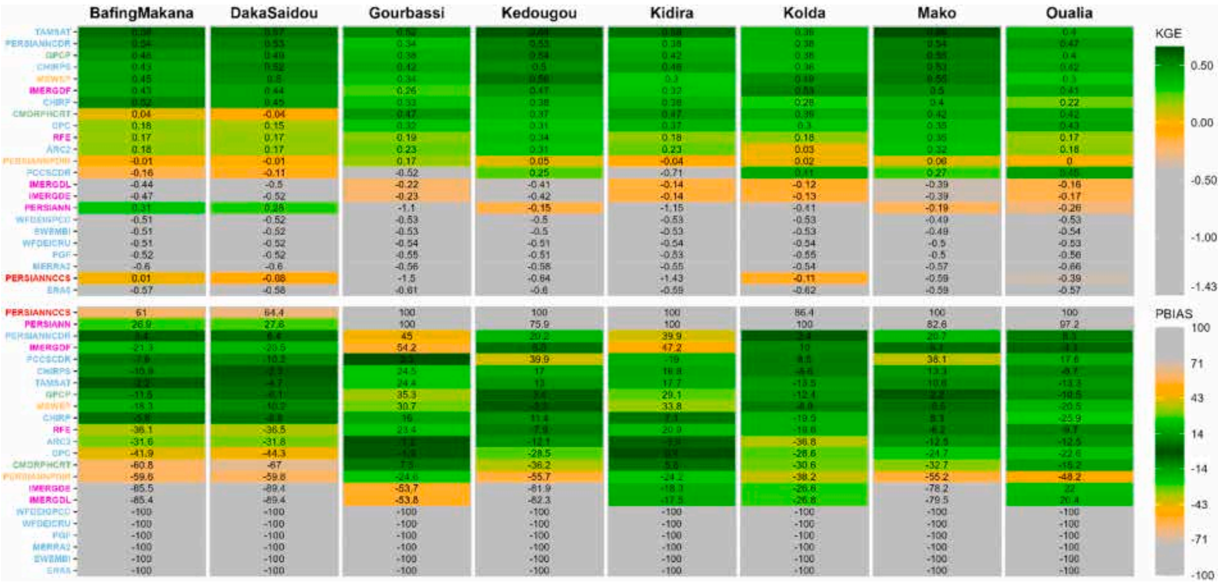


Fig. 9. Comparison of catchment rainfall at the daily time step using GPEGCC and observed data.

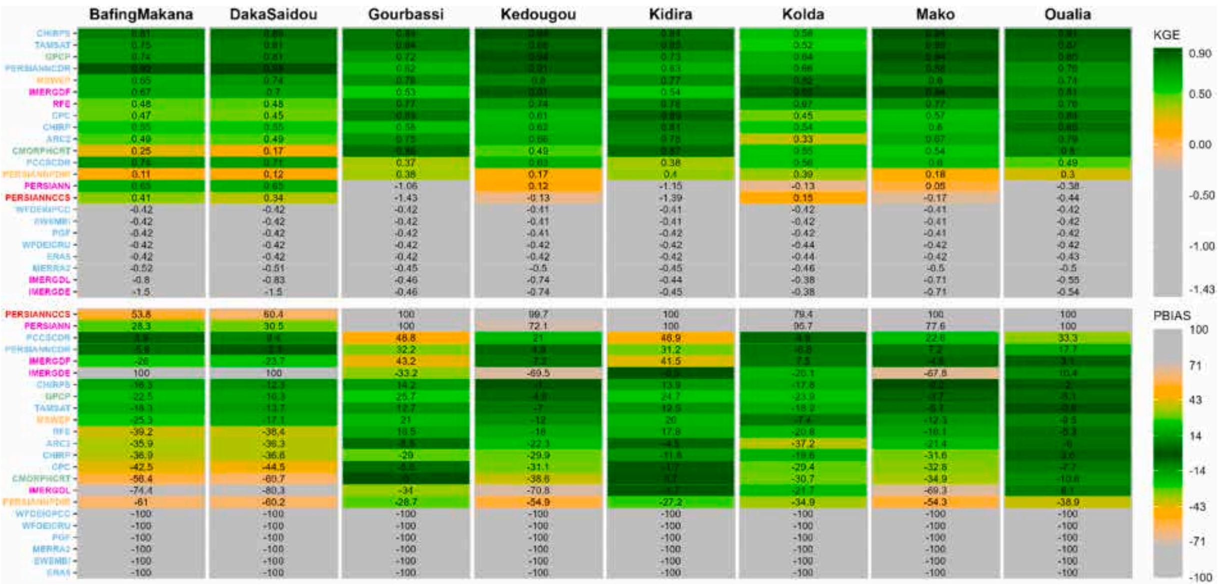


Fig. 10. Comparison of catchment rainfall at the monthly time step using GPEGSC and observed data.

The selection criterion adopted—excluding any product with a negative KGE across all basins and time steps—resulted in a selection of fifteen products out of the twenty-three initially evaluated. The selected products—TAMSAT, PERSIANN-CDR, GPCP, MSWEP, IMERGDF, CHIRPS, CMORPH-CRT, CHIRP, CPC, PCCS-CDR, RFE, PERSIANN-PDIR, PERSIANN, and PERSIANN-CCS—stand out for their performance and relatively low estimation errors.

2.3.3. Calibration and cross-validation of models

In hydrological modeling, selecting appropriate calibration and validation periods is crucial to ensure the representativeness and robustness of the model under different climatic conditions. In this study, the choice was guided by the Standardized Precipitation Index (SPI) of observed mean rainfall and basin flow indices, ensuring that both wet and dry years were included in the selected periods (Fig. 12).

To achieve this, specific calibration and validation periods were defined for each basin within the period 1984–2015, considering the differences in the lengths of data series for rainfall, PET, and streamflow. These periods were preceded by a two-year model

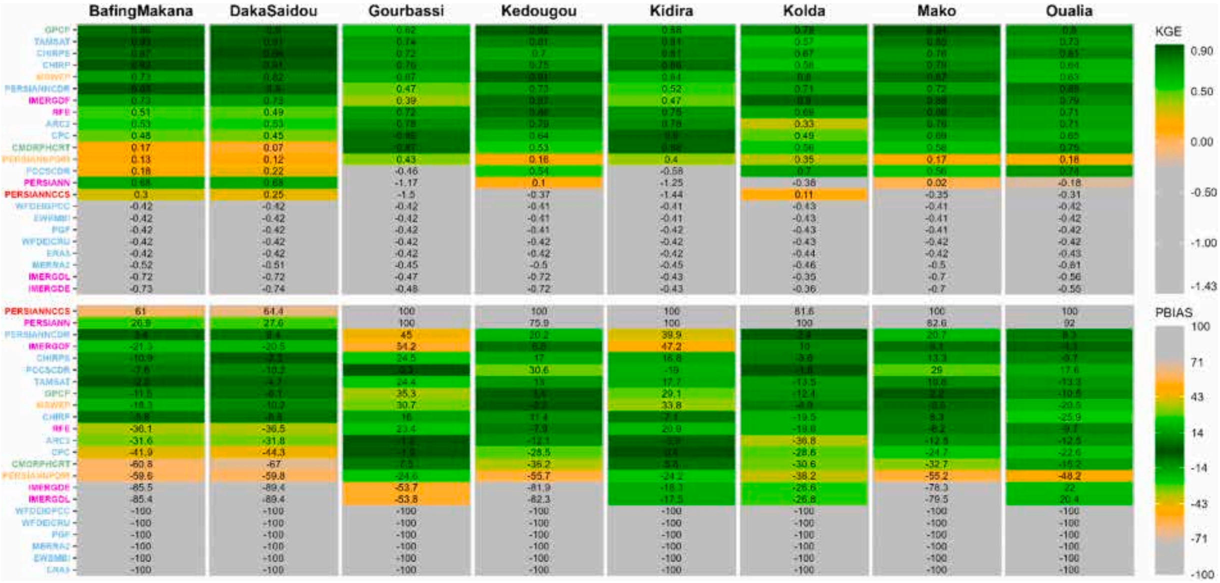


Fig. 11. Comparison of catchment rainfall at the monthly time step using GPEGCC and observed data.

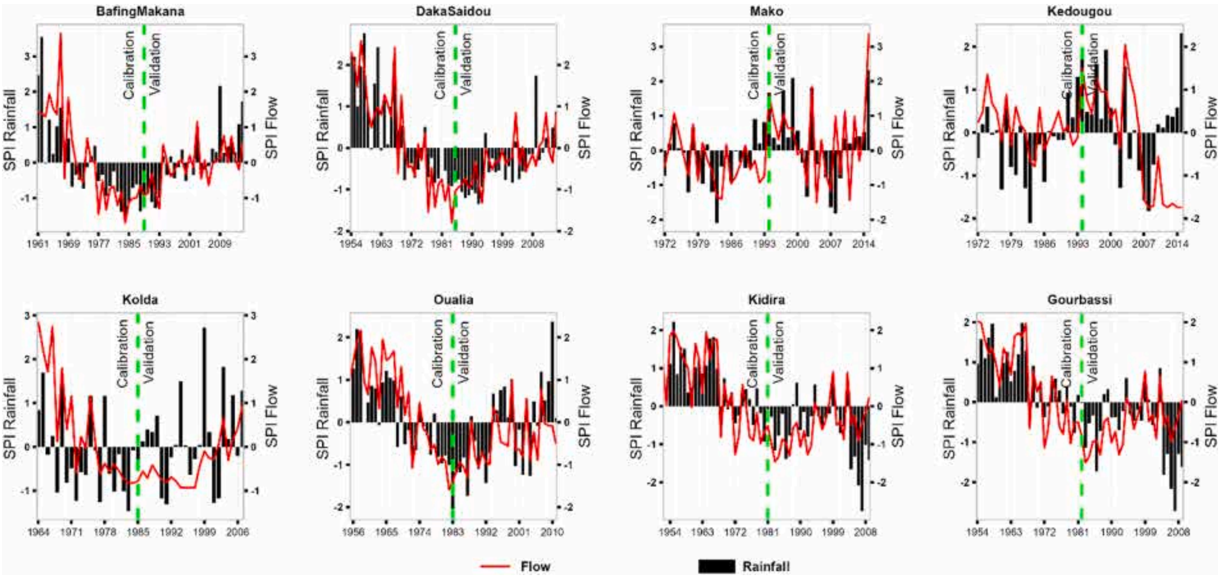


Fig. 12. Variation in annual rainfall and streamflow SPIs for the eight basins studied. The green dashed line indicates the calibration and validation periods for each basin.

initialization phase. The models were calibrated on period 1 and validated on period 2, and then the process was reversed and repeated using both observed rainfall (Fig. 12) and gridded rainfall (Fig. 13).

The KGE was used as the objective function to optimize model parameters. Cross-validation allowed the identification of the best parameter sets governing the rainfall-runoff relationship for each catchment (Bodian et al., 2016).

Finally, these parameters were then applied to flow simulations using gridded precipitation data (GPEGCC) to evaluate their ability to reproduce observed streamflows. The KGE and the PBIAS are used to quantify the accuracy of the simulations.

2.3.4. Flow simulation with gridded rainfall datasets

Model calibration and cross-validation using observed and gridded rainfall data allow for the determination of model parameters that best capture the rainfall-runoff relationship. These parameters are then applied to flow simulations using gridded rainfall products. The objective is to evaluate the capacity of gridded rainfall datasets as input data for hydrological models and to assess their ability to simulate streamflows in the studied basins compared to ground-based observations. The KGE and the PBIAS are used to

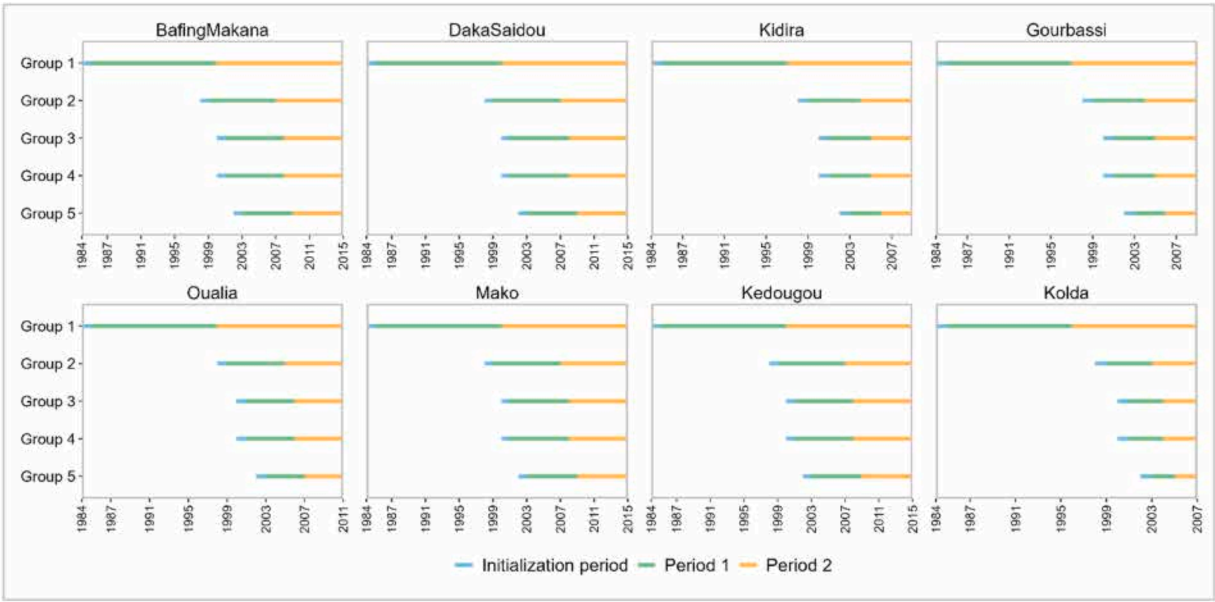


Fig. 13. Calibration and cross-validation periods for models using gridded rainfall, classified by rainfall dataset group and basin.

quantify the accuracy of the simulations.

3. Results

3.1. Analysis of model performance in calibration/cross-validation with observed and gridded rainfall data

Fig. 14 presents the performance of the models during calibration and cross-validation with observed rainfall data. The models demonstrate robust performance in calibration across all studied basins, with KGE values generally exceeding 0.75 and PBIAS values remaining below 10 % including at the daily time step (GR4J). A modest deterioration in model performance is observed during validation (KGE > 0.6), particularly for the Oualia basin, where the decline is more pronounced.

Fig. 15 and Appendix B display the results of model calibration and cross-validation using GPEGCC. During calibration, the models

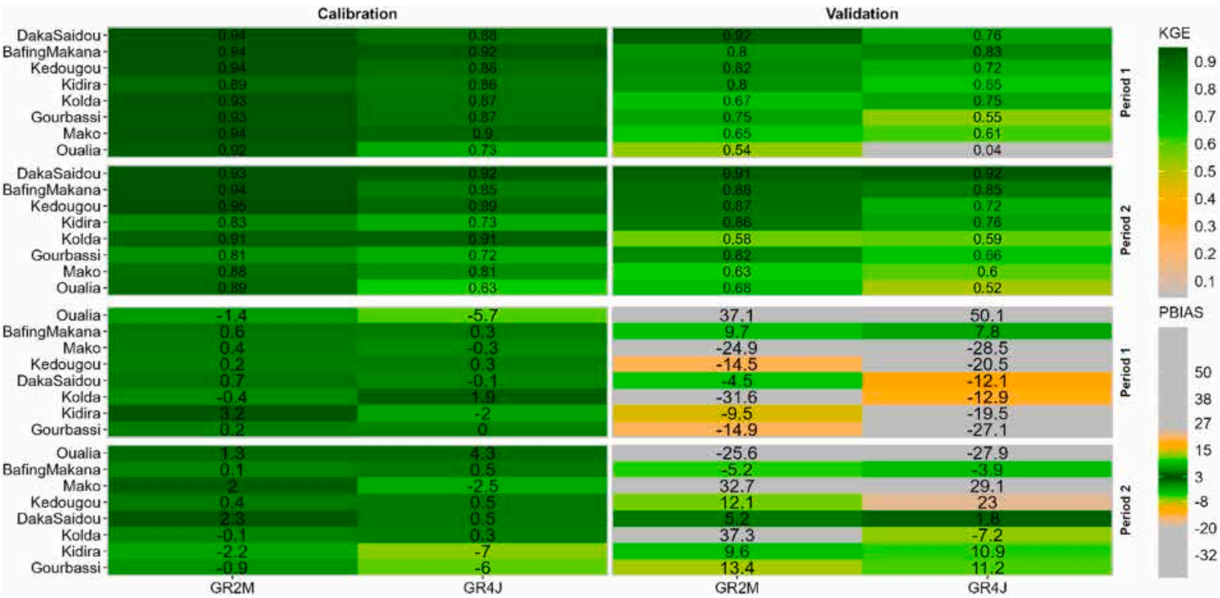


Fig. 14. Model performance in calibration and cross-validation with observed rainfall data. The order of Period 1 and Period 2 follows the calibration sequence.

satisfactorily reproduce observed streamflows at the Bafing Makana, Daka Saïdou, Kidira, Gourbassi, Mako, and Kédougou stations, with KGE values generally above 0.75 and PBIAS values often below 10 %. During validation, model performance declines across these six basins but remains high for several products including at the daily time step. KGE remain above 0.5 for 6–10 products and above 0.75 in several basins with TAMSAT, IMERGDF, GPCP, and MSWEP. Results are highest at Bafing Makana and Daka Saidou which are the 2 basins with the most complete hydrometric time series (Fig. 3). With GR4J, KGE values decline for a handful of additional products but no systematic decline is observed. PBIAS values indicates a tendency toward underestimation.

The results for the other two basins (Oualia and Kolda) exhibit rather unusual behavior in both calibration and validation. The KGE values in calibration are lower than those observed for the six other basins, with values generally falling in the range 0.75–0.5. During validation, KGE values fall drastically below 0.5, accompanied by high PBIAS values in these basins. Only 1–2 products achieve a KGE above 0.5 and only at the monthly scale. PBIAS values reveal an overestimation in Oualia and an underestimation in Kolda.The calibration parameters that yield the best results in validation—both with observed rainfall data and GPEGCC—are subsequently used to simulate streamflows in the studied basins using GPEGCC.

3.2. Simulation of flows with gridded rainfall datasets using parameters obtained in calibration/validation

The model parameter sets that best capture the rainfall-runoff relationship in cross-validation with observed and gridded data were used to simulate streamflows over the entire period of available data for each product and each basin. Fig. 16 presents the KGE and PBIAS values of the simulations compared to observed streamflows. Analysis of this figure indicates that the parameters obtained using gridded rainfall (GPEGCC) then produce the most accurate simulations with gridded datasets, in contrast to those derived from observed data. This highlights the importance of (re-)calibrating the rainfall-runoff models with the gridded rainfall datasets.

Moreover, the parameters obtained from GPEGCC consistently yield the best simulations, though performance varies across basins depending on the type of model used. In the Kidira and Gourbassi basins, KGE values range from 0.52 to 0.96, with estimation errors generally below 10 %. In the Bafing basin, KGE values range from 0.52 to 0.96, with estimation errors ranging from −28.7–50.2 %.

In the Gambia basin, at the Mako and Kédougou stations, the parameters obtained with GPEGCC result in the best simulations, with KGE values between 0.52 and 0.92. However, simulation errors indicate that GPEGCC underestimates streamflows at Mako and Kédougou. For the Bakoye basin at Oualia, the simulations are relatively accurate, though the products also tend to underestimate flows. In contrast, for the Kolda basin, the products do not perform well in simulation.

Hydrographs are employed to translate the numerical performance of individual precipitation datasets in reproducing the hydrological dynamics across the 8 basins. Fig. 17 and Appendix C reveal that the IMERGDF, MSWEP, GPCP, and TAMSAT precipitation products, which exhibit relatively high KGE values in simulation, successfully reproduce the general shape of the observed hydrographs across the studied watersheds. These products effectively capture the amplitiude and timing of peak flows, demonstrating an overall agreement with observed trends. However, in several basins the peak flows occurs up to 1 month earlier and with several products estimate an earlier start of the hydrological season. In some catchments low-flow conditions are overestimated, likely due to hydrological model calibration and their high sensitivity to low rainfall, which results in higher simulated streamflows during dry periods. Conversely, peak flows are underestimated by certain products, partly as a result of rainfall underestimation (Fig. 11) especially during intense localized precipiation events, as well as model calibration which may underestimate the watershed's

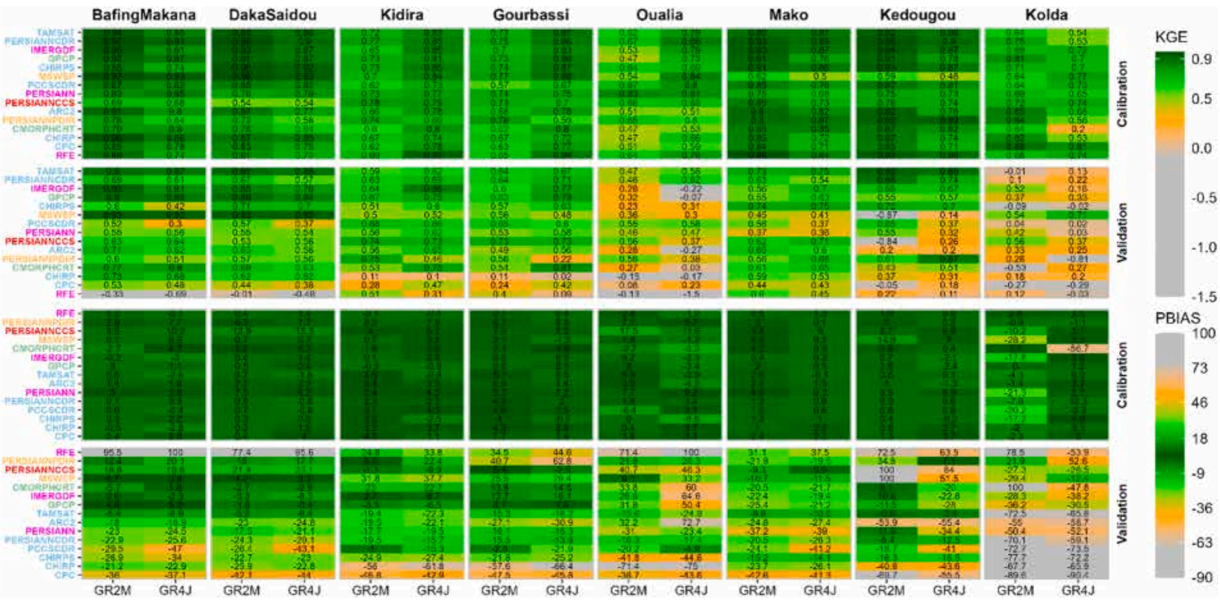


Fig. 15. Model performance in calibration (Period 1) and validation (Period 2) using gridded rainfall (GPEGCC).

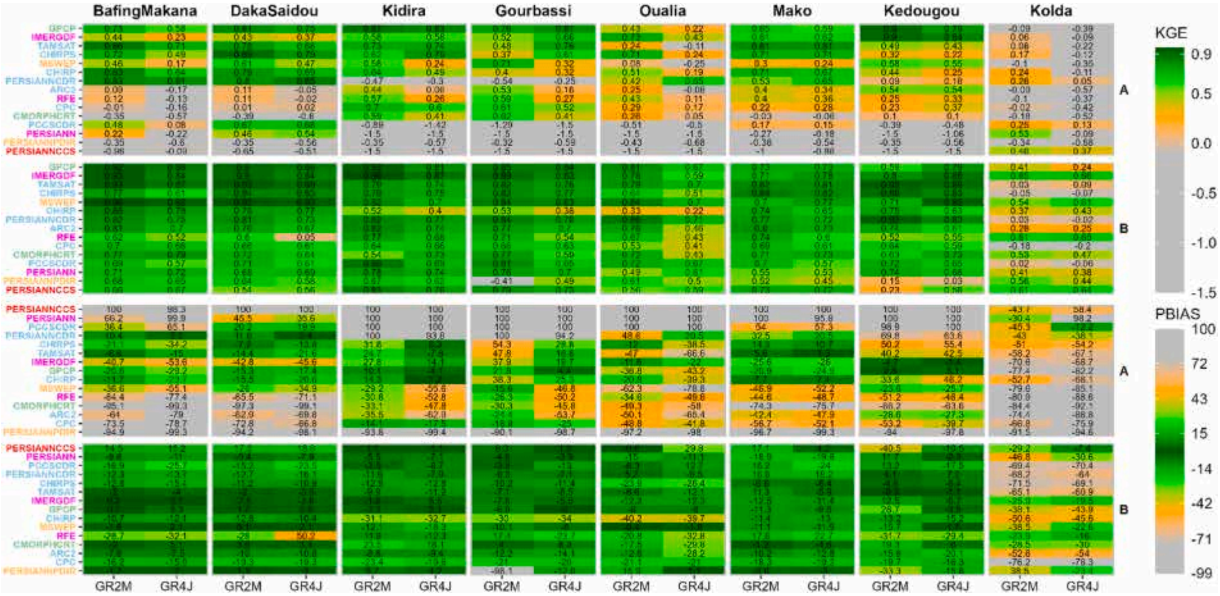


Fig. 16. GPEGCC performance in simulation using model parameters obtained in calibration and cross-validation: (A) Observed rainfall and (B) GPEGCC-derived rainfall.

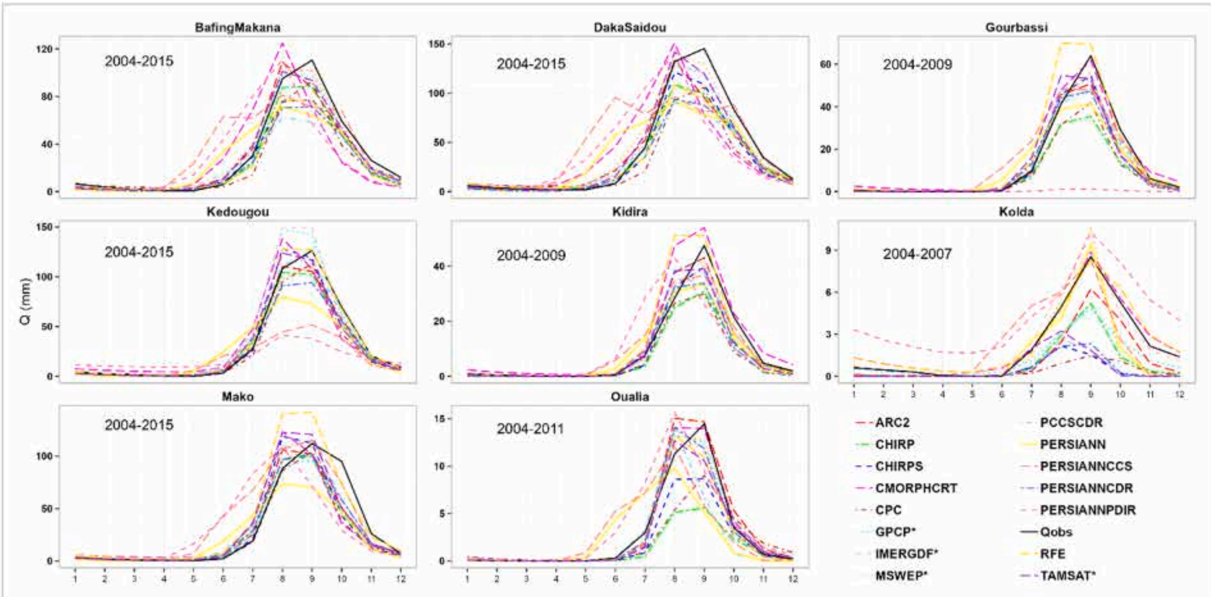


Fig. 17. Monthly mean hydrographs of streamflows simulated using GPEGCC with the GR2M model. The asterisk (*) indicates the best-performing precipitation products.

hydrological response to intense rainfall. These findings emphasize that, while the selected precipitation products effectively reproduce hydrological dynamics on a broad scale, their ability to capture hydrological extremes, even more so at the daily time step, must be further investigated.

The average performance of each precipitation product was calculated based on the mean KGE values obtained from all model simulations per basin (Fig. 18). Analysis of Fig. 18 indicates that the ranking of products varies across basins, reflecting differences in their respective performances. However, some products demonstrate consistent reliability, frequently ranking in either the top or bottom half across multiple basins. Overall, IMERGDF, which integrates in situ, satellite, and reanalysis data, emerges as the best-performing product considering its consistently high KGE values across basins and time steps. It is followed closely by MSWEP, GPCP, and TAMSAT, all of which are composite products combining in situ and satellite data. In contrast, among the multi-source

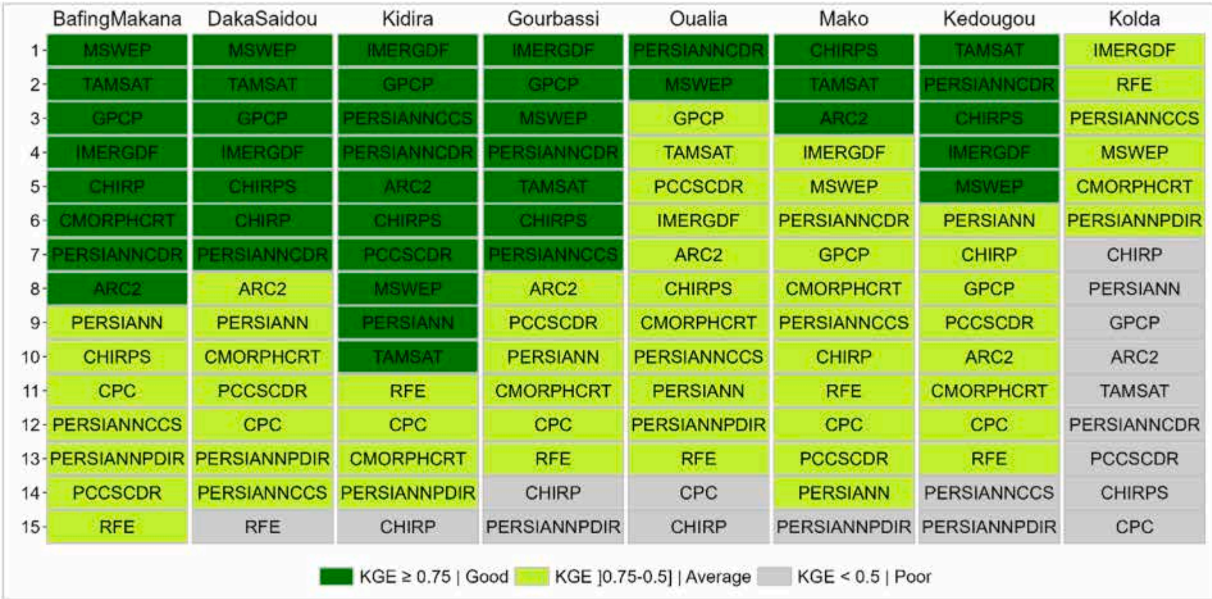


Fig. 18. Classification of products according to their performance in GPEGCC basin simulation.

products, PCCS-CDR and PERSIANN-PDIR exhibit the lowest performance.

4. Discussion

The results led to evaluating the performance of 15 widely used precipitation gridded datasets against streamflow from 8 basins in West Africa at both daily and monthly time scales. Despite difficulties in a couple of basins, several of the products provided encouraging results when used with GR2M and GR4J hydrological models. The four best products (IMERGDF, TAMSAT, MSWEP and GPCP) produced mean KGE above 0.75. The highest-performing products in this study exhibit different spatial resolutions (ranging from 0.0375° to 1°), suggesting that spatial resolution does not have a decisive impact on their performance in hydrological modelling. Streamflow simulation is however not directly influenced by spatial resolution, as long as mean rainfall over the basin is accurately estimated (Nkiaka et al., 2017). The quality, density, and spatial distribution of the observation network therefore play a greater role, as they directly influence the accuracy of basin-wide rainfall estimates. Here, using the same station network to interpolate both observed and gridded rainfall over the catchments improved partially the agreement between rainfall estimates. However, basin-wide rainfall assessments remain uncertain in the absence of dense rainfall networks and it is recommended to use GPEGCC to increase both the number and spatial distribution of rainfall values exploited (Villarini et al., 2008; Levin et al., 2023). The poor performance of the CPC product in this study may be linked to the low density of ground stations and the quality of the raw data used to construct it. For instance, only 12 out of 200 operational rainfall stations in Mali transmit reports via the Global Telecommunication System (GTS) (Nicholson et al., 2003).

The global conceptual models applied here consider the entire watershed as a homogeneous unit, averaging the hydrological balance without explicitly incorporating spatial variations in hydrological processes or input data. This simplification may reduce the relevance of spatialized precipitation inputs, such as the gridded rainfall centroids used in this study. The hydrological models used in this study also introduce uncertainties. Discrepancies between simulated and observed flows can stem from both model and input data uncertainties (Kingumbi, 2006; Kingumbi et al., 2007; Bodian et al., 2016). Flow measurements may also contain errors due to gaps in observation records, inaccuracies in rating curves, or missing data periods. Depending on the size and complexity of the watershed, hydrological model performance assessments may therefore be misleading (Dembélé et al., 2020). The poor performance of the Kolda and Oualia basins can be partly attributed such modelling difficulties. In the Kolda basin, the quality of hydrometric data is notably a limiting factor. In fact, the Kolda station began malfunctioning in 2008, contributing to data uncertainty and potential model performance degradation. The length of data records may then play a role here as for certain products less than 5 years were available to calibration/validation in the Kolda catchment.

In contrast, the largest Oualia basin (87000 km2) spans a vast area covering multiple climatic zones and land uses, producing a complex hydrological response which may explain the limited model performance, already observed in Ndiaye et al. (2024). Contrasting rainfall regimes within different parts of the basin introduce uncertainties in precipitation spatialization and evapotranspiration estimates, affecting the consistency of hydrological simulations. For instance, a model may accurately capture hydrological dynamics in one region of the basin but fail in other areas with distinct climatic conditions, resulting in over- or underestimations of total basin runoff. These two basins are also those with the lowest annual module. When runoff is low, uncertainties in precipitation, evapotranspiration, and internal hydrological processes become more significant, leading to deterioration in simulation performance

(Trudel et al., 2017; Dallaire et al., 2021).

Overall, our results indicate strong agreement between satellite precipitation estimates and ground observations for 15 out of 23 products. These findings confirm the growing potential of gridded precipitation products identified by Gosset et al. (2013) on AMMA-CATCH sites, Casse et al. (2015) on the Niger basin, Bodian et al. (2016) on Bafing Makana, Faty et al. (2018) on the Gambia basin, and Kouakou et al. (2023) on West and Central Africa. The most valid precipitation products in this study combine in situ and satellite data. Similar findings were reported by Kouakou et al. (2023) in West and Central Africa, underscoring the importance of in situ observations. Poméon et al. (2017) also demonstrated the high performance of composite datasets in West Africa. Gascon (2016) found that bias-corrected precipitation products were more robust than raw ones, including in the Senegal River basin (Stisen and Sandholt, 2010). Conversely, Bâ et al. (2018) noted that bias-corrected PERSIANN-CDR did not improve hydrological simulations. Here bias corrected precipitation products (including CMORPH-CRT) provided acceptable performance (KGE>0.5 in many basins but proved below other products.

5. Conclusion

This research aimed to evaluate the suitability of twenty-three gridded precipitation products in rainfall-runoff across eight catchments in West Africa, including five sub-basins of the Senegal River (Bafing Makana, Daka Saïdou, Kidira, Gourbassi, and Oualia), two of the Gambia River (Mako and Kédougou), and one of the Casamance River (Kolda). Two approaches (GPEGSC and GPEGCC) were used to interpolate mean gridded rainfall over each catchment and compare with observed rainfall. The GR2M and GR4J hydrological models were then applied to assess the capacity of fifteen shortlisted products to simulate observed streamflows at monthly and daily time steps.

The best parameter sets from cross-validation were employed to simulate streamflows and the model performance was assessed using the Kling-Gupta Efficiency (KGE) and Percentage Bias (PBIAS) criteria.

The results demonstrate that composite precipitation products (integrating multiple data sources) yield here the most accurate streamflow simulations. Specifically, the IMERGDF dataset yielded the most accurate simulations, followed by MSWEP, GPCP, and TAMSAT. Conversely, the in situ CPC product performed poorly for hydrological modeling of Senegal's major river systems. Parameters obtained using gridded precipitation data (GPEGCC) produced better simulations than those derived from observed rainfall data, highlighting the importance of (re-)calibrating hydrological models with gridded datasets. Gridded precipitation products performed particularly well in Bafing Makana but exhibited weaker performance in Kolda and Oualia where low flows, catchment size and data quality introduced greater modelling difficulties.

Given the limited availability and restricted access to observed rainfall data, especially in West Africa, our findings suggest that IMERGDF, MSWEP, GPCP, and TAMSAT offer valuable alternatives for hydrological simulations. This research also highights the lower performance of several products, which must therefore be subject to additional bias corrections and research to be employed in the climatic context of the Casamance, Gambia, and Senegal River basins. Future research could explore calibration/validation techniques over different time windows to determine the minimum length of hydrological data required for accurate hydrological simulations. This is essential for gridded precipation datasets to support reconstructing streamflow time series in poorly gauged or ungauged basins, enhancing our understanding of water resources in regions with increasing water demand.

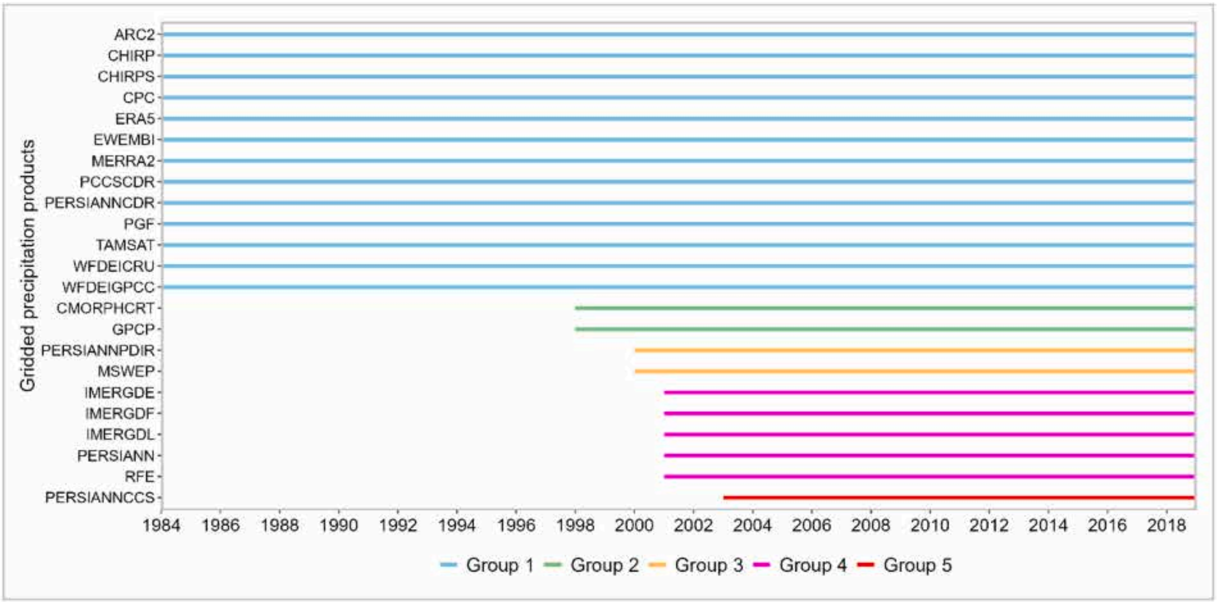
CRediT authorship contribution statement

Ansoumana Bodian: Writing – review & editing, Validation, Supervision, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Omar Goudiaby:** Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Andrew Ogilvie:** Writing – review & editing, Validation, Supervision, Methodology, Conceptualization. **Alain Dezetter:** Writing – review & editing, Validation, Supervision, Methodology, Formal analysis, Conceptualization. **Papa Malick Ndiaye:** Writing – review & editing, Methodology, Formal analysis. **Ibrahima Diouf:** Writing – review & editing, Validation, Methodology, Data curation.

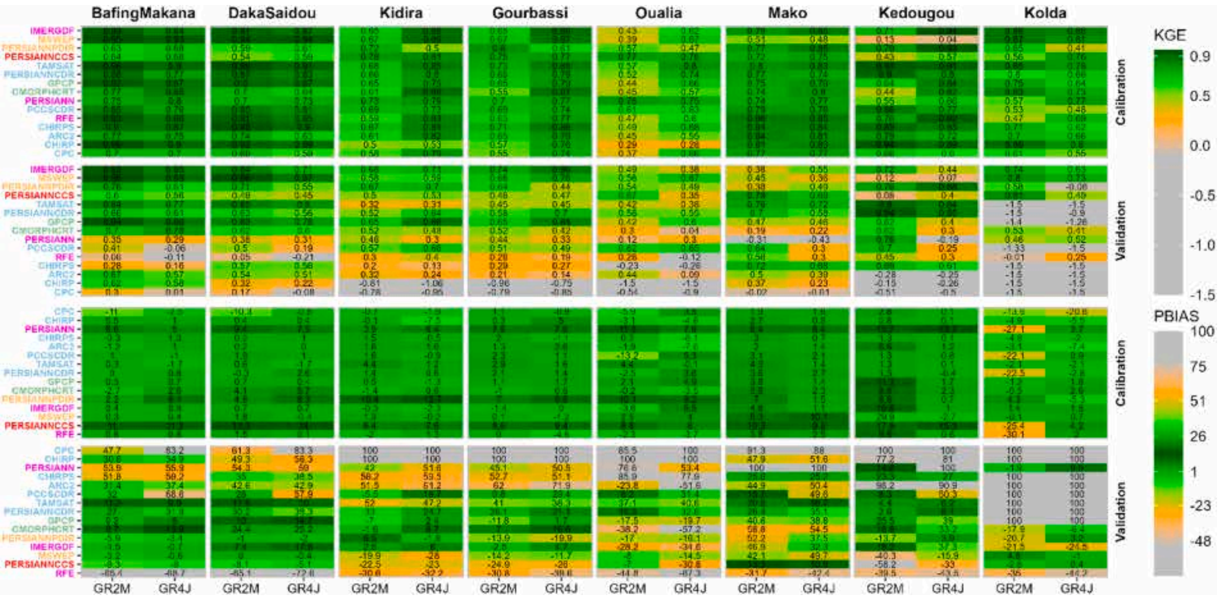
Declaration of Competing Interest

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

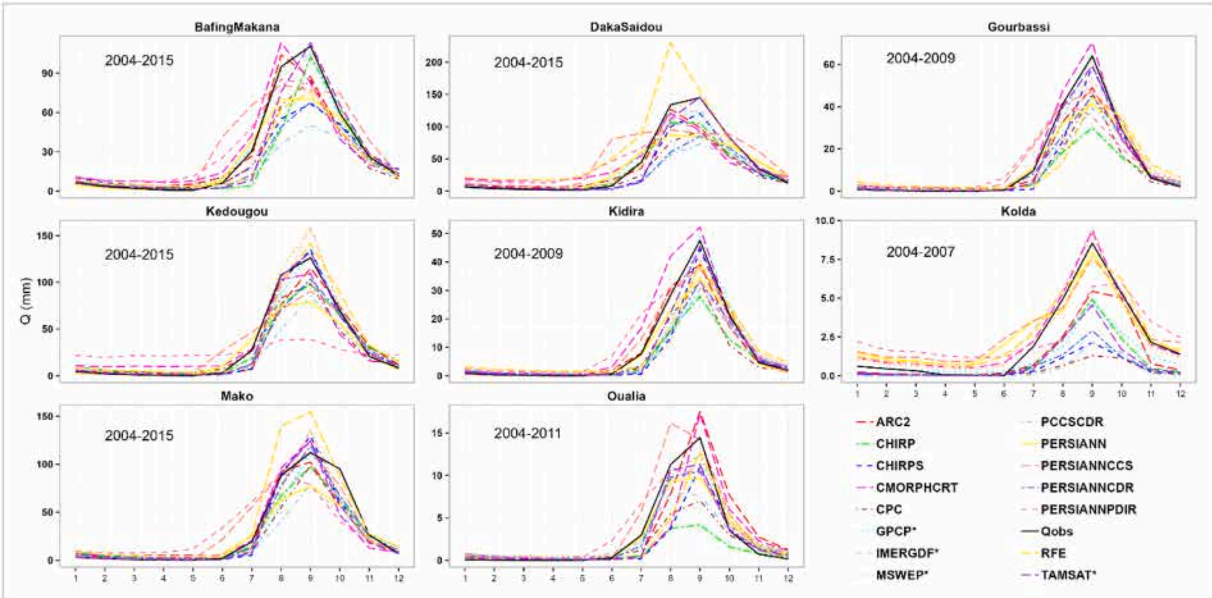
Appendix A. Groups of gridded precipitation products defined according to series length



Appendix B. Model performance in calibration (Period 2) and validation (Period 1) with GPEGCC



Appendix C. Monthly mean hydrographs simulated from GPEGCC with the GR4J model



Data availability

The authors do not have permission to share data.

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