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Sensitivity of global hydrological models to potential evapotranspiration estimation methods in the Senegal River Basin (West Africa)

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ABSTRACT

Study region: Senegal River Basin in West Africa
Study focus: This paper aims to evaluate the sensitivity of global hydrological models to potential evapotranspiration (PET) methods in the Senegal River Basin. Potential evapotranspiration is estimated using 21 methods and its influence on the performance of three GR models (GR4J, GR5J and GR6J) is investigated in five catchments. The data used are mean rainfall, discharge and observed and calculated PET over the period 1984–1995. PET is calculated based on observed climate data and those from NASA POWER reanalysis data. The methodology consists in: (i) comparing the consistency of reanalysis data with respect to the observed PET, (ii) assessing the robustness of GR models and their sensitivity to different PET estimation methods. The evaluation criteria used to assess the performance of the hydrological model are KGE and PBIAS.
New hydrological insights for the region: Good consistency is obtained between PET calculated with observed and reanalysis data. The GR4J and GR5J are more efficient to simulate flows in the Senegal River sub-basins. The aerodynamic PET methods perform well with the three hydrological models. However, in this context where data are scarce, temperature methods such as Droogers and Allen are a good choice for hydrological modeling. The results also show that the GR models have the ability to adapt to poorly estimated PET.

1. Introduction

In West Africa, water resources are highly variable due to climatic fluctuations, resulting in a recrudescence in extreme weather phenomena such as droughts and floods. It is therefore important to understand the spatiotemporal variability of the components of the hydrological cycle (precipitation, evapotranspiration, runoff, etc.) for a good knowledge of water resources (Traoré et al., 2014) and for better planning of adaptation strategies in a context of climate change. Indeed, climate change can affect the spatiotemporal distribution of water resources and negatively impact human activities (Jun et al., 2012). In West Africa, the problem of hydro-climatic

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data availability is particularly acute. Available flow records are often incomplete, discontinuous and of short duration, making them difficult to use for reliable hydrological analysis (Bodian et al., 2012; Tramblay et al., 2021). In addition, the low density of measurement networks is limiting the spatiotemporal analysis of hydro-climatological variables (Bodian et al., 2012; Mahmood and Jia, 2019). In this context, it is important to have high-performance tools that are adapted to improve knowledge of water resources, which is the basis for better water resource management. Moreover, these tools make it possible to better analyze the impacts of climate change and human activities on river regimes (Tramblay et al., 2021) by making the most of the often longer and more complete climatic information available.

In this respect, hydrological models are important tools for water resource management because they enable the transformation of climatic variables into hydrological variables (Smith et al., 2019; Delaigue et al., 2022). There are several hydrological models (Traoré et al., 2014) and their choice depends on the study context, input variables, data availability and the model's robustness in simulating flows (Flores et al., 2021). The different types of models are distinguished by their input variables, the parameters to be calibrated, the processes to be modeled at the watershed scale and whether they are physical, conceptual, distributed or semi-distributed (Traoré et al., 2014). So-called physical models are more complex and require a lot of data that is difficult to obtain in the West African context. For this reason, so-called conceptual or global hydrological models are more widely used in the West African context for flow simulation. The GR (Génie Rural) models used in this study fall into the conceptual category. They were developed by the INRAE (Institut National de Recherche Agronomique et l'Environnement, in French). GR models have the advantage of requiring minimal data and being robust in simulating flows (Hublart et al., 2015; Brulebois et al., 2018; Flores et al., 2021). At the daily time step, there are currently three GR models in operation: GR4J (Perrin et al., 2003), GR5J (Le Moine, 2008) and GR6J (Pushpalatha et al., 2011). GR4J is the most widely used of the existing daily GR models in West Africa because it has been in operation the longest of all GR daily models (Sambou et al., 2011; Traoré et al., 2014; Bodian et al., 2016, 2018; Kodja et al., 2018). Given that GR4J is the most widely used daily GR model in West Africa, it is necessary to assess the performance of other recently developed daily GR models in order to determine their added value in relation to GR4J.

For GR models, the watershed is considered as a homogeneous entity, and physical factors (soil, land use, vegetation) are not represented in the modeling process. As a result, only two input variables are required to estimate discharge at the outlet (Perrin et al., 2003; Delaigue et al., 2022). These are rainfall and potential evapotranspiration. The latter is the most difficult component to estimate, due to its complexity and the climatic variables required for its estimation. Depending on the climatic variables required to estimate evapotranspiration, four categories of methods have been identified (Xu and Singh, 2001). Aerodynamic methods (Dalton, 1802; Trabert, 1896), temperature-based methods (Hargreaves, 1975; Hargreaves and Samani, 1985), radiation-based methods (Makkink, 1957; Priestley and Taylor, 1972) and combinatorial methods (Penman, 1963; Allen et al., 1998). Aerodynamic methods are the oldest and are based on Dalton's theory (Dalton, 1802) that evaporation is proportional to wind speed and saturation deficit. Temperature and radiation-based methods mainly integrate these two variables (temperature and solar radiation). Combinatorial methods can integrate several climatic variables: temperature, wind speed, solar radiation and relative humidity. Of all these methods, the Penman-Monteith method has become a global standard because of its performance under different climatic conditions (Allen et al., 1998; Djaman et al., 2016; Ndiaye et al., 2020a).

The numerous PET formulas available, the climate data to be mobilized and the level of expertise required for their implementation make it difficult to choose an appropriate PET method for hydrological modeling of a given basin (Seiller and Anctil, 2016). Moreover, there is as yet no consensus on the most appropriate PET method to use for hydrological modelling (Jayathilake and Smith, 2020). The most sophisticated methods, Penman-Monteith in particular, are not necessarily the most widely used (Andréassian et al., 2004; Oudin et al., 2005) due to the large number of climatic variables that it incorporates. PET is known to be less variable over time (compared to rainfall) and therefore has a limited influence on the performance of hydrological models (Andréassian et al., 2004; Oudin et al., 2005). However, a few studies worldwide (Palmele, 1972; Paturel et al., 1995; Andréassian et al., 2004; Oudin et al., 2005; Zhao et al., 2013; Seiller and Anctil, 2016; Kodja et al., 2020) have investigated the sensitivity of hydrological models to different PET estimation methods. In this regard, Palmele (1972) sought to analyze the impact of PET errors on hydrological model outputs for nine watersheds in the USA. He concluded that a constant 20% PET bias has a cumulative effect and can lead to errors in hydrograph fluctuation (peak and recession). Andréassian et al. (2004) analyzed the sensitivity of 42 PET estimation methods on the GR4J and TOPMODEL models in France. Their results showed that PET methods do not have too much influence on model performance, and a simplistic method gives the same performance gain as a complex method like Penman. Oudin et al., (2005) evaluated 27 PET methods in terms of streamflow simulation efficiency on a large sample of 308 catchments located in France, Australia and the USA. They concluded that simple temperature and radiation-based methods are suitable for rainfall-flow models. Seiller and Anctil (2016) evaluated 24 PET methods for their influence on hydrological projections in Canada and Germany. Their results show that hydrological models have the ability to adapt to PET methods during the calibration process. Their results showed that hydrological models are generally more sensitive to temperature and radiation-based methods than aerodynamic ones. Pimentel et al. (2023) recently evaluated the sensitivity of the Hargreaves, Priestley and Taylor and Jensen-Haise methods to the Word-wide HYPE global hydrological model in 318 catchments around the world. Their results show that the performance of the methods varies according to climate zones. Indeed, based on Köppen's (1918) climate classification, they suggested the use of the Jensen-Haise method in continental climates, the Hargreaves method in tropical and arid climates, and the Priestley-Taylor method in temperate and polar zones. This is an interesting study, as it shows that the subject is still relevant today and requires evaluation across climatic zones. Crucially, the number of PET methods used in their study is a limitation, as they investigate only radiation and temperature-based methods. What about other types of methods? Furthermore, West African watersheds are not included in this study. Hydrological processes differ according to geographical and climatic zones. It is therefore important to determine the most appropriate PET methods for hydrological modeling in West African basins. The aim of this work is thus to analyze the sensitivity of the three GR daily models to different PET estimating methods, in order to determine the appropriate data and tools for a better knowledge of water resources in the Senegal River basin.

2. Materials and methods

2.1. Study area

The Senegal River basin covers an area of over 300,000 km^2 (Bodian, 2011) and is made up of three geographical zones (OMVS, 2022): the upper basin, the valley and the delta. The population of the Senegal River basin is estimated at 7.5 million in 2020, rising to 11–17 million in 2050 (OMVS, 2022). The development of irrigated and flood-recession agriculture, hydroelectric production, navigation whilst preserving essential ecosystem services represents a major challenge for the basin's water resources (OMVS, 2022). This study concerns the upper basin, in particular the five sub-basins controlled by the Bafing Makana, Daka Saidou, Kidira, Gourbassi and Oualia hydrometric stations (Fig. 1). These stations have the particularity of not being influenced by the dams commissioned by the OMVS (Organisation pour la Mise en Valeur du fleuve Sénégal, in French). Climatically, the upper basin extends from north to south over three climatic zones (Dione, 1996): Sahelian (annual rainfall $\leq$ 500 mm), Sudanian (annual rainfall between 500 mm and 1500 mm) and Guinean (annual rainfall $\geq$ 1500 mm). Over the period 1984–2015, mean annual rainfall at basin scale is 1426 mm at Bafing Makana, 1577 mm at Daka Saidou, 1121 mm at Gourbassi, 1008 mm Kidira and 914 mm at Oualia. On a monthly scale, maximum rainfall is recorded in August and September, with values ranging from 198 to 415 mm (Fig. 2).

2.2. Data

Two sources of meteorological data are used in this work. Observed data and NASA reanalysis data.

2.2.1. Observed data

2.2.1.1. Rainfall data. Daily rainfall data were obtained from the national meteorological services of Senegal, Mali and Guinea. Fig. 3 shows that there are many gaps in the rainfall data, especially in recent periods. In the upper Senegal River basin, there are 54 stations with gaps ranging from 0.53% to almost 80%. For each basin, the stations located within the catchment are used to spatially interpolate rainfall (Fig. 1). There are seven (7) stations for the Bafing basin, six (6) for the Faleme basin and eleven (11) for the Oualia basin, i.e. a

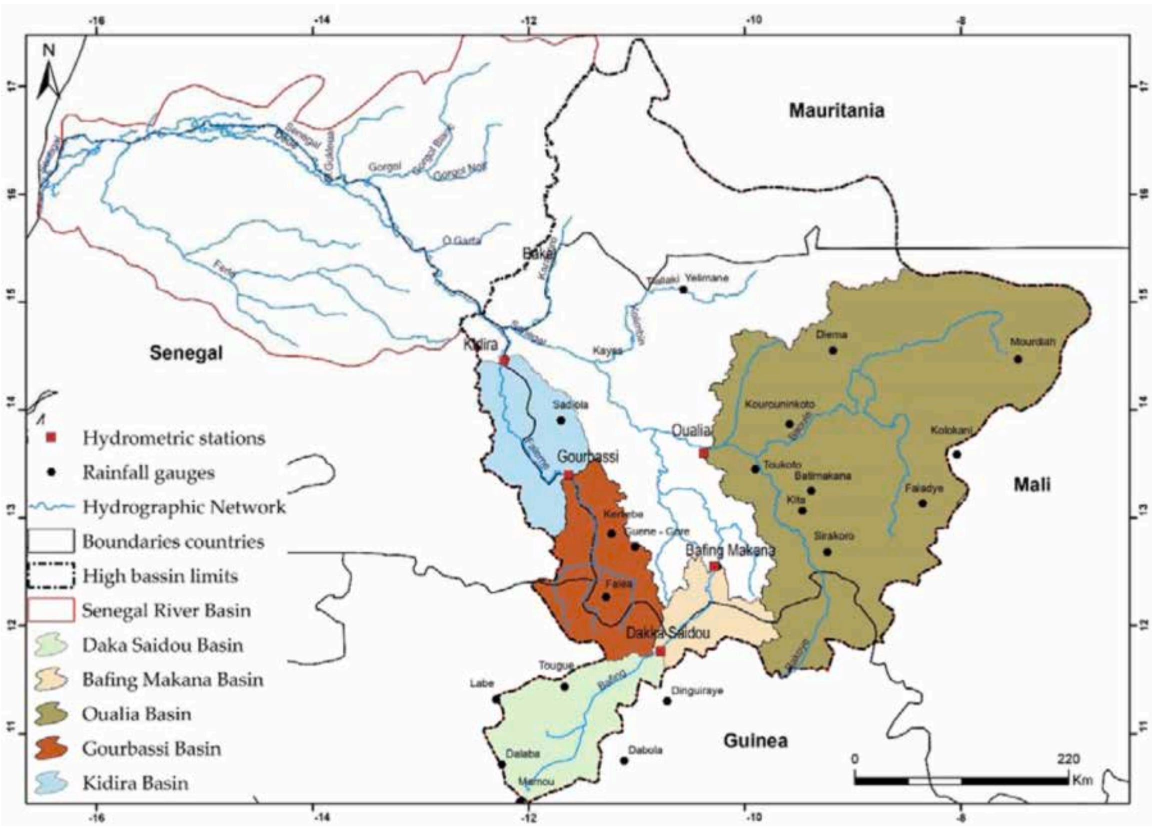

Fig. 1. Location of the study area.

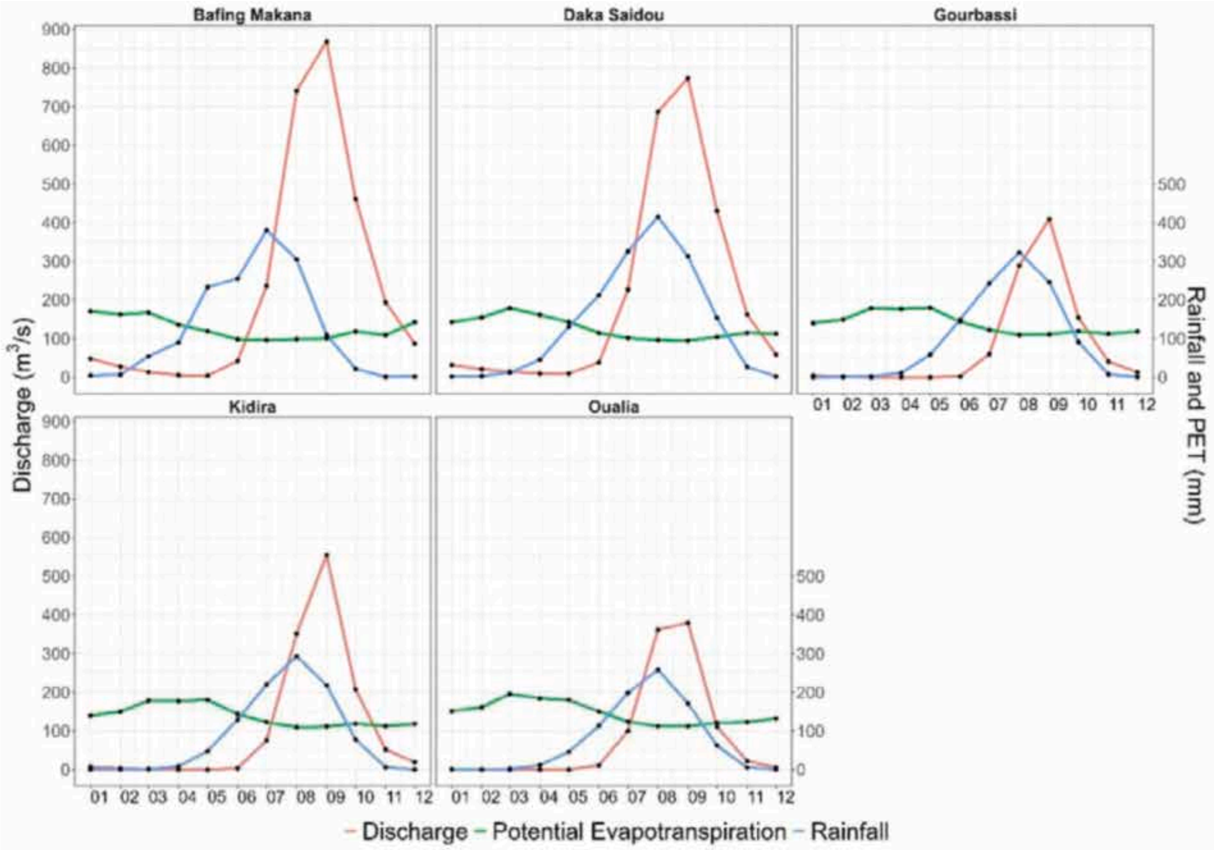

Fig. 2. Mean monthly flow, rainfall, and potential evapotranspiration over the 1984–2015 period for the five watersheds selected.

total of 24 stations are used in the study (*cf.* Fig. 1). For the Bafing basin, the longest series runs from 1950 to 2019 for Labe and Mamou, and the shortest series is 2000–2019 for the Dalaba station. Gap percentages vary from 0.2% to 80%, depending on the station. For the Faleme basin, the series obtained range from 1950 to 2009, with gap percentages from 0.9% to 27%. In the Bakoye basin, the longest series (1950–2011) is obtained at the Oualia station. Gap percentages vary from 0% to 41% depending on the station. The significant gaps over the last few decades are due to increased difficulties in accessing daily rainfall data in the region, partly because of a decline in observation networks and partly because of high acquisition costs (Bodian et al., 2016; 2020). In order to have complete series for all basins and variables (rain, PET, discharge), the period 1984–1995 is used for this study.

2.2.1.2. Discharge data. The hydrological data comes from the OMVS database and concerns five hydrometric stations from three tributaries of the Senegal river: the Bafing (at Bafing Makana and Daka Saidou stations), Faleme (at Kidira and Gourbassi) and Bakoye (at Oualia). Table 1 provides an inventory of data from each station. Compared to rainfall data, hydrological data gaps are low, ranging from 0.04% to 16% depending on the station.

2.2.1.3. Potential evapotranspiration data. For potential evapotranspiration, observed climate data from the Bamako Senou, Kenieba, Kita, Labe, Nioro du Sahel and Siguiri stations were obtained from the meteorological services of Guinea and Mali. The data consisted of temperature (max and min), relative humidity (max and min), sunshine duration and wind speed on a daily time step. Table 2 shows the periods covered by the climatic data collected. Data, except for Siguiri station, is only available for one to two-year periods but there are no gaps in the time series. They are used to calculate evapotranspiration using the Penman-Monteith reference method (Allen et al., 1998).

2.2.2. Reanalysis data

Since observed PET data are only available for a few stations and for short periods, reanalysis data from NASA Earth Science/ Applied Science Program (https://power.larc.nasa.gov, last access April, 2023) were used to calculate evapotranspiration for all stations. For more information on these data, readers may refer to the earlier studies by Ndiaye et al., (2020a), (2020b), (2021). These data consist of daily times series of maximum and minimum temperature (°C), mean relative humidity (%), wind speed (m/s) and solar radiation (MJ/m^2/d) over the period 1984–2020. The coordinates of the rainfall stations in the basins are used to extract the reanalysis data for the 1984–1995 period selected for the study, due to the limited availability of the observed PET data over this period.

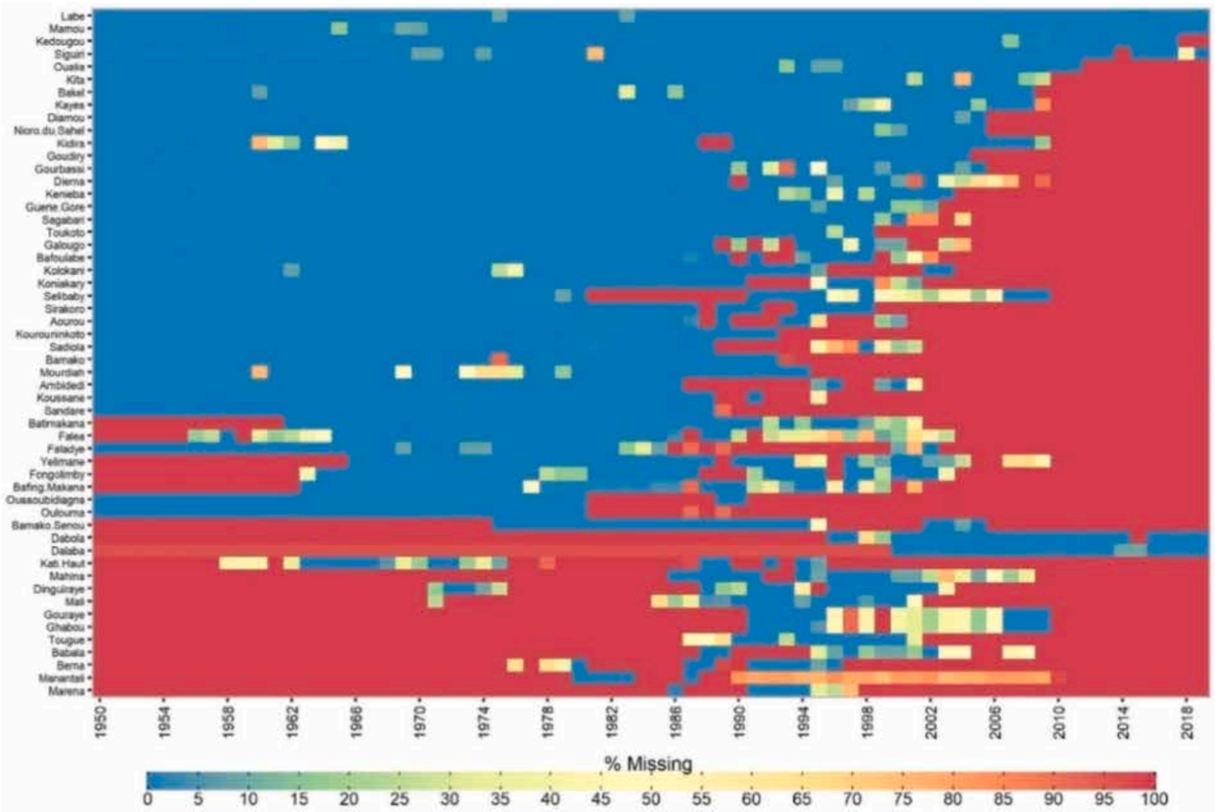

Fig. 3. Inventory of daily rainfall data from stations in the upper Senegal River basin.

Table 1
Inventory of hydrological data from the hydrometric stations selected for the study.

Stations	Areas of Basins (km^2)	Latitude	Longitude	Start of time series	End of time series	%Gap
Bafing Makana	22,419	12.55	-10.28	02/01/1961	21/04/2016	0.04
Daka Saidou	15,061	11.95	-10.62	27/05/1952	21/04/2016	1.02
Gourbassi	28,515	13.40	-11.63	02/01/1954	24/03/2016	0.17
Kidira	15,680	14.45	-12.22	01/05/1951	24/03/2016	16
Oualia	87,931	13.60	-10.38	01/06/1954	24/03/2016	1.9

Table 2
Inventory of observed climatic variables for PET calculation.

Stations	Latitude	Longitude	Start of time series	End of time series
Bamako Senou	12.53	-7.95	01/01/2002	31/12/2003
Kenieba	12.85	-11.23	01/01/2003	31/12/2003
Kita	13.06	-9.47	01/01/2003	31/12/2003
Labe	11.31	-12.30	01/01/1984	31/12/1995
Nioro du Sahel	15.23	-9.60	01/01/2002	31/12/2002
Siguiri	11.43	-9.17	01/01/1984	31/12/1996

2.3. Presentation of PET methods and hydrological models

2.3.1. PET estimation methods

Evapotranspiration is estimated using the Penman-Monteith method (Allen et al., 1998) and by twenty other methods classified into four categories: aerodynamic methods, temperature-based methods, radiation-based methods and combinatorial methods. The characteristics of these methods are given in Table 3. Combinatorial and Penman-Monteith methods integrate a minimum of 3–4 climatic variables: temperature, relative humidity, solar radiation and wind speed. Aerodynamic methods require 2 variables, such as temperature and wind speed. Solar radiation (or sunshine duration) and temperature (max and min) are the only variables required for the radiation and temperature-based categories.

2.3.2. Hydrological Models description

A detailed description of the GR models (GR4J, GR5J and GR6J) can be found in several studies (Perrin et al., 2003; Le Moine, 2008; Pushpalatha et al., 2011) but their basic principles are summarized below (Fig. 4). The GR4J model has four parameters: X1 (mm) production reservoir capacity, X2 (mm/day) surface-ground exchange coefficient, X3 (mm) maximum transfer reservoir capacity and

Table 3
Characteristics of the 21 PET estimation methods used.

Methods	References	Formulation	Abreviation	Number of Variables	N°
Penman-Monteith	Allen et al. (1998)	$ET_0 = \frac{0.408\Delta(Rn - G) + \frac{\gamma Cn}{T + 273.3}u2(es - ea)}{\Delta + \gamma(1 + Cdu2)}$	PM	4	(Eq. 1)
Aerodynamic	Dalton (1802)	$ET_0 = (0.3648 + 0.07223 \times u2) \times (es - ea)$	DN		(Eq. 2)
	Trabert (1896)	$ET_0 = 0.3075 \times \sqrt{u2} \times (es - ea)$	TR		(Eq. 3)
	Penman (1948)	$ET_0 = 0.35 \times (1 + 0.24 \times u2) \times (es - ea)$	PN	2	(Eq. 4)
	Rohwer (1931)	$ET_0 = 0.44 \times (1 + 0.27 \times u2) \times (es - ea)$	RH		(Eq. 5)
	Mahringer (1970)	$ET_0 = 0.15072 \times \sqrt{3.6u2} \times (es - ea)$	MH		(Eq. 6)
Temperature	Hargreaves (1975)	$ET_0 = 0.0135 \times 0.408 \times Rs \times (T + 17.8)$	HG		(Eq. 7)
	Hargreaves and Samani (1985)	$ET_0 = 0.0023 \times (T + 17.8) \times (Tmax - Tmin)^{0.5} \times Ra$	HS		(Eq. 8)
	Trajkovic and Stojvic (2007)	$ET_0 = 0.0023 \times (T + 17.8) \times (Tmax - Tmin)^{0.424} \times Ra$	TJ	1	(Eq. 9)
	Droogers et Allen (2002)	$ET_0 = 0.0025 \times (T + 16.8) \times (Tmax - Tmin)^{0.5} \times Ra$	DA		(Eq. 10)
	Heydari and Heydari (2014)	$ET_0 = 0.0023 \times Ra \times (T + 9.519) \times (Tmax - Tmin)^{0.611}$	HH		(Eq. 11)
Radiation	Makkink (1957)	$ET_0 = 0.61 \times \frac{\Delta}{\Delta + \gamma} * \frac{Rs}{\lambda} - 0.012$	MK		(Eq. 12)
	Jensen and Haise (1963)	$ET_0 = 0.025(T - 3) \times Rs$	JH		(Eq. 13)
	Priestley-Taylor (1972)	$ET_0 = \alpha \times \frac{\Delta}{\Delta + \gamma} \times \frac{Rn}{\lambda}$	PT	1	(Eq. 14)
	Abtew (1996)	$ET_0 = 0.53 \times \frac{Rs}{\lambda}$	AB		(Eq. 15)
	Oudin (2005)	$ET_0 = Rs \times \frac{T + 5}{100}$	OD		(Eq. 16)
Combinatory	Penman (1963)	$ET_0 = \left[\frac{\Delta}{\Delta + \gamma} \times (Rn - G) + \frac{\gamma}{\Delta + \gamma} \times 6.43 \times (1 + 0.053 \times u2) \times (es - ea)\right]/\lambda$	PEN		(Eq. 17)
	Doorenbos-Pruitt (1977)	$ET_0 = \left[\frac{\Delta}{\Delta + \gamma} \times (Rn - G) + 2.7 \times \frac{\gamma}{\gamma + \Delta} \times (1 + 0.864 \times u2) \times (es - ea)\right]/\lambda$	DP		(Eq. 18)
	Valiantzas 1 (2013)	$ET_0 = 0.0393 \times Rs \times \sqrt{T + 9.5} - 0.19 \times Rs^{0.6} \times \varphi^{0.15} + 0.048 \times (T + 20) * \left(1 - \frac{Hr}{100}\right) \times u2^{0.7}$	Val1	4	(Eq. 19)
	Valiantzas 2 (2013)	$ET_0 = 0.0393 \times Rs \times \sqrt{T + 9.5} - 0.19 \times Rs^{0.6} \times \varphi^{0.15} + 0.078 \times (T + 20) \times \left(1 - \frac{Hr}{100}\right)$	Val2		(Eq. 20)
	Valiantzas 3 (2013)	$ET_0 = 0.0393 \times Rs \times \sqrt{T + 9.5} - 0.19 \times Rs^{0.6} \times \varphi^{0.15} + 0.0061 \times (T + 20) \times (1.12 \times T - Tmin - 2)^{0.7}$	Val3		(Eq. 21)

Read: ET_0 reference evapotranspiration (mm), u2 represents wind speed measured at 2 m from the ground (m-1 s), (es - ea) saturation deficit (KPa/°C), Rs is solar radiation MJ/m2/d, T is mean temperature, Tmax maximum temperature, Tmin minimum temperature and Ra is extraterrestrial radiation, Δ is the saturation vapor pressure curve (KPa/°C), γ the psychometric constant (KPa/°C), λ is the latent heat of vaporization (MJ/m2/d), Rs is the short-wave solar radiation (MJ/m2/d), T is the mean temperature $(°C)^2$, Rn is the net radiation (MJ/m2/d), Tmax maximum temperature (°C), α is a constant value (1.26 for humid areas and 1.74 for semi-arid areas) and the C_test a coefficient that is equal to 0.025 and Tx= −3. These coefficients are considered constant for a given region (Xu and Singh, 2001). φ, represents the latitude of the station in radian degrees, λ is the latent heat of vaporization (MJ/m2/J).

X4 (days) is the base time of unit hydrograph 1 (UH1). The contribution of groundwater to runoff is controlled by parameter X2. If X2 < 0, groundwater contributes to surface runoff and if X2 > 0, surface runoff feeds groundwater. Examples of GR4J parameter values obtained can be found in the scientific literature (Smith et al., 2019; Zeng et al., 2019; Wei et al., 2021). GR5J is a modification of GR4J and incorporates a new X5 parameter. This parameter makes it possible to account for underground exchanges within complex watersheds (Flores et al., 2021). Parameter X5 thus allows the import and export of deep water from aquifers or reservoirs close to the basin (Pushpalatha et al., 2011). It is dimensionless and can be positive or negative. In the GR6J model, a sixth parameter X6 (mm) represents an exponential reservoir. Compared with GR4J and GR5J, the GR6J model is designed to enable better simulation of low-flow rates thanks to this exponential reservoir (Gosset, 2014; Delaigue et al., 2022). This parameter X6 cannot be negative, so it has values greater than or equal to zero (Flores et al., 2021). Fig. 4 shows the conceptual diagram of the three GR models operating at a daily time step.

2.4. Methods

The methodological approach comprises four main phases: (i) validation of the PET calculated with the reanalysis data against that calculated with the observed climate variables, (ii) calculation of the average rainfall and PET for the five sub-basins, (iii) evaluation of the performance of the three models and (iv) sensitivity analysis of the GR models to the 21 methods for estimating evapotranspiration.

2.4.1. Validation of PET calculated from reanalysis data with observed data

The PET calculated from ground observations at the six stations is compared with PET calculated from reanalysis data using 21 methods. The evaluation criteria used are the Kling Gupta Efficiency (KGE, Gupta et al., 2009) and the percentage bias (PBIAS), which are expressed by the following formulas:

$$KGE = 1 - \sqrt{(r-1)^2 + (\beta-1)^2 + (\alpha-1)^2} \tag{22}$$

$$PBIAS = \left[\frac{\frac{1}{n}\sum_{i=1}^{n}(V_{sim} - V_{obs})}{\frac{1}{n}\sum_{i=1}^{n}(V_{sim})}\right] \times 100 \tag{23}$$

Where r is Pearson's correlation coefficient, β is bias and α variability, V_{sim} simulated variable, V_{obs} observed variable and n is series length.

2.4.2. Calculation of basin rainfall and evapotranspiration

Average rainfall over the catchments was calculated from rainfall gauge data (Fig. 1) using the inverse distance weighting (IDW) interpolation method (Bodian et al., 2012, 2020), available in Hydraccess (Vauchel, 2004). Evapotranspiration for each station was calculated by the Penman-Monteith method and by twenty other methods presented in Table 3. Then, for each of the 21 methods, the

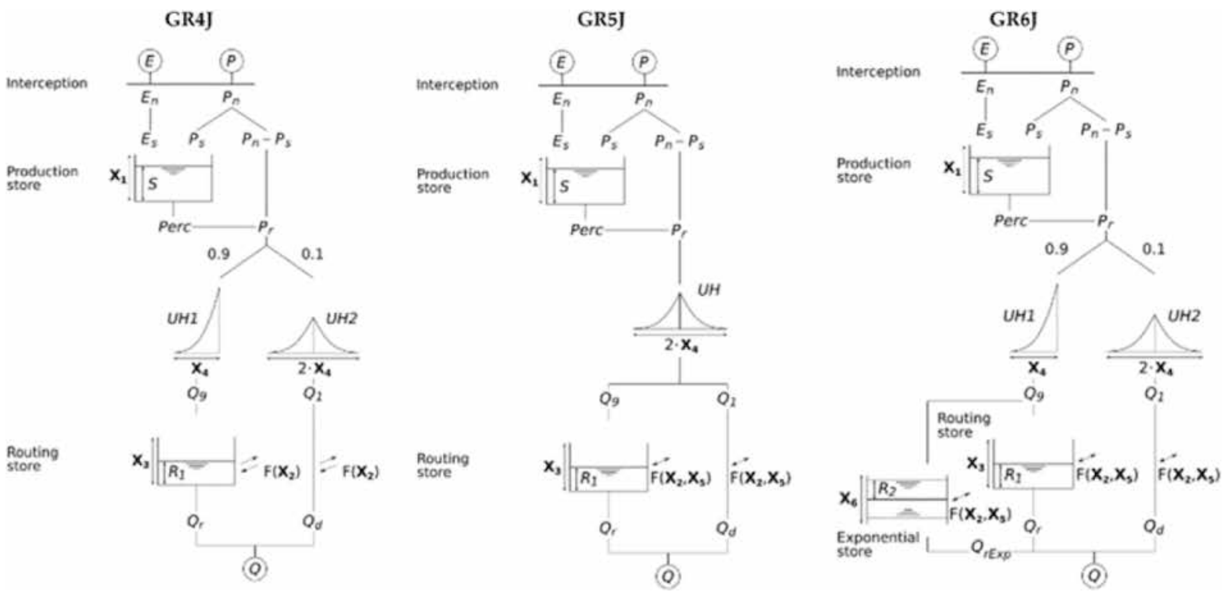

Fig. 4. Structure of GR4J (Perrin et al., 2003), GR5J (Le Moine, 2008) and GR6J (Pushpalatha et al., 2011) models.

average PET across each catchment was calculated using the IDW method.

2.4.3. Calibration/validation of GR models

Each of the three GR hydrological models was calibrated and then validated with Penman-Monteith PET and that of the 20 other methods. For this purpose, the period of availability of PET data (1984–1995) was divided into two sub-periods: P1 (1984–1990) for calibration and P2 (1991–1995) for validation. For each sub-period, a model initialization time of two years was used. The "Calibration Michel" (Michel, 1991) proposed by default in the package airGR is used in this study to calibrate each GR model with different PET methods. The algorithm combines a global and local approach. First, a screening is performed using either a rough predefined grid or a list of parameter sets. Then a steepest descent local search algorithm is performed, starting from the result of the screening procedure. A screening is first performed either based on a rough predefined grid (considering various initial values for each parameter) or from a list of initial parameter sets. For this search, since the ranges of parameter values can be quite different, simple mathematical transformations are applied to parameters to make them vary in a similar range and get a similar sensitivity to a predefined search step. This is done using the TransfoParam functions. During the steepest descent method, at each iteration, we start from a parameter set of NParam values (NParam being the number of free parameters of the chosen hydrological model) and we determine the 2*NParam-1 new candidates by changing one by one the different parameters (+/- search step). All these candidates are tested and the best one kept to be the starting point for the next iteration. At the end of each iteration, the search step is either increased or decreased to adapt the progression speed. A composite step can occasionally be done. The calibration algorithm stops when the search step becomes smaller than a predefined threshold which is our objective function. Here the KGE (Gupta et al., 2009) is used. The best set of parameters identified in this screening phase is then used as a starting point for the steepest descent local search algorithm. By applying this calibration process, we had 74 iterations with 697 runs.

Model performance is then assessed by the KGE and PBIAS previously described (Eqs. (22) and (23)). In addition to these criteria, flow quantiles are determined to analyze model performance in simulating different types of flow. Low-water flows represented by Q95 is the value exceeded by 95% of flows, mean flows by Q50 and peak flows by Q5.

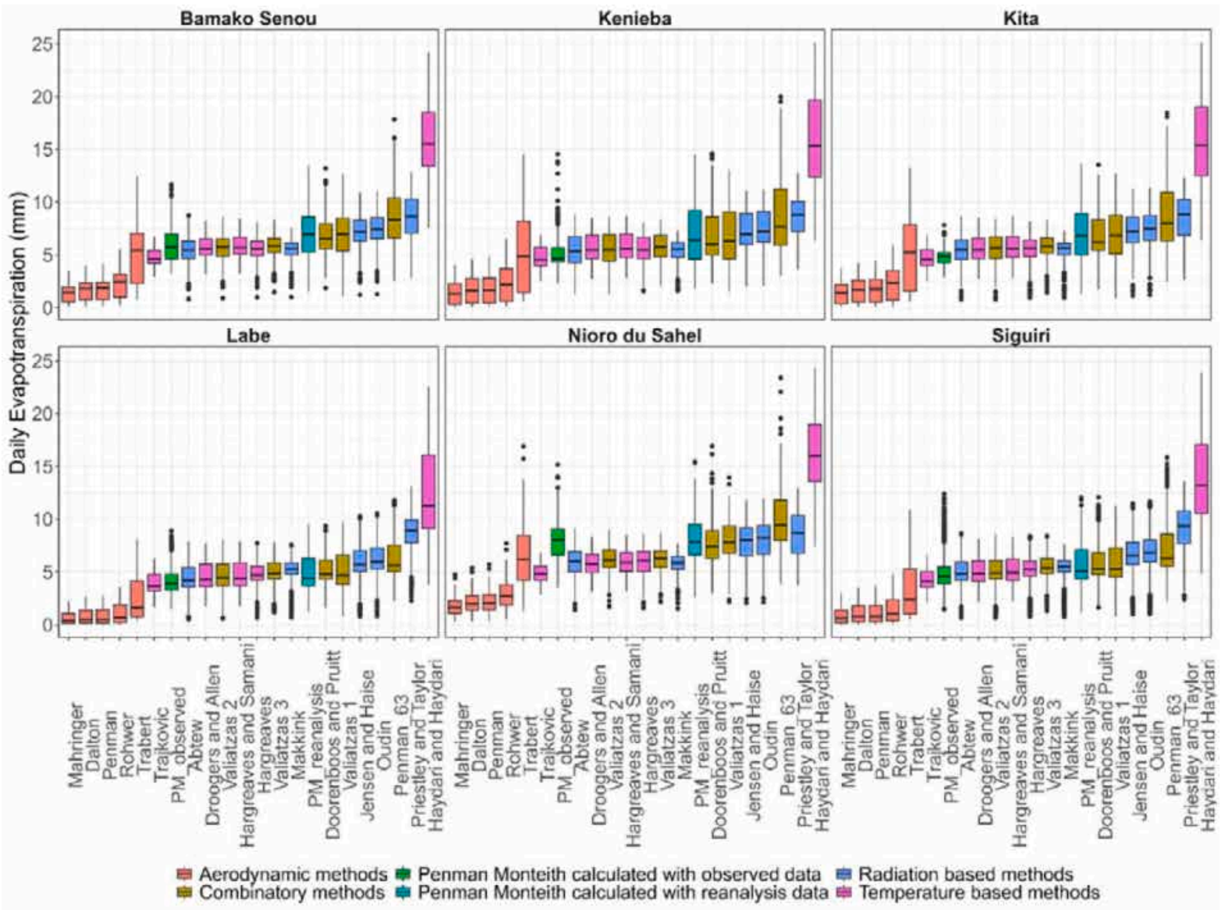

Fig. 5. Daily evapotranspiration calculated with observed and reanalysis data.

2.4.4. Sensitivity analysis of GR models to PET estimation methods

According to Andréassian et al., (2004), there are two types of methods to analyze the sensitivity of a hydrological model to potential evapotranspiration sources: the static approach and the dynamic method. The static approach involves calibrating the model with observed reference data and applying the same parameters to simulate flows according to the different PET methods. The dynamic method, on the other hand, involves calibrating the model not only with observed reference data, but also with all the PET methods. This method shows the model's ability to readjust to the errors of different methods. The dynamic approach is used in this work.

3. Results

3.1. Validation of PET calculated from reanalysis data vs. observed data

PET calculated from reanalysis data is compared at the Labe, Siguiri, Kita, Kenieba, Bamako Senou and Nioro du Sahel stations, where the observed climate variables (temperature, sunshine duration, relative humidity and wind speed) were available to calculate PET using the Penman-Monteith method. Fig. 5 shows the boxplots of daily PET calculated from observed and reanalysis data using each method, while Fig. 6 shows the KGE barplots. Compared with the observed PET, the best performances are obtained by the combinatorial methods of Doorenboss-Pruit and Valiantzas 2, the temperature-based methods of Droogers-Allen and Hagreaves-Samani and the radiation-based method of Abtew. Heydari-Heydari (temperature-based), Priestley-Taylor (radiation-based) and aerodynamic methods are less robust. KGEs vary from −1.19–0.54 and PBIAS from 1.8% to 43%, depending on the station. All other methods tend to overestimate evapotranspiration, with the exception of aerodynamic methods, which underestimate it by 85%.

3.2. Performance of GR models

As a reminder, each model was calibrated over the P1 period (1986–1990) and then validated over the P2 period (1991–1995). Fig. 7 shows the monthly hydrograph of observed and simulated discharge over the calibration and validation period. Table 4 summarizes the KGE and PBIAS values obtained in calibration and validation, and the quantiles of simulated and observed daily flows. The models performed best in the Bafing basin (at Bafing Makana and Daka Saidou stations), with KGE values ranging from 0.87 to 0.91 in calibration and from 0.69 to 0.93 in validation. PBIAS remain below 20% in both calibration and validation. All three GR models performed well in the Bafing basin, but the best results were obtained by the GR4J model at Bafing Makana and the GR6J model at

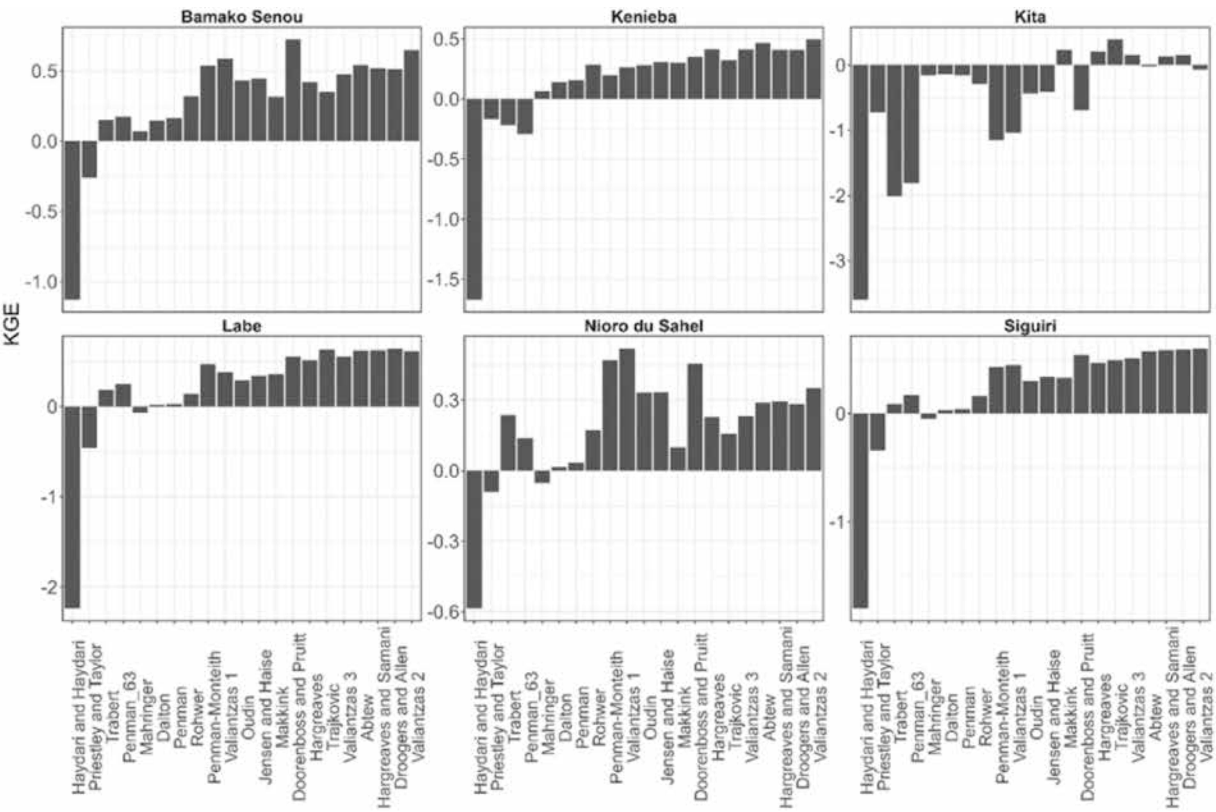

Fig. 6. KGE bar plot of PET calculated with observed and reanalysis data.

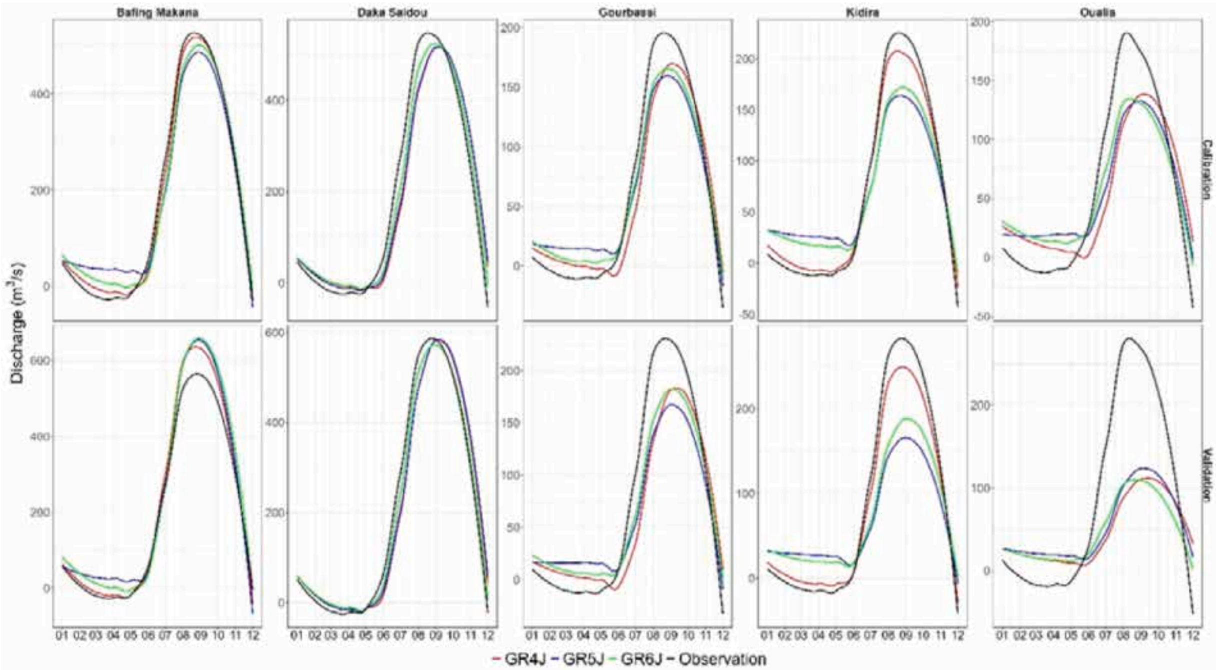

Fig. 7. Monthly hydrograph of observed and simulated flows in calibration and validation periods.

Table 4
KGE, PBIAS, and flow quantiles in calibration and validation.

Stations		Calibration (1986–1990) Q95 (mm)	Q50 (mm)	Q05 (mm)	KGE	PBIAS	Validation (1991–1995) Q95 (mm)	Q50 (mm)	Q05 (mm)	KGE	PBIAS
	Qobs	0.0018	0.1755	2.7868			0.0017	0.1982	3.0609		
	GR4J	0.0463	0.1693	2.9799	0.94	-0.1	0.0514	0.1989	3.5914	0.84	10.1
Bafing Makana	GR5J	0.1518	0.2070	2.8399	0.89	0.2	0.1524	0.2071	3.9267	0.69	16.3
	GR6J	0.0828	0.2026	2.9194	0.91	0.8	0.0969	0.2588	3.7617	0.72	19.8
	Qobs	0.0253	0.1992	4.3300			0.0286	0.2270	4.6135		
Daka Saidou	GR4J	0.0555	0.2545	4.0523	0.87	-0.1	0.0506	0.3004	4.5708	0.9	1.8
	GR5J	0.0389	0.2863	4.0877	0.88	1	0.0310	0.3571	4.8629	0.89	3.4
	GR6J	0.0817	0.2650	4.1693	0.91	0.7	0.0767	0.2817	4.5986	0.93	-0.3
	Qobs	0.0000	0.0088	1.0529			0.0000	0.0149	0.4506		
	GR4J	0.0096	0.0339	0.8393	0.78	-4.7	0.0109	0.0415	1.3395	0.71	-12.3
Kidira	GR5J	0.0606	0.0929	0.6821	0.8	0.2	0.0605	0.0929	0.9004	0.68	-12.8
	GR6J	0.0353	0.0799	0.8313	0.83	0.3	0.0347	0.0922	0.8917	0.75	-6.4
	Qobs	0.0000	0.0131	1.5557			0.0000	0.0203	2.1681		
Gourbassi	GR4J	0.0132	0.0448	1.6252	0.87	0	0.0206	0.0653	1.6749	0.81	-7.2
	GR5J	0.0717	0.1122	1.3975	0.79	-0.2	0.0712	0.1117	1.4685	0.54	-21.1
	GR6J	0.0370	0.0889	1.4675	0.79	0	0.0387	0.1088	1.7159	0.61	-13.3
	Qobs	0.0000	0.0006	0.2632			0.0000	0.0036	0.4723		
Oualia	GR4J	0.0064	0.0170	0.1609	0.8	-1.7	0.0091	0.0186	0.1634	0.28	-41.1
	GR5J	0.0162	0.0242	0.1439	0.82	0.6	0.0210	0.0240	0.2083	0.34	-35.1
	GR6J	0.0061	0.0207	0.1757	0.87	0.1	0.0053	0.0211	0.1765	0.29	-43.4

Daka Saidou (Table 4). They also tend to overestimate the various flow classes, especially at Bafing Makana. For the Faleme basin at Kidira and Gourbassi, the KGE values of all three models range from 0.78 to 0.87 in calibration and from 0.54 to 0.81 in validation. The error percentages are also below 20%, and the models tend to underestimate flows in the Faleme basin, especially in validation. The models still overestimate low-water flows. The models perform less well in the Bakoye basin at Oualia. Indeed, in validation, model performance dropped sharply, with KGEs below 0.40. The models also underestimated Bakoye flows, with error percentages of over 40% for all three models. Individually, for the Bakoye basin, the GR5J model is the most robust of the three models, with KGEs of 0.82 and 0.34 and PBIASs of 0.6% and 35% in calibration and validation. The models overestimate mean and low-water flows and underestimate peak flows at Oualia. Overall, the results in each of the five basins show that the three GR models reproduce flows in a similar way in terms of histograms and overall performance.

3.3. Model performance in calibration and validation using different PET methods

The three GR models were then calibrated and validated using the 21 PET estimation methods. Fig. 8 illustrates the monthly hydrograph obtained for each station and each GR model (in validation) with PET data from the 21 different methods. Fig. 9 provides heatmaps of the corresponding KGE and PBIAS values. Using PET from all 21 methods, the GR models can reproduce the overall flow regime, however, there are significant differences in terms of performance values. Aerodynamic methods yield the best performance across all three GR models, followed by the Droogers and Allen temperature-based method in the Bafing basin. The same observations apply to the Faleme basin at Kidira and Gourbassi. All GR models behave in broadly the same way when using a specific PET method. However, aerodynamic and temperature-based models are consistently more robust. Compared to the other basins, the results in the Bakoye (Oualia station) are quite distinct. Indeed, in calibration, all three GR models and all PET methods performed well, with KGE above 0.70 and PBIAS below 10%. In validation, however, model performance deteriorated, with KGE below 0.70 and PBIAS over 20%, depending on the PET estimation method used. In terms of GR models, the best performance at Oualia was obtained by the GR5J model, calibrated and validated using the aerodynamic methods of Dalton, Mahringer and Rohwer. In validation, the KGEs of the aerodynamic methods remain higher than 0.60. PBIAS value also show that for flows at the Bafing Makana and Daka Saidou stations, the models overestimate flows for most of the PET methods used. Only the aerodynamic methods show an underestimation of flows by the various models. On the other hand, at the Kidira, Gourbassi and Oualia stations, for almost all PET methods, the three GR models underestimated flows, especially in validation.

4. Discussion

The errors found here in the PET calculated from reanalysis data can be traced to the input variables of the PET methods. Indeed, Ndiaye et al. (2021) assessed the robustness of reanalysis of climatic variables (temperature, relative humidity and wind speed) against observed data for a number of stations in the Senegal River basin. They conclude that there is a good agreement between observed temperatures (max and min) and those from the reanalysis data, with KGEs greater than 0.50. However, for wind speed and relative humidity, the correlation remains weak. This may explain why temperature-based methods are more robust than others, including Penman-Monteith, which incorporate wind speed and relative humidity. However, despite the lower performance of some methods, all of these methods are used in the GR model calibration/validation phase. This allows us to assess how the estimation errors of some PET

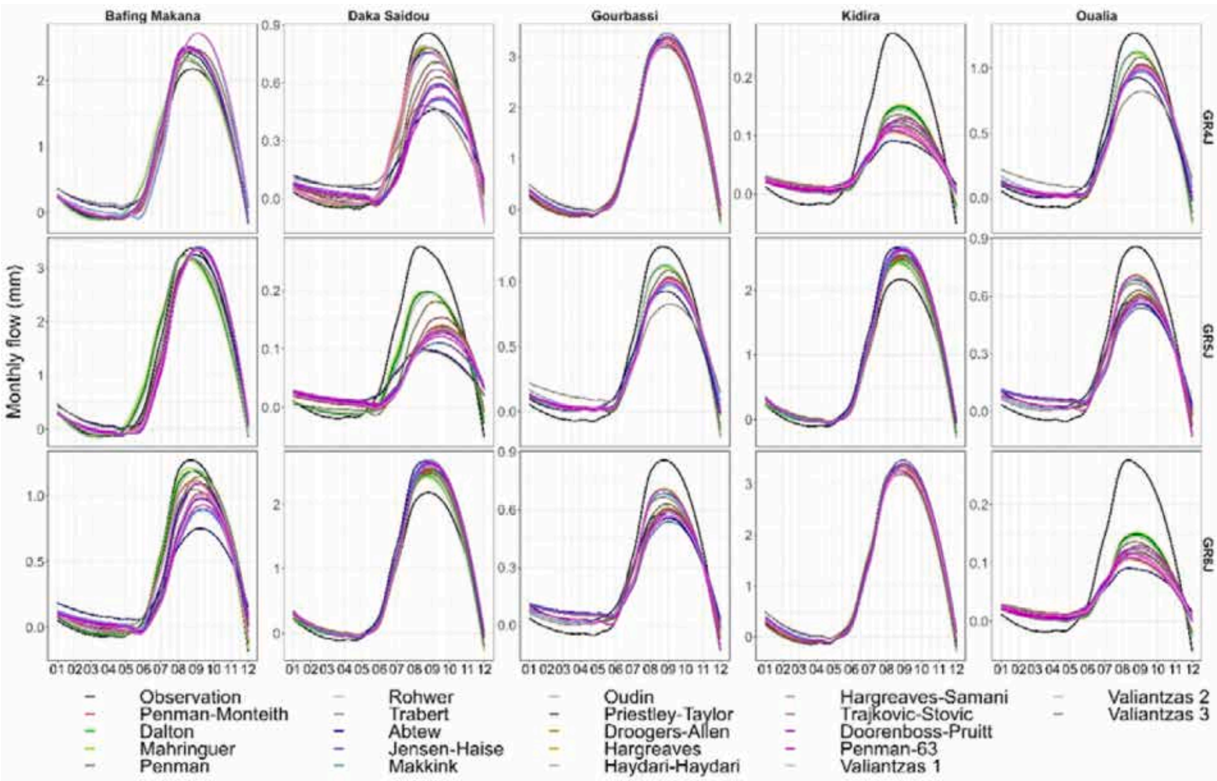

Fig. 8. Monthly hydrograph of observed and simulated by the three models as a function of the 21 PET methods.

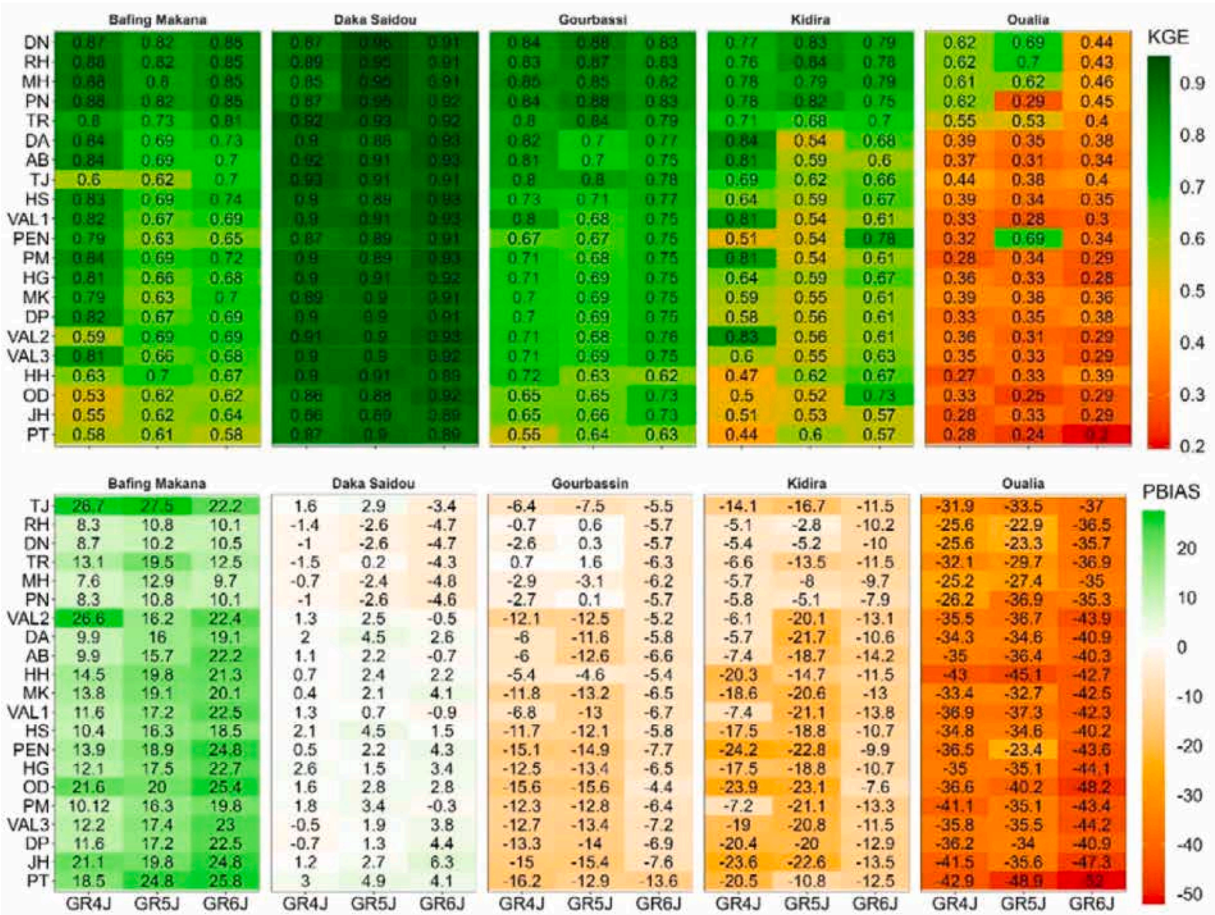

Fig. 9. Heatmap of KGE for simulated and observed flows in validation period (red: DN Dalton, RH Rohwer, MH Mahringuer, PN Penman (aerodynamic), TR Trabert, DA Droogers and Allen, AB Abtew, TJ Trajkovic, Val 1, 2, 3 Valiantzas 1, 2, 3, HS Hargreaves and Samani, PEN Penman (combinatory),HG, Hargreaves, MK Makkink, HH Heydari and Heydari, OD Oudin, JH Jensen and Haise, PT Priestley and Taylor).

methods influence the performance of the hydrological models.

The performance of the three GR models was evaluated using the Penman-Monteith method considered as the reference method (Allen et al., 1998). The GR4J model is the more robust than GR5J and GR6J in the Senegal River sub-basins. All GR models also tend here to overestimate flows. Overestimation of flows by GR4J was noted in the Senegal River by Bodian et al. (2018). It should also be noted that model performance varies from one basin to another. Performance is generally good for the Bafing and Faleme basins. However, for the Oualia basin, which has a much larger surface area than the other basins, the performance of all three models is good during calibration, but deteriorates during validation. This deterioration during the validation period is generally linked to the absence of optimization functions and readjustment of model parameters (Gupta et al., 2009). Indeed, in calibration process the model parameters are adjusted with the KGE in order to have the best performance of models. However, in validation process, there is no optimization parameter. The difference in model performance depending on the catchment could be explained by the fact that GR models are sensitive to catchment size (Tian et al., 2018). These authors thus noted that the GR4J model is more robust in small (spatially more homogeneous) basins than large basins, given the structure of this model. The basins where the models perform better are almost similar in terms of surface area. Indeed, the surface area of the Bafing basin at Makana is 22,419 km^2 and 15,061 km^2 at Daka Saidou. The Faleme at Kidira has a surface area of 28,515 km^2 and 15,680 km^2 at Gourbassi. All these watersheds are also located in the Sudano-Guinean climatic zone between isohyets 1,000 and 1,500 mm. This shows that they are relatively homogeneous from a spatial point of view. However, the Bakoye basin at Oualia stands out from the others in terms of its surface area and climatic range. It covers an area of 87,931 km^2 and spans three climates: Sahelian, Sudanian, and Guinean. Accordingly, a global hydrological model will be unable to represent the different runoff processes operating in different parts of such a large, heterogeneous catchment. These results appear to confirm the works of Ávila et al. (2022) who noted that global models are limited in their ability to represent the hydrological regimes of basins larger than 50,000 km^2, due to their heterogeneity and spatial variability.

After analyzing the models' performance in simulating observed flows, 21 PET estimation methods were used to calibrate/validate the GR4J, GR5J, and GR6J models. The choice of a method can be made on the basis of its performance and the number of climatic variables it incorporates. In this respect, methods based on temperature, radiation, and aerodynamics have the same performance gain as the more complex Penman-Monteith method, which requires more climatic variables. The classification (Fig. 10) shows that the best performance of GR models was achieved by the aerodynamic methods of Dalton, Rohwer, and Mahringer. This result is a little surprising, since in the evaluation of PET methods in relation to observed data, these aerodynamic methods were less robust, with error percentages in excess of 50%. They have very low PET values and tend to underestimate evapotranspiration. This situation shows that GR models have the capacity to readjust the estimation errors of PET methods. These results are in line with other studies (Palmele, 1972; Paturel et al., 1995; Andréassian et al., 2004; Oudin et al., 2005) which have shown that GR models can readjust simulated flows to the systematic errors of PET methods. The performance of aerodynamic PET models may be explained by their structure. These aerodynamic methods are governed by relative humidity and wind speed. However, in the Senegal River basin, Ndiaye et al., (2020b) have shown that evapotranspiration is more sensitive to variations in relative humidity and wind speed. The performance of these aerodynamic methods can also be analyzed in terms of their influence on model parameters. The two parameters most influenced by the PET methods are X1 and X2 (Fig. 11). In fact, it can be seen that due to their low PET values, aerodynamic methods exert less pressure on parameter X1, which represents the capacity of the production reservoir. For this reason, they have the highest X1 values compared with the other methods. This can be explained by the fact that reservoir controlled by parameter X1 is fed by rain and emptied by evapotranspiration. The higher the evapotranspiration, the more this reservoir is emptied, and vice versa. The X2 parameter is best suited to the various PET methods (Andréassian et al., 2004). According to these authors, X2 is positive when the PET is overestimated (water gain for the reservoir) and negative when it is underestimated (water loss for the reservoir). This is confirmed in this study, as all methods that underestimate PET have a negative X2. The Heydari and Heydari and Priestley-Taylor methods, which overestimate PET, produce generally positive X2 values. On the other hand, the results of this study are out of step with those of Oudin et al. (2005), who noted that aerodynamic methods were the least robust of the 27 PET methods evaluated in 308 watersheds in the USA, France and Germany. In wetter regions, evapotranspiration is much more influenced by temperature and solar radiation (Irmak et al., 2003; Ambas and Baltas, 2012). In arid and semi-arid regions, on the other hand, wind speed and saturation deficit play a major role in evapotranspiration. For this reason, aerodynamic methods generally tend to be more robust in arid and semi-arid regions. After the aerodynamic methods, Droogers and Allen's temperature-based and Abtew's radiation-based methods perform well for flow simulation. These results corroborate the findings of Oudin et al., (2005) who noted that the performance of rainfall-runoff models can be improved by using a simple temperature-based method. However, the radiation-based method proposed by Oudin et al., (2005) is not the best of the radiation-based methods. It is ranked among the three least efficient methods in the context of the Senegal River basin. Abtew's method is better than Oudin's among the radiation-based methods. The Droogers and Allen (DA) temperature-based method has the advantage of requiring only temperature data, which is easier to obtain in the West African context. Furthermore, because of its number of climatic variables and its performance gain, which is identical to that of Penman-Monteith, the DA method is

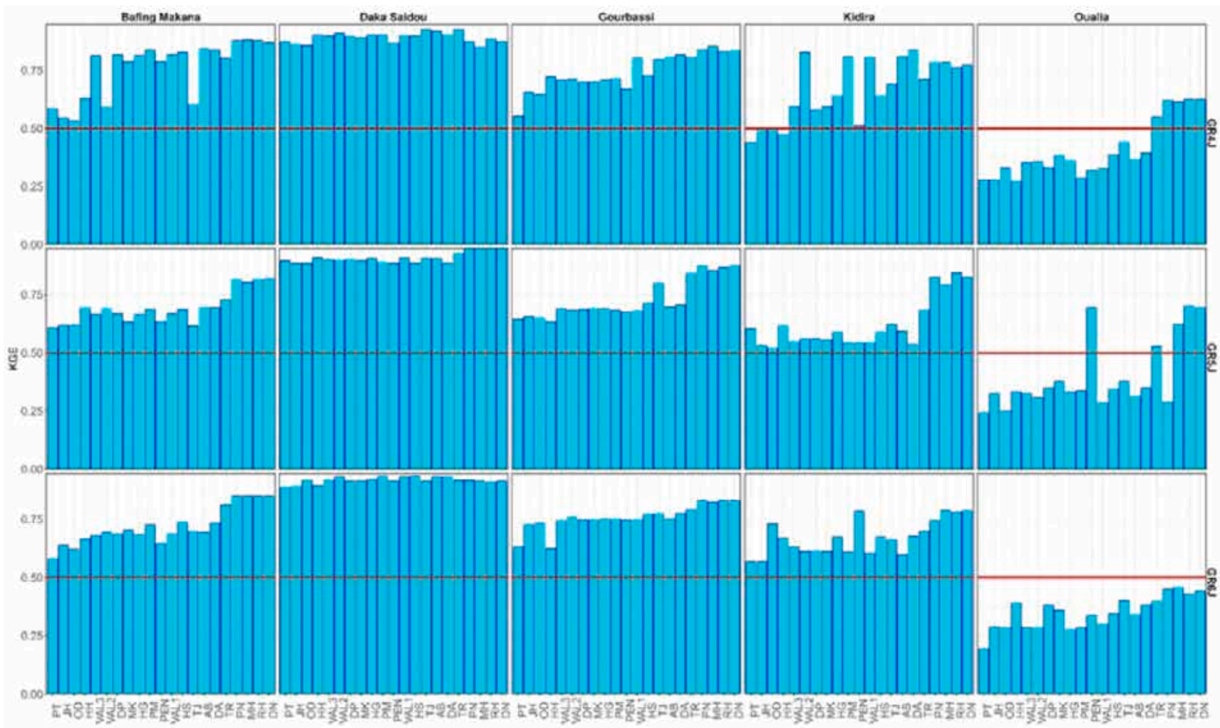

Fig. 10. Classification of methods by order of performance (red line represents the average KGE value over the validation period) (read: DN Dalton, RH Rohwer, MH Mahringuer, PM Penman-Monteith, PN Penman (aerodynamic), TR Trabert, DA Droogers and Allen, AB Abtew, TJ Trajkovic, Val 1, 2, 3 Valiantzas 1, 2, 3, HS Hargreaves and Samani, PEN Penman (combinatory),HG, Hargreaves, MK Makkink, HH Heydari and Heydari, OD Oudin, JH Jensen and Haise, PT Priestley and Taylor).

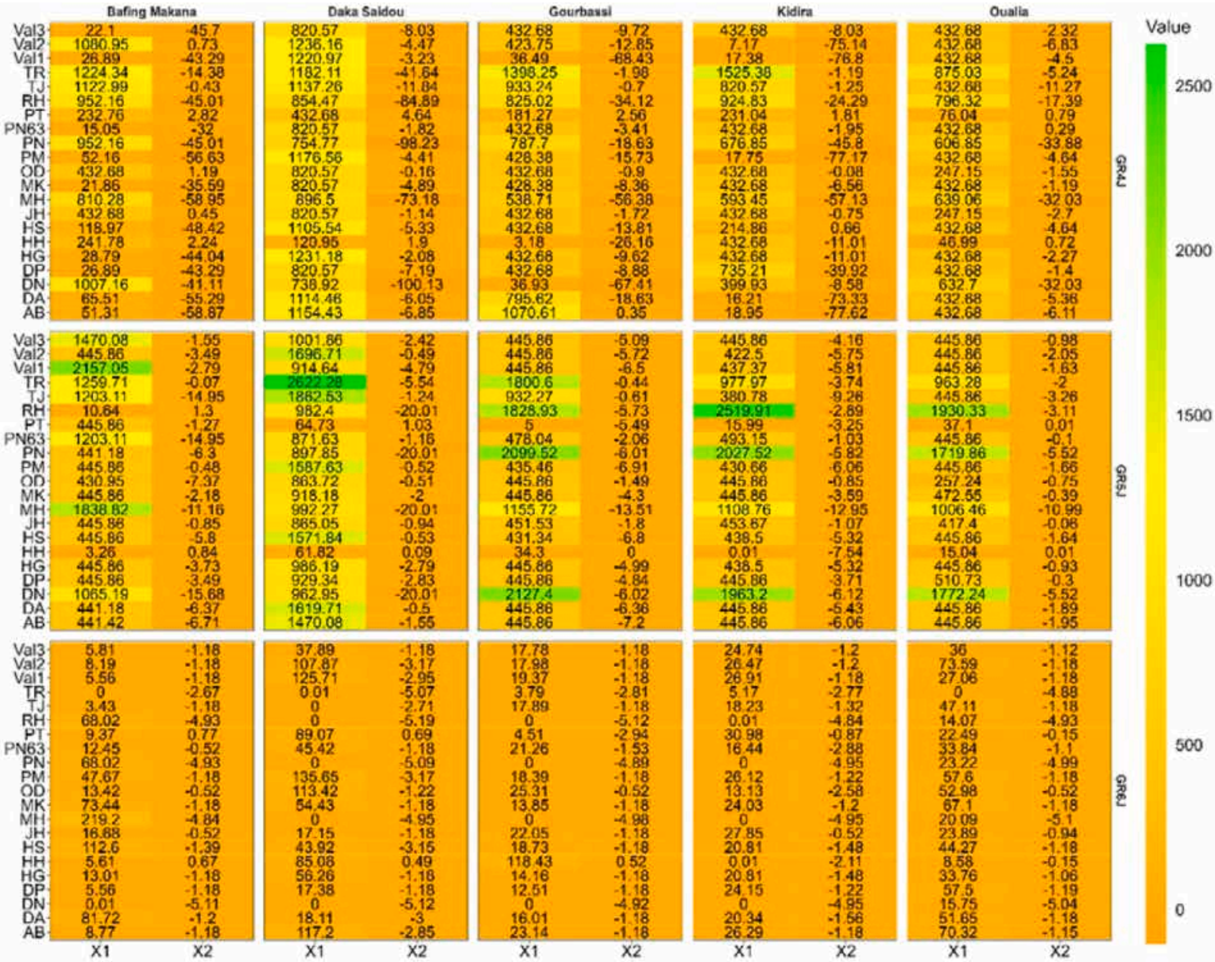

Fig. 11. Influence of PET methods on model parameters X1 and X2 (read: DN Dalton, RH Rohwer, MH Mahringuer, PM Penman-Monteith, PN Penman (aerodynamic), TR Trabert, DA Droogers and Allen, AB Abtew, TJ Trajkovic, Val 1, 2, 3 Valiantzas 1, 2, 3, HS Hargreaves and Samani, PEN Penman (combinatory),HG, Hargreaves, MK Makkink, HH Heydari and Heydari, OD Oudin, JH Jensen and Haise, PT Priestley and Taylor).

more appropriate than aerodynamic methods, which are certainly efficient but require more climatic variables. However, the aim of this work is to propose a simple, high-performance method for hydrological modelling. Finally, given the complexity and uncertainty involved in estimating wind speed and relative humidity, we would gain more by using temperature-based methods like DA. This is because temperature data, even from reanalysis, are shown to have fewer uncertainties than other climate variables (Ndiaye et al., 2021). However, the GR models used in this study are conceptual lumped models and do not explicitly account for the physical characteristics of each watershed (topography, landcover, vegetation, etc.) which influence the variability of hydrological processes over space and time. Therefore, the sensitivity of distributed hydrological models to PET methods must also be investigated and compared with global hydrologic models.

5. Conclusion

This paper aims to evaluate the sensitivity of global hydrological models to potential evapotranspiration estimated from 21 methods using observed and reanalysis data in the Senegal River Basin. The results show that all three GR models at a daily time step can be reliably used in the Senegal River basin to simulate flows. However, if we are interested in average flows and high flows, the GR4J and GR5J models are preferable. For low-flow simulation, however, the GR6J model is more robust. The results also highlight the lower performance of the GR models in the largest basin, where the global model fails to represent accurately the heterogeneous hydrological processes. Thus, all three models performed less well when simulating flows at the Oualia station in the Bakoye basin.

Observed and reanalysis data are used to calculate daily PET values according to 21 methods. Combinatory methods and temperature-based methods provide the most accurate estimation. However, the aerodynamic methods underestimate PET and some temperature and radiation-based methods (Heydari and Heydari and Priestley-Taylor) overestimate it. With regard to the sensitivity of GR models to the different PET estimation methods, all three GR models showed an ability to readjust the estimation errors of the PET methods. In order of performance, aerodynamic methods (Dalton, Rohwer, Mahringuer) were the most robust, followed by temperature-based methods (Droogers and Allen, Hargreaves and Samani). These aerodynamic methods are governed by wind speed and relative humidity, which are more complex and involve many uncertainties. Given the difficulty in accessing climatic data, Droogers and Allen's temperature-based method is more appropriate for hydrological modelling in the Senegal River basin. This Droogers and Allen method has the same or even better performance than the Penman-Monteith method and integrates only temperature data, which are easier to obtain and have fewer uncertainties. This method could also be used to study the hydrological regimes of other rivers in West Africa where ground data is often scarce.

CRediT authorship contribution statement

Andrew Ogilvie: Writing – review & editing, Visualization, Validation, Supervision, Project administration, Funding acquisition, Formal analysis. **Omar Goudiaby:** Validation, Software, Methodology, Data curation. **Papa Malick NDIAYE:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Alain Dezetter:** Writing – review & editing, Validation, Supervision, Project administration, Formal analysis, Conceptualization. **Ansoumana Bodian:** Writing – review & editing, Writing – original draft, Validation, Supervision, Project administration, Methodology, Investigation, Formal analysis, Conceptualization.

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.

Data availability

Data will be made available on request.

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References

Abtew, W., 1996. Evapotranspiration measurement and modeling for three wetland systems in South Florida. Water Resour. Bull. 32 (3), 465–473.
Allen, R., Pereira, L., Raes, D., Smith, M., 1998. Crop evapotranspiration. Guideline for computing crop requirements, *FAO-Irrigation and drainage*. paper 56.
Ambas, V.T., Baltas, E., 2012. Sensitivity analysis of different evapotranspiration methods using a new sensitivity coefficient. Glob. Nest J. 14, 335–343.
Andréassian, V., Perrin, C., Michel, C., 2004. Impact of imperfect potential evapotranspiration knowledge on the efficiency and parameters of watershed models. J. Hydrol. 19–35. https://doi.org/10.1016/j.jhydrol.2003.09.030.
Ávila, L., Silveira, R., Campos, A., Rogiski, N., Gonçalves, J., Scortegagna, A., Freita, C., Aver, A., Fan, F., 2022. Comparative evaluation of five hydrological models in a large-scale and tropical river basin. Water 14, 3013. https://doi.org/10.3390/w14193013.
Bodian, A., Dezetter, A., et Dacosta, H., 2012. Apport de la modélisation pluie-débit pour la Connaissance de la ressource en eau: application au Haut bassin du fleuve Sénégal. Climatologie Vol. 9, 109–125. https://doi.org/10.4267/climatologie.223.
Bodian, A., Dezetter, A., Deme, A., Diop, L., 2016. Hydrological evaluation of TRMM rainfall over the upper Senegal River Basin. Hydrology *3*, 15. https://doi.org/10.3390/hydrology3020015.
Bodian, A., Dezetter, A., Diop, L., Deme, A., Djaman, K., Diop, A., 2018. Future climate change impacts on streamflows of Two Main West Africa river basins: senegal and Gambia. Hydrology 5, 21. https://doi.org/10.3390/hydrology5010021.
Bodian, A., Diop, L., Panthou, G., Dacosta, H., Deme, A., Dezetter, A., Ndiaye, P.M., Diouf, I., Vichel, T., 2020. Recent trend in hydroclimatic conditions in the Senegal River Basin. Water *12*, 436. https://doi.org/10.3390/w12020436.
Bodian A., 2011. *Approche par modélisation pluie-débit de la connaissance régionale de la ressource en eau : application dans le haut bassin du Fleuve Sénégal*, thèse de doctorat, Université Cheikh Anta Diop de Dakar, 211 pages. Available on line : http://hydrologie.org/THE/BODIAN.pdf.
Brulebois, E., Ubertosi, M., Castel, Th, Richard, Y., Sauvage, S., Perez, J.-M.S., Le Moine, N., Amiotte-Suchet, Ph, 2018. Robustness and performance of semi-distributed (SWAT) and global (GR4J) hydrological models throughout an observed climatic shift over contrasted French watersheds. Open Water J. 5, 1. ⟨https://scholarsarchive.byu.edu/openwater/vol5/iss1/4⟩.
Dalton, J., 1802. Experimental essays on the constitution of mixed gases; on the force of steam of vapor from waters and other liquids in different temperatures, both in a Torricellian vacuum and in air on evaporation and on the expansion of gases by heat. Mem. Manch. Lit. Philos. Soc. vol. 5, 535–602 partie 2.
Delaigue, O., Brigode, P., Thirel, G., Coron, L. airGRteaching: an open-source tool for teaching hydrological modeling with R.
Dione, O., 1996. Evolution Climatique Récente et Dynamique Fluviale dans les Hauts Bassins des Fleuves Sénégal et Gambie, Thèse de doctorat Université de Lyon 3 Jean Moulin. ORSTOM, Paris, France, p. 438p.. ⟨https://www.documentation.ird.fr/hor/fdi:010012551⟩.
Djaman, K., Tabari, H., Balde, A.B., Diop, L., Futakuchi, K., et Irmak, S., 2016. Analyses calibration and validation of evapotranspiration models to predict grass-reference evapotranspiration in the Senegal river delta. J. Hydrol.: Reg. Stud. vol. 8, 82–94. https://doi.org/10.1016/j.ejrh.2016.06.003.
Doorenbos, J., Pruitt, W.O., 1977. Guidelines for Predicting Crop Water Requirements; FAO Irrigation and Drainag, Paper No. 24. FAO, Rome, Italy.
Droogers, P., Allen, R.G., 2002. Estimating reference evapotranspiration under inaccurate data conditions. Irrig. Drain. Syst. 16, 33–45. https://doi.org/10.1023/A:1015508322413.
Flores, N., Rodríguez, R., Yépez, S., Osores, V., Rau, P., Rivera, D., Balocchi, F., 2021. Comparison of three daily rainfall-runoff hydrological models using four evapotranspiration models in four small forested watersheds with different land cover in South-Central Chile. Water *13*, 3191. https://doi.org/10.3390/w13223191.
Gosset, C., 2014. *Quel apport des données satellites d'enneigement pour le calage d'un modèle hydrologique sur des bassins de montagne ?* (Doctoral dissertation, Master Science de la Terre et de l'univers, hydrologie, hydrogéologie. In: et sols. Université Paris Sud.

Gupta, H.V.K., Yilmaz, G.K.K., Martinez, G.F., 2009. Decomposition of the mean squared error and NSE performance criteria: Implications for improving hydrological modeling. J. Hydrol. 377, 80–91. https://doi.org/10.1016/j.jhydrol.2009.08.003.
Hargreaves, G.H., 1975. Moisture availability and crop production. Trans. ASAE 18, 980–984.
Hargreaves, G.H., Samani, Z.A., 1985. Reference crop evapotranspiration from temperature. Am. Soc. Agric. Eng. 1985 (1), 96–99.
Heydari, M.M., Heydari, M., 2014. Evaluation of pan coefficient equations for estimating reference crop evapotranspiration in the Arid Region. Arch. Agron. Soil Sci. 60 (5), 715–731. https://doi.org/10.1080/03650340.2013.830286.
Hublart, P., Ruelland, D., García De Cortázar Atauri, I., Ibacache, A., 2015. Reliability of a conceptual hydrological model in a semi-arid Andean catchment facing water-use changes. Proc. IAHS 371, 203–209. https://doi.org/10.5194/piahs-371-203-2015.
Irmak, S., Allen, R.G., Whitty, E.B., 2003. Daily grass and alfalfa-reference evapotranspiration estimates and alfalfa-to-grass evapotranspiration ratios in Florida. J. Irrig. Drain. Eng. 129, 360–370. https://doi.org/10.1061/(ASCE)0733-9437(2003)129:5(360).
Jayathilake, D., I., Smith, T., 2020. Understanding the role of hydrologic model structures on evapotranspiration-driven sensitivity. Hydrol. Sci. J. 65 (9), 1474–1489. https://doi.org/10.1080/02626667.2020.1754421.
Jensen, M.E., Haise, H.R., 1963. Estimating evapotranspiration from solar radiation. J. Irrig. Drain. Div. 89, 15–41.
Jun, W., Xinhua, W., Meihua, G., Xuyan, X.U., 2012. Impact of Climate Change on Reference Crop Evapotranspiration in Chuxiong City, Yunnan Province. Procedia Earth Planet Sci. 5, 113–119. https://doi.org/10.1016/j.proeps.2012.01.019.
Kodja, D.J., Akognongbé, A.J.S., Amoussou, E., Mahé, G., Vissin, E.W., Paturel, J.-E., Houndénou, C., 2020. Calibration of the hydrological model GR4J from potential evapotranspiration estimates by the Penman-Monteith and Oudin methods in the Ouémé watershed (West Africa). Proc. IAHS 383, 163–169. https://doi.org/10.5194/piahs-383-163-2020.
Kodja, D.J., Mahé, G., Amoussou, E., Boko, M., Paturel, J.E., 2018. Assessment of the performance of rainfall-runoff model GR4J to simulate Streamflow in Ouémé Watershed at Bonou's outlet (West. Africa). https://doi.org/10.20944/preprints201803.0090.v1.
Köppen, W., 1918. Klassification der Klimate nach Temperatur, Niederschlag and Jahreslauf. Petermanns Geogr. Mitt. 64, 193–203, 243–248. koeppen-geiger.Vu-Wien.ac.at/Koeppen.htm.
Le Moine N., 2008. Le bassin versant de surface vu par le souterrain: une voie d'amélioration des performances et du réalisme des modèles pluie-débit ? PhD Thesis, Université Pierre et Marie Curie, Paris, 324 pp. ⟨https://theses.hal.science/tel-02591478⟩.
Mahmood, R., Jia, S., 2019. Observed and simulated hydro-climatic data for the lake Chad basin, Africa, Data in brief. Sci. Total Environ. 693, 25. ⟨https://doi.org/10.1016/j.scitotenv.2019.04.021⟩.
Mahringer, W., 1970. Verdunstungsstudien am Neusiedler See. Arch. Meteorol. Geophys. Bioklimatol. Ser. B 18, 1–20.
Makkink, G.F., 1957. Testing the Penman formula by means of lysimeters. J. Inst. Water Eng. 11, 277–288.
Michel, C., 1991. Hydrologie appliquée aux petits bassins ruraux. Hydrology handbook (in French). Cemagref, Antony, France.
Ndiaye, P.M., Bodian, A., Diop, L., Deme, A., Dezetter, A., Djaman, K., Ogilvie, A., 2020a. Trend and sensitivity analysis of reference evapotranspiration in the Senegal River Basin Using NASA Meteorological Data. Water 12, 1957. https://doi.org/10.3390/w12071957.
Ndiaye, P.M., Bodian, A., Diop, L., Deme, A., Dezetter, A., Djaman, K., 2020b. Evaluation and calibration of alternative methods for estimating reference evapotranspiration in the Senegal River Basin, 2020a Hydrology 7, 24. https://doi.org/10.3390/hydrology7020024.
Ndiaye, P.M., Bodian, A., Diop, L., Dezetter, A., Guilpart, E., Deme, A., Ogilvie, A., 2021. Future trend and sensitivity analysis of evapotranspiration in the Senegal River Basin. J. Hydrol. Reg. Stud. 35 https://doi.org/10.1016/j.ejrh.2021.100820.
OMVS, 2022. Révision du Schéma Directeur d'Aménagement et de Gestion des Eaux (SDAGE), Version provisoire, 299 pages (Consultation date: July, 2023).
Oudin, L., 2005. Recherche d'un Modèle D'évapotranspiration Potentielle Pertinent Comme Entrée d'un Modèle Pluie-Débit Global (Search for a Relevant Potential Evapotranspiration Model as Input for a Global RainFlow Model). Ph.D. Thesis, L'école National de Génie Rural, des Eaux et Des Forêts (ENGREF), 2005, Paris, France; 496p. (In French). Available online: ⟨https://pastel.archivesouvertes.fr/file/index/docid/499816/filename/memoire.pdf⟩ (accessed on 15 March 2023).
Palmele, L.H., 1972. Errors in output of hydrologic models due to errors in input potential evapotranspiration. Water Resour. Res. vol. 8 (n°2), 348–359.
Paturel, J.E., Servat, E., Vassiliadis, A., 1995. Sensitivity of conceptual rainfall-runoff algorithms to errors in input data – case of the GR2M model. J. Hydrol. 168, 111–125.
Penman, H.L., 1948. Natural evaporation from open water, bare soil and grass. Proc. Roy. Meteorol. Soc. 193, 120–145.
Penman, H.L., 1963. Vegetation and hydrology; technical communication, n°53. Commonw. Bur. Soil. Harpenden 125p (UK).
Perrin, C., Michel, C., Andréassian, V., 2003. Improvement of a parsimonious model for streamflow simulation. J. Hydrol. *279*, 275–289.
Pimentel, R., Arheimer, B., Crochemore, L., Andersson, J.C.M., Pechlivanidis, I.G., Gustafsson, D., 2023. Which potential evapotranspiration formula to use in hydrological modeling world-wide? Water Resour. Res. 59, e2022WR033447 https://doi.org/10.1029/2022WR033447.
Priestley, C.H.B., Taylor, R.J., 1972. On the assessment of surface heat flux and evaporation using large scale parameters. Mon. Weath. Rev. 100, 81–92.
Pushpalatha, R., Perrin, C., Le Moine, N., Mathevet, T., Andréassian, V., 2011. A downward structural sensitivity analysis of hydrological models to improve low-flow simulation. J. Hydrol. *411* (1-2), 66–76.
Rohwer, C., 1931. Evaporation from Free Water Surfaces; Technical Bulletin 271. US Department of Agriculture, Washington, DC, USA.
Sambou, S., Boye, M., Malang, B.A., Malanda-Nimy, E.N., Bodian, A., Mussa, K., Hamadoun, S., 2011. Calage et validation des modèles hydrologiques GR4J et GR2M sur le bassin du Bafing en amont de Bafing-Makana: vers l'étude de l'impact du climat sur les ressources en eau de la retenue de Manantali. Communication à la sixième édition des Journées Scientifiques du 2iE, Campus 2iE Ouagadougou, 4-8.
Seiller, G., Anctil, F., 2016. How do potential evapotranspiration formulas influence hydrological projections? Hydrol. Sci. J. 61 (12), 2249–2266. https://doi.org/10.1080/02626667.2015.1100302.
Smith, K.A., Barker, L.J., Tanguy, M., Parry, M.S., Harrigan, S., Legg, T.P., Prudhomme, C., Hannaford, J., 2019. A multi-objective ensemble approach to hydrological modelling in the UK: an application to historic drought reconstruction, 2019 Hydrol. Earth Syst. Sci. 23, 3247–3268. https://doi.org/10.5194/hess-23-3247-2019.
Tian, Y., YXu, Y.-P., Yang, Z., Wang, G., Zhu, Q., 2018. Integration of a Parsimonious Hydrological Model with Recurrent Neural Networks for Improved Streamflow Forecasting. Water 10, 1655. https://doi.org/10.3390/w10111655.
Trabert, W., 1896. Neue beobachtungen über verdampfungsgeschwindigkeiten (New observations about evaporation rates). Meteorol. Z. 13, 261–263.
Trajkovic, S., Stojvic, V., 2007. Effect of wind speed on accuracy of Turc method in humid climate. Archit. Civ. Eng. 5, 107–113, 2007.
Tramblay, Y., Rouché, N., Paturel, J.-E., Mahé, G., Boyer, J.-F., Amoussou, E., Bodian, A., Dacosta, H., Dakhlaoui, H., Dezetter, A., Hughes, D., Hanich, L., Peugeot, C., Tshimanga, R., Patrick, L., 2021. ADHI: the African Database of Hydrometric Indices (1950–2018), 2021 Earth Syst. Sci. Data 13, 1547–1560. https://doi.org/10.5194/essd-13-1547-2021.
Traoré, V.B., Sambou, S., Tamba, S., Fall, S., Diaw, A.T., Cissé, M.T., 2014. Calibrating the rainfall-runoff model GR4J and GR2M on the Koulountou river basin, a tributary of the Gambia river. Am. J. Environ. Prot. 3 (1), 36–44. https://doi.org/10.11648/j.ajep.20140301.15.
Valiantzas, J., 2013. Simple ET0 of Penman's equation without wind/or humidity data. II: comparisons reduced Set-FAO and other methodologies. Am. Soc. Civ. Eng. 139, 9–19. https://doi.org/10.1061/(ASCE)IR.19434774.0000502.
Vauchel, P., 2004. Derniers développements du logiciel Hydraccess, Actes des Séminaires et ateliers scientifiques du 30e de l'ORSTOM/IRD en Équateur. pp. 247–251.
Wei, X., Guo, S., Xiong, L., 2021. Improving efficiency of hydrological prediction based on meteorological classification: a case study of GR4J Model. Water 13, 2546. https://doi.org/10.3390/w13182546.
Xu, C.Y., Singh, V.P., 2001. Evaluation and generalization of temperature-based methods for calculating evaporation. Hydrol. Process. 14, 305–319.
Zeng, l, Xiong, L., Liu, D., Chen, J., Kim, J.-S., 2019. Improving parameter transferability of GR4J model under changing environments considering nonstationarity, 2029 Water 11. https://doi.org/10.3390/w11102029.
Zhao, L., Xia, J., Xu, Ch-Y., Wang, Zh, Sobkowiak, L., 2013. Evapotranspiration estimation methods in hydrological models. *J. Geogr. Sci*ences 23 (n°2), 359–369. https://doi.org/10.1007/s11442-013-1015-9.