Sensitivity of global hydrological models to different PET 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 evapotranspiration estimating methods in the Senegal River Basin. For this, 21 estimating methods of evapotranspiration are used to analyze their effect on GR models (GR4J, GR5J and GR6J) performance. The data used are mean rainfall, discharge and observed and calculated PET over the period 1984-1995. The 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 sensibility 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 the mean and high flow and the GR6J is best for low flow. The aerodynamic methods perform well according to the three models. However, is this context where data are rare and scarce, the temperature method like Droogers and Allen is a good choice for hydrological modelling. The results show also that the GR model has the ability to adapt to the errors on the PET.

Keywords: Global models, Evapotranspiration methods, Sensitivity Analysis, Hydrological Modelling, Senegal River Basin.

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 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; Casse et al., 2015; 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; Toudjia, 2017) 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 few 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 three GR models: 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 is the oldest among GR daily models (Sambou et al., 2011; Traoré et al., 2014; Bodian et al., 2016, 2018; Kodia et al., 2018). Given that GR4J is the first and 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 taken into account in the modeling process. As a result, 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 Sing, 2001). Aerodynamic methods (Dalton, 1802; Trabert, 1896), temperature-based methods (Hargreaves, 1975; Hargreaves and Samani, 1985), radiation-based methods (Makking, 1957; Priestley and Taylor, 1972) and combinatorial methods (Penman, 1963; Penman-Monteith, 1998). Aerodynamic methods are the oldest and are based on Dalton's theory (1820) 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 is recommended as the 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 (Siller and Anctil, 2016; Birhanu et al., 2018). Moreover, there is as yet no consensus on the most appropriate PET method to use for hydrological modelling (Jayathilake and Smith, 2021). 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 (compared with rainfall) and therefore has little influence on the performance of hydrological models (Andréassian et al., 2004; Oudin et al., 2005). However, a few studies worldwide (Parmele, 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. Seller 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. However, the number of PET methods used is a limitation of the work. In fact, these methods are classified as radiation and temperature-based. What about other types of methods? West African watersheds are not included in this study. Hydrological processes differ according to eco-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 to analyze the sensitivity of the three GR 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 km² (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 to 17 million in 2050 (OMVS, 2022). The basin's water resources represent a major challenge for the development of irrigated and flood-recession agriculture, hydroelectric production, navigation and ecosystem management (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 (Figure 1). These stations have the particularity of not being influenced by the various dams built by 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 ≤ 500 mm), Sudanian (annual rainfall between 500 mm and 1500 mm) and Guinean (annual rainfall ≥ 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.

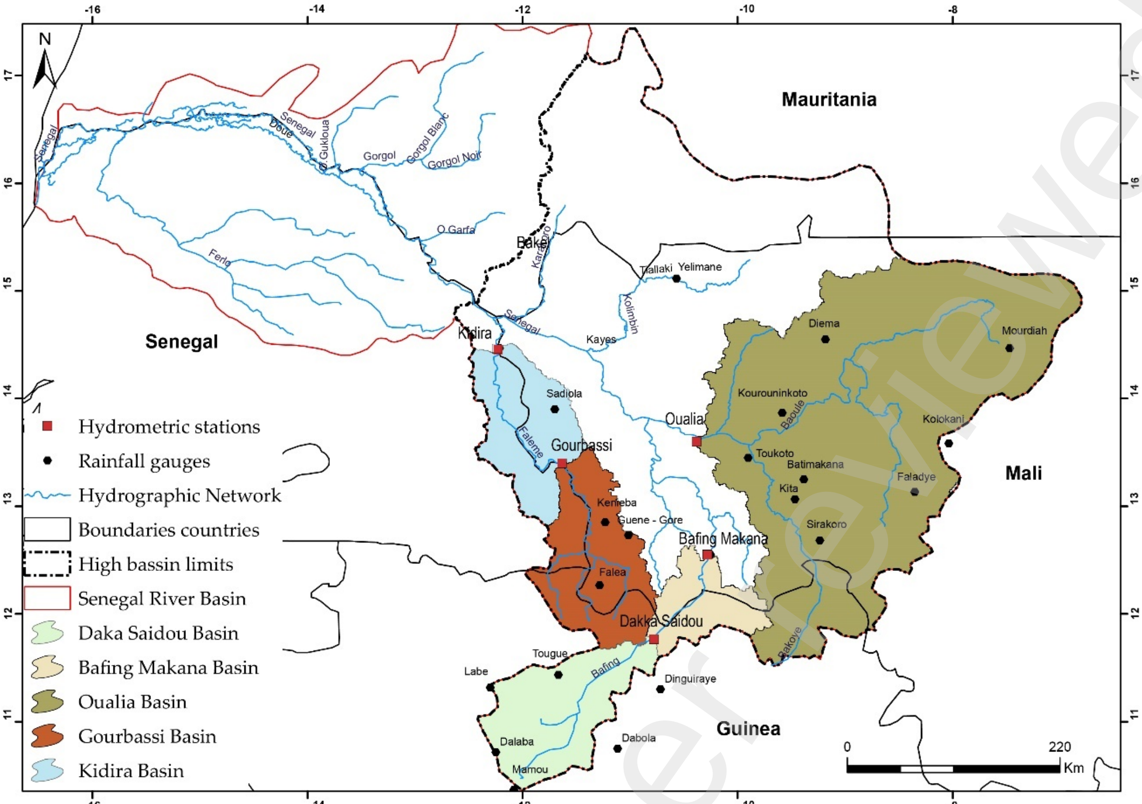

Figure 1 : Location of the study area

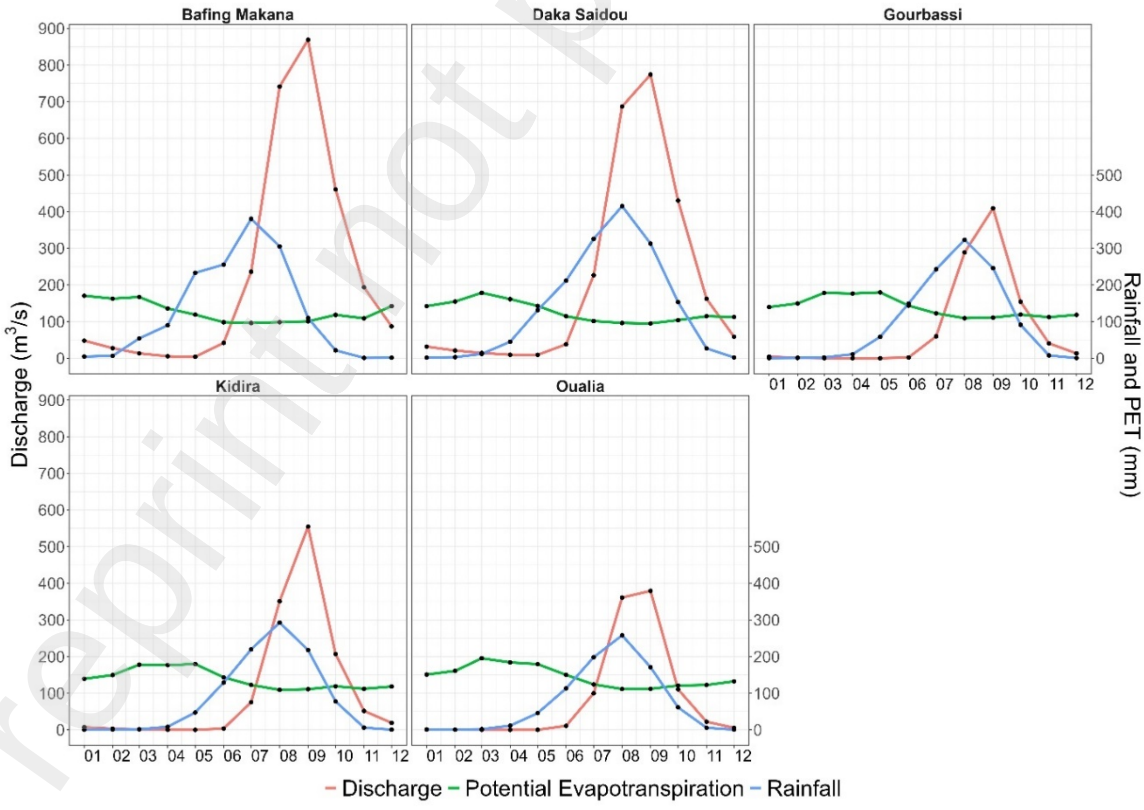

Figure 2: Mean monthly flow, rainfall and potential evapotranspiration over the 1984-2015 period for the various watersheds selected.

2.2. Data

Two types 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. Figure 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, only the stations used to calculate average rainfall are retained (Figure 1). These are seven (7) stations for the Bafing basin, six (6) for the Faleme basin and eleven (11) for the Oualia basin. This makes a total of 24 stations used in the study (*cf.* Figure 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 by 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 the difficult access to daily rainfall data because of their high acquisition cost (Bodian et al., 2016; 2020). In order to have the same length period for all basin and variables (rain, PET, Flow), the period 1984-1995 is retained for this study.

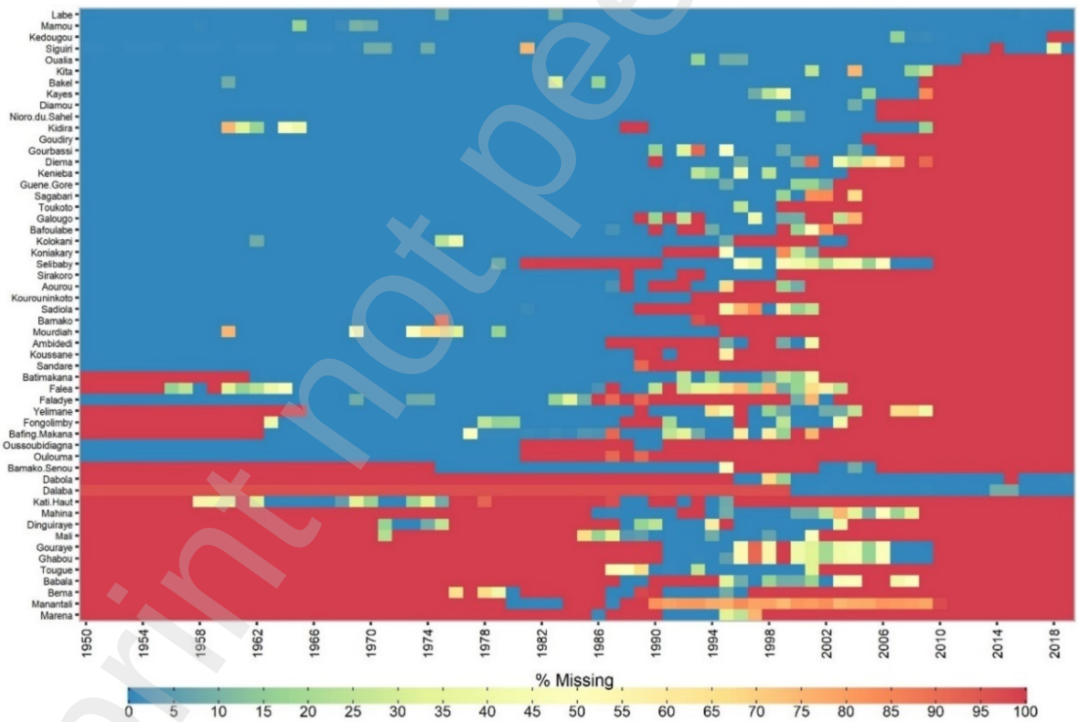

Figure 3: Inventory of daily rainfall data from stations in the upper Senegal River basin

2.2.1.2. Discharge data

The hydrological data come from the OMVS database. These are data from five hydrometric stations controlling the Bafing (Bafing Makana and Daka Saidou), Faleme (Kidira and Gourbassi) and Bakoye (Oualia) sub-basins. Table 1 gives an inventory of data from each station. Compared with rainfall data, hydrological data gaps are low, ranging from 3% to 16% depending on the station.

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

Stations	Areas of Basins (km²)	Latitude	Longitude	Start of time series	End of time series	%Gap
Bafing Makana	22419	12,55	-10,28	02/01/1961	21/04/2016	15
Daka Saidou	15061	11,95	-10,62	27/05/1952	21/04/2016	3
Gourbassi	28515	13,40	-11,63	02/01/1954	24/03/2016	4
Kidira	15680	14,45	-12,22	01/05/1951	24/03/2016	16
Oualia	87931	13,60	-10,38	01/06/1954	24/03/2016	7

2.2.1.3. Evapotranspiration data

For 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. There are no gaps in the available periods. They are used to calculate evapotranspiration using the Penman-Monteith reference method (Allen et al., 1998).

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

2.2.2. Reanalysis data

Since observed PET data are only available for a few stations, reanalysis data from NASA Earth Science/Applied Science Program (https://power.larc.nasa.gov, last access April, 2023) are used to calculate evapotranspiration for all stations. For more information on these data, readers may refer to Stackhouse et al, (2020) and earlier studies by Ndiaye et al, (2020a, 2020b, 2021). These data consist of daily chronicles of maximum and minimum temperature (°C), mean relative humidity (%), wind speed (m/s) and solar radiation (MJ/m²/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 availability of the PET observed over this period.

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 to 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.

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	2	(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		(Eq. 4)
	Rohwer (1962)	$ET_0 = 0.44 \times (1 + 0.27 \times u2) \times (es - ea)$	RH		(Eq. 5)
	Mahinger (1970)	$ET_0 = 0.15072 \times \sqrt{3.6}u2 \times (es - ea)$	MH		(Eq. 6)
Temperature	Hargreaves (1975)	$ET_0 = 0.0135 \times 0.408 \times Rs \times (T + 17.8)$	HG	1	(Eq. 7)
	Hargreaves et Samani (1985)	$ET_0 = 0.0023 \times (T + 17.8) \times (Tmax - Tmin)^{0.5} \times Ra$	HS		(Eq. 8)
	Trajkovic (2007)	$ET_0 = 0.0023 \times (T + 17.8) \times (Tmax - Tmin)^{0.424} \times Ra$	TJ		(Eq. 9)
	Droogers et Allen (2012)	$ET_0 = 0.0025 \times (T + 16.8) \times (Tmax - Tmin)^{0.5} \times Ra$	DA		(Eq. 10)
	Heydari et Heydari (2012)	$ET_0 = 0.0023 \times Ra \times (T + 9.519) \times (Tmax - Tmin)^{0.611}$	HH		(Eq. 11)
Radiation	Makking (1957)	$ET_0 = 0.61 \times \frac{\Delta}{\Delta + \gamma} * \frac{Rs}{\lambda} - 0.012$	MK	1	(Eq. 12)
	Jensen et 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		(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)	$ET_0 = \left[\frac{\Delta}{\Delta + \gamma} \times (Rn - G) + \frac{\gamma}{\Delta + \gamma} \times 6.43 \times (1 + 0.053 \times$	PEN	4	(Eq. 17)
	Doorenbos-Pruitt (1977)	$ET_0 = \left[\frac{\Delta}{\Delta + \gamma} \times (Rn - G) + 2.7 \times \frac{\gamma}{\gamma + \Delta} \times (1 + 0.864 \times u2) \times (es - \right. /\lambda$	DP		(Eq. 18)
	Valiantzas 1 (2013)	$ET_0 = 0.0393 \times Rs \times \sqrt{T + 9.5} - 0.19 \times Rs^{0.6} \times \varphi^{0.15} + ($	Val1		(Eq. 19)
	Valiantzas 2 (2013)	$ET_0 = 0.0393 \times Rs \times \sqrt{T + 9.5} - 0.19 \times Rs^{0.6} \times \varphi^{0.15} + ($	Val2		(Eq. 20)
	Valiantzas 3 (2013)	$ET_0 = 0.0393 \times Rs \times \sqrt{T + 9.5} - 0.19 \times Rs^{0.6} \times \varphi^{0.15} + ($	Val3		(Eq. 21)

Read: ET_0 reference evapotranspiration (mm), u2 represents wind speed measured at 2 m from the ground (m-1s), (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, 2000). φ, represents the latitude of the station in radian degrees, λ is the latent heat of vaporization (MJ/m2/J).

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 et al., 2008; Pushpalatha et al., 2011; Coron et al., 2017, 2020) but their basic principles are summarized below (Figure 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 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 vice versa. If X2 > 0, surface runoff feeds groundwater. Various GR4J parameter values exist 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 take account of underground exchanges between complex watersheds (Flores et al., 2021). Parameter X5 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, GR6J should enable better simulations of low-flow rates thanks to its 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). Figure 4 shows the conceptual diagram of the three GR models at daily time step.

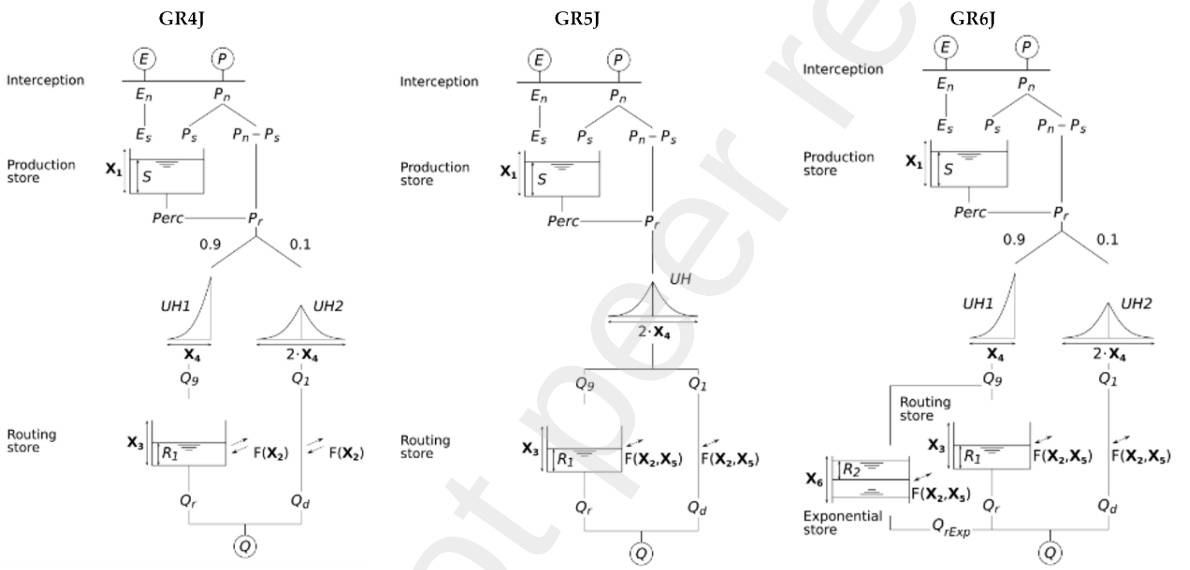

Figure 4: Structure of GR4J (Perrin et al., 2003), GR5J (Le Moine et al., 2008) and GR6J (Pushpalatha et al., 2011) models.

2.4. Methods

The methodological approach comprises four main phases: (i) validation of the PET calculated with the reanalysis against that calculated with the observed climate variables, (ii) calculation of the average rainfall and PET for the five 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 observed PET of the six stations is compared with that calculated by the 21 methods from reanalysis data. 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:

$$KGE = 1 - \sqrt{(r-1)^2 + (\beta - 1)^2 + (\alpha - 1)^2} \quad \text{(Eq. 22)}$$

$$PBIAS = \left[\frac{\frac{1}{n}\sum_{i=1}^{n} (V_{sim} - \mathrm{V_{obs}})^2}{\frac{1}{n}\sum_{i=1}^{n} (V_{sim})} \right] \times 100 \quad \text{(Eq. 23)}$$

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. Calculate of mean rainfall and evapotranspiration

Mean rainfall for the various catchments was calculated from data of the selected rainfall stations (Figure 1c) using the inverse distance squared (IDW) interpolation method (Bodian et al., 2012, 2020), available in Hydraccess (Vauchel, 2004). Evapotranspiration for each station was calculated by the Penman-Monteith method considered as the standard method and by twenty other methods presented in Table 3. Then, for each of the 21 methods, the average PET of the basins was calculated using the IDW method.

2.4.3. Calibration/validation of GR models

Each of the three 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. Model performance is assessed by the KGE and PBIAS previously described (Eq. 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 Q05 is the value not exceeded by 5% of flows, mean flows by Q50 and peak flows by Q95.

2.4.4. Sensitivity analysis of GR models to PET estimation methods

According to Andréassian et al, (2004), there are two types of methods for analyzing the sensitivity of a hydrological model to different methods of estimating evapotranspiration: 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. This is the dynamic approach used in this work.

3. Results and discussion

3.1. Validation of PET calculated from reanalysis with that observed

Validation of reanalysis data is carried out for the Labe, Siguiri, Kita, Kenieba, Bamako Senou and Nioro du Sahel stations, which have the observed climate variables (temperature, sunshine duration, relative humidity and wind speed) required to calculate PET using the Penman-Monteith method. Figure 5 shows the boxplots of daily PET calculated from observed and reanalysis data using different methods, while Figure 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. Haydari-Haydari (temperature-based), Priestley-Taylor (radiation-based) and aerodynamic methods are less robust. KGEs vary from -1.19 to 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%. These results show that the uncertainty in the reanalysis data can be sought in 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 from a number of stations in the Senegal River basin. They conclude that there is good agreement between observed temperatures (max and min) and those from the reanalysis, 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 their differences from observations, all these methods are used in the GR model calibration/validation process. This allows us to see whether the estimation errors of the PET methods will not influence the performance of the hydrological models or their parameters.

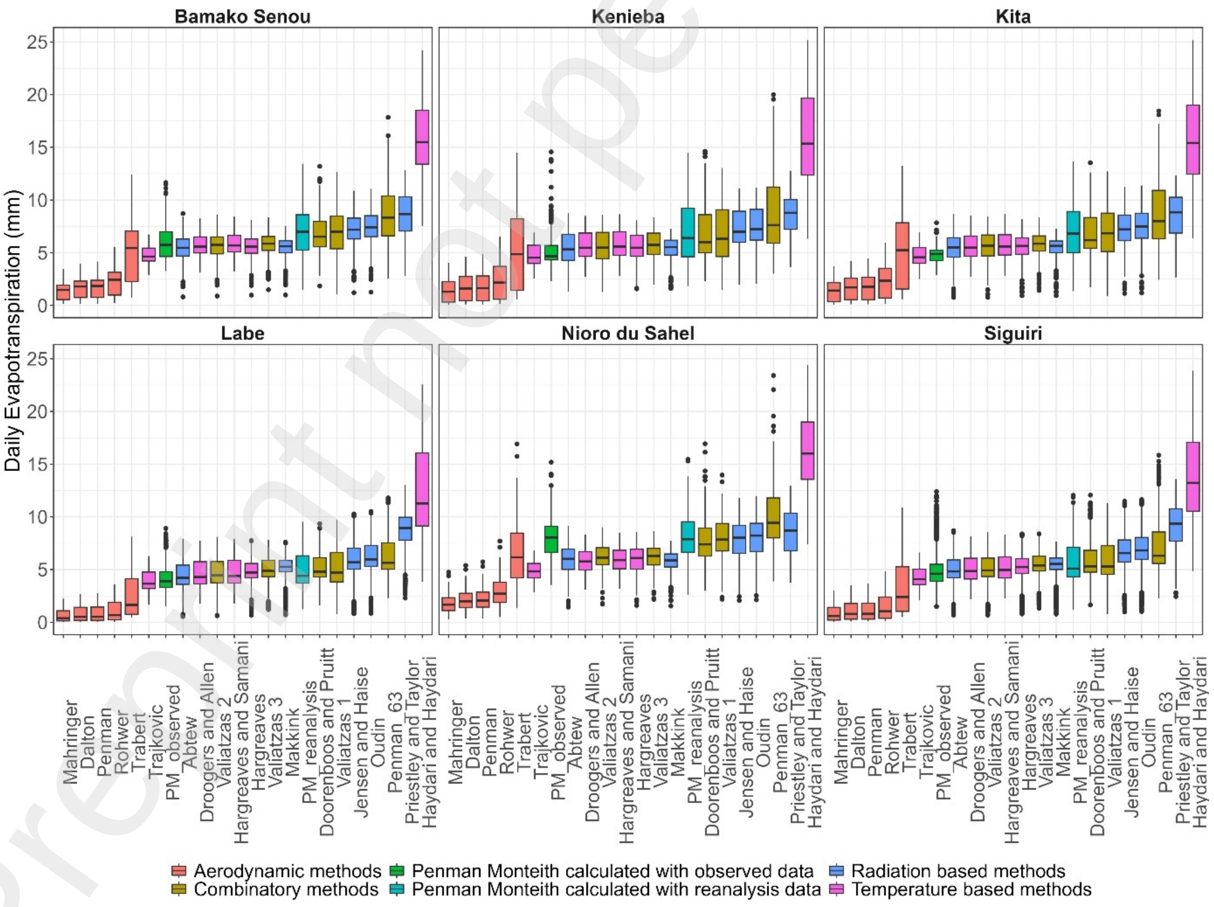

Figure 5: Daily evapotranspiration calculated with observed and reanalysis data

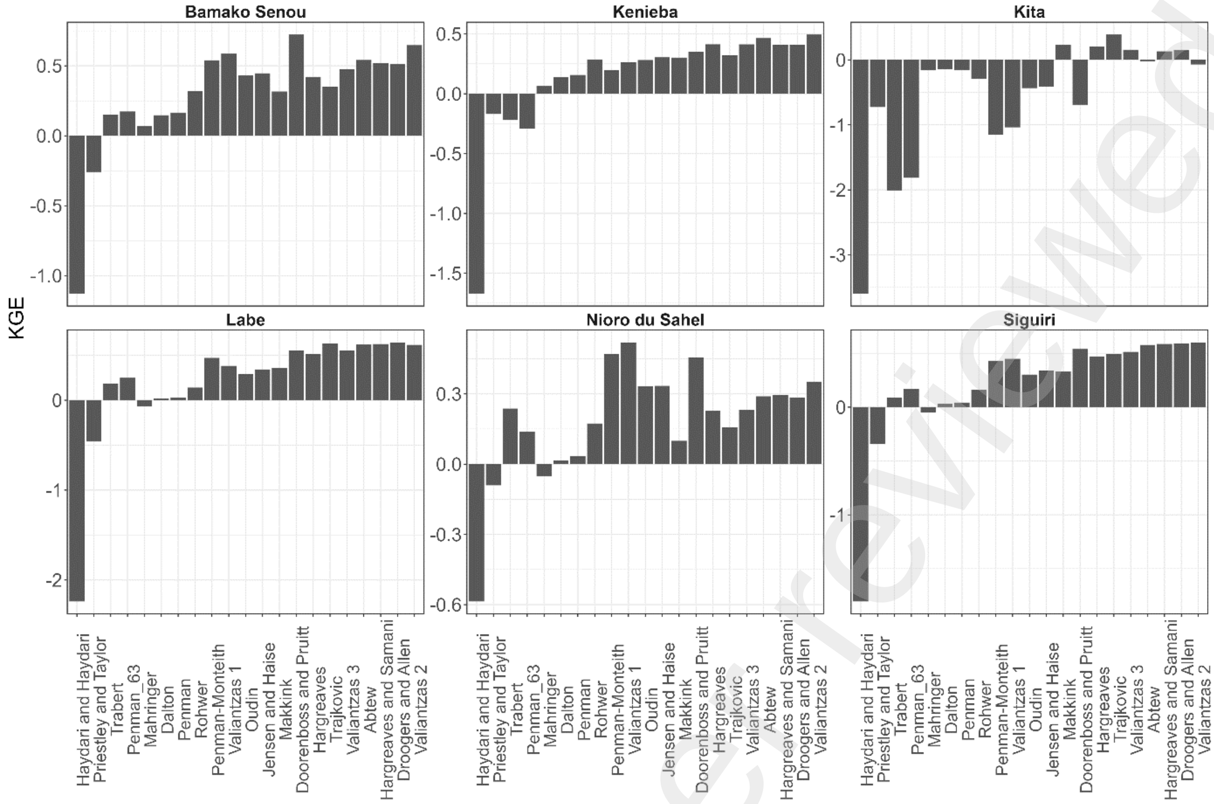

Figure 6: KGE bar plot of PET calculated PET with observed and reanalysis data

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). Figure 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 during calibration and validation, and the quantiles of simulated and observed daily flows. The models performed best in the Bafing basin (Bafing Makana and Daka Saidou), with KGE values ranging from 0.87 to 0.91 in calibration and from 0.69 to 0.93 in validation. PBIAS are 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 Daka Saidou (Table 4). They also tend to overestimate the various flow classes, with the exception of the Daka Saidou station, where peak flows are slightly underestimated. The GR6J model reproduces low-water flows better than the GR4J and GR5J models. 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. However, unlike the other basins, 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 model's overestimate means and low-water flows and underestimate peak flows at Oualia. Overall, the results show that the three models behave in almost the same way depending on the basins.

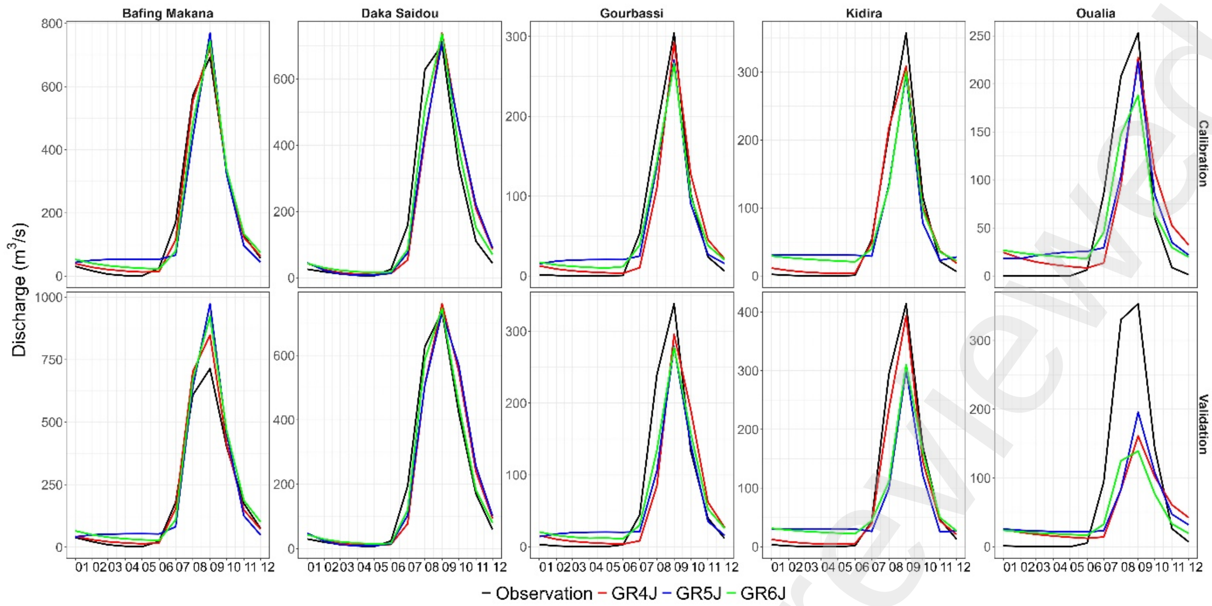

Figure 7: Cumulative curves of observed and simulated basin flows for the three calibration and validation models

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

Stations		Calibration (1986-1990)					Validation (1991-1995)				
		Q05 (mm)	**Q50 (mm)**	**Q95 (mm)**	**KGE**	**PBIAS**	**Q05 (mm)**	**Q50 (mm)**	**Q95 (mm)**	**KGE**	**PBIAS**
Bafing Makana	Qobs	0,0018	0,1755	2,7868			0,0018	0,1755	2,7868		
	GR4J	0,0463	0,1693	2,9799	0,94	-0,1	0,0514	0,1989	3,5914	0,84	10,1
	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
Daka Saidou	Qobs	0,0253	0,1992	4,3300			0,0253	0,1992	4,3300		
	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
Kidira	Qobs	0,0000	0,0088	1,0529			0,0000	0,0088	1,0529		
	GR4J	0,0096	0,0339	0,8393	0,78	-4,7	0,0109	0,0415	1,3395	0,71	-12,3
	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
Gourbassi	Qobs	0,0000	0,0131	1,5557			0,0000	0,0131	1,5557		
	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
Oualia	Qobs	0,0000	0,0006	0,2632			0,0000	0,0006	0,2632		
	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

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

The three GR models were calibrated and validated using 21 PET estimation methods. Figure 8 shows the monthly hydrograph in calibration and validation with PET data from the different methods. Figure 9 shows heatmaps of KGE and PBIAS values. The flows simulated by the different PET methods follow the same direction as the observed flows. However, in terms of values, there is significant differences according to PET methods. Aerodynamic methods give the best performance for all three GR models, followed by the Droogers and Allen temperature-based method. The same observations apply to the Faleme basin at Kidira and Gourbassi. All GR models behave in broadly the same way according to the different PET methods. However, aerodynamic and temperature-based models are always more robust. Compared with the other basins, Oualia presents a relatively special situation. 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 KGEs below 0.70 and PBIASs of 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, where we note a deterioration in model performance, the KGEs of the aerodynamic methods are higher than 0.60. PBIAS also shows that for the Bafing Makana and Daka Saidou basins, 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, for the Kidira, Gourbassi and Oualia basins, for almost all PET methods, the three GR models underestimated flows, especially in validation. This under/overestimation can be explained by the fact that the methods tend to under/overestimate PET compared with observed PET. Indeed, aerodynamic methods that underestimate PET also tend to underestimate model-estimated flows.

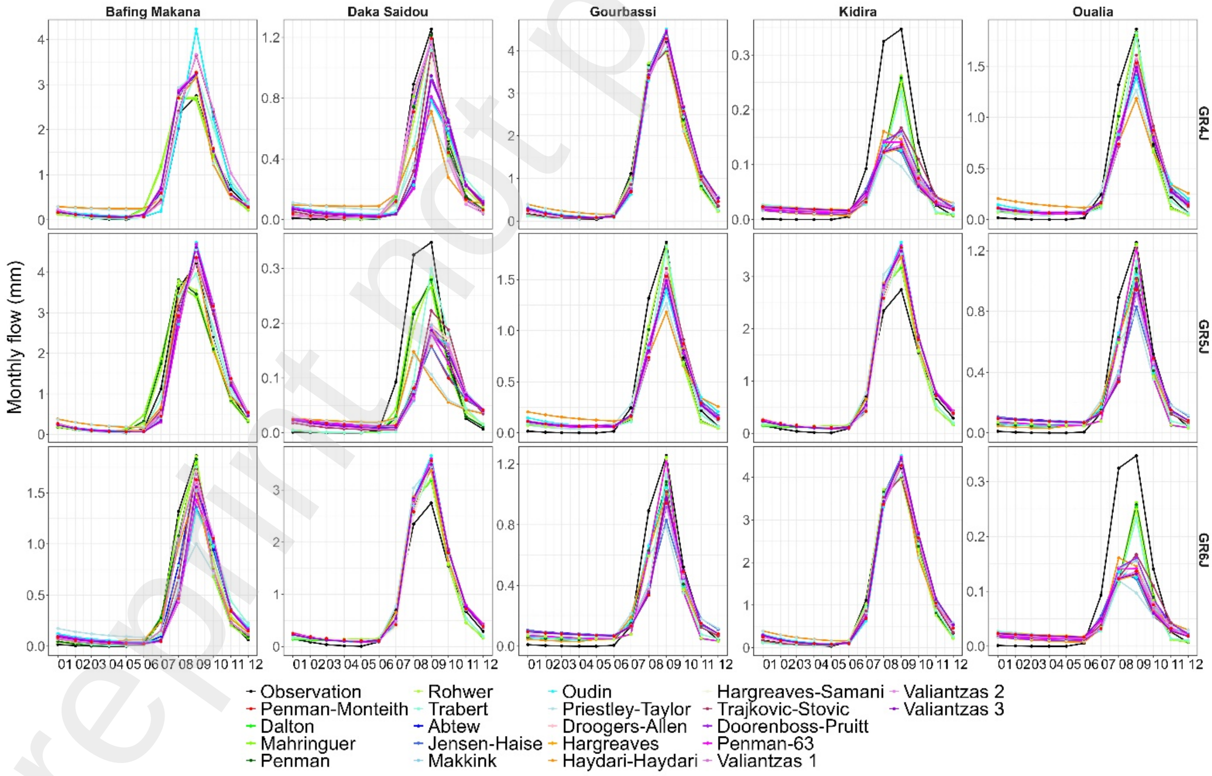

Figure 8: Monthly hydrograph of observed and simulated by the three models as a function of the 20 PET methods.

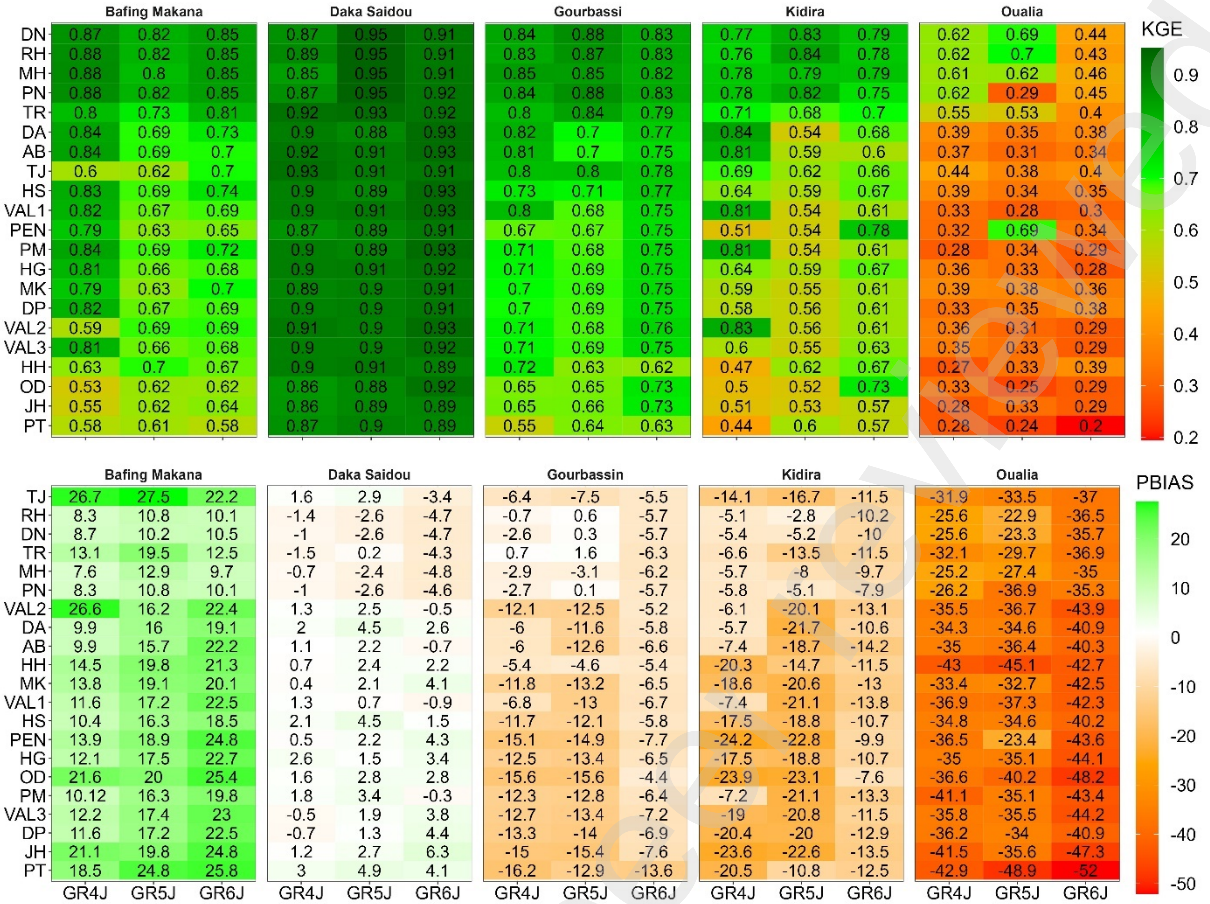

Figure 9: Heatmap of KGE for simulated and observed flows in validation period (red: DN Dalton, RH Rohwer, MH Mahringuer, PN Penman (aerodynamic), TR Trabert, DA Droogers and Allen, AB Abtew, TJ Trajkovic, Val 1, 2, 3 Valiantzas 1, 2, 3, HS Hargreaves and Samani, PEN Penman (combinatory),HG, Hargreaves,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

4. Discussion

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 more robust in the Bafing Makana and Daka Saidou basins. For the other basins of Kidira, Gourbassi and Oualia, the GR5J model gives the best performance. GR models also tend to overestimate flows. Overestimation of flows by GR4J was noted in the Senegal River by Bodian et al., (2018). The GR6J model performs better in simulating low-water flows. This is understandable because this model was designed to take better account of low-water flows. Unlike GR4J, which is less robust in simulating low-water flows (Bodian et al., 2018), GR5J and GR6J incorporate a parameter (X5) that takes into account bidirectional exchanges between surface water and groundwater (Le Moine, 2008). 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 22419 km² and 15061 km² at Daka Saidou. The Faleme at Kidira has a surface area of 28515 km² and 15680 km² at Gourbassi. All these watersheds are also located in the Sudano-Guinean climatic zone between isohyets 1000 and 1500 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 87931 km² and spans three climates: Sahelian, Sudanian and Guinean. By way of comparison, the first models were tested in the Orgeval basin (France), with a surface area of 104 km² (Edijatno, 1991), which is considerably smaller than the surface area of the Oualia basin. In addition, Ávila et al (2022) noted that global models are limited in their ability to represent the hydrological regimes of basins larger than 50,000 km², 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 (Figure 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 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 (Figure 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 (Andréssean 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 Haydari and Haydari 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. What's more, because of its number of climatic variables and its performance gain, which is identical to that of Penman-Monteith, the DA method is 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. What's more, 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, have fewer uncertainties than other climate variables (Ndiaye et al., 2021).

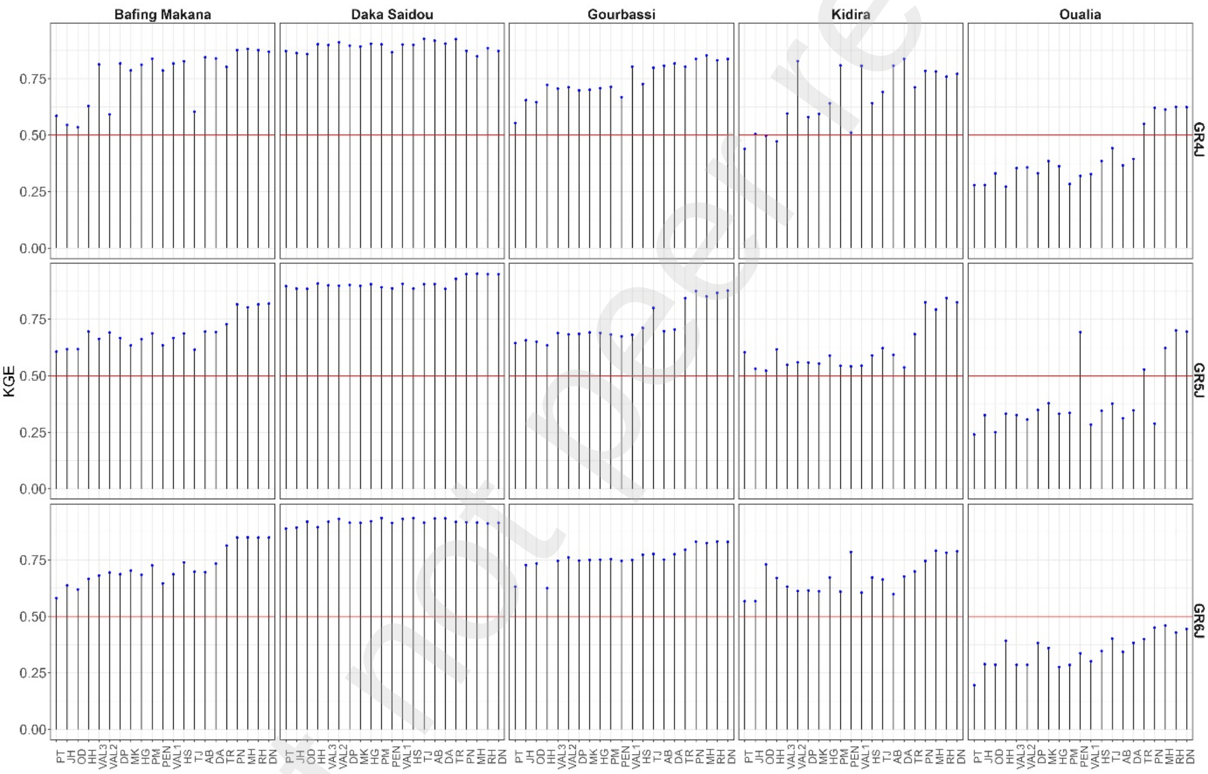

Figure 10: Classification of methods by order of performance (red line represents the average KGE value over the validation period) (read: DN Dalton, RH Rohwer, MH Mahringuer, PM Penman-Monteith, PN Penman (aerodynamic), TR Trabert, DA Droogers and Allen, AB Abtew, TJ Trajkovic, Val 1, 2, 3 Valiantzas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

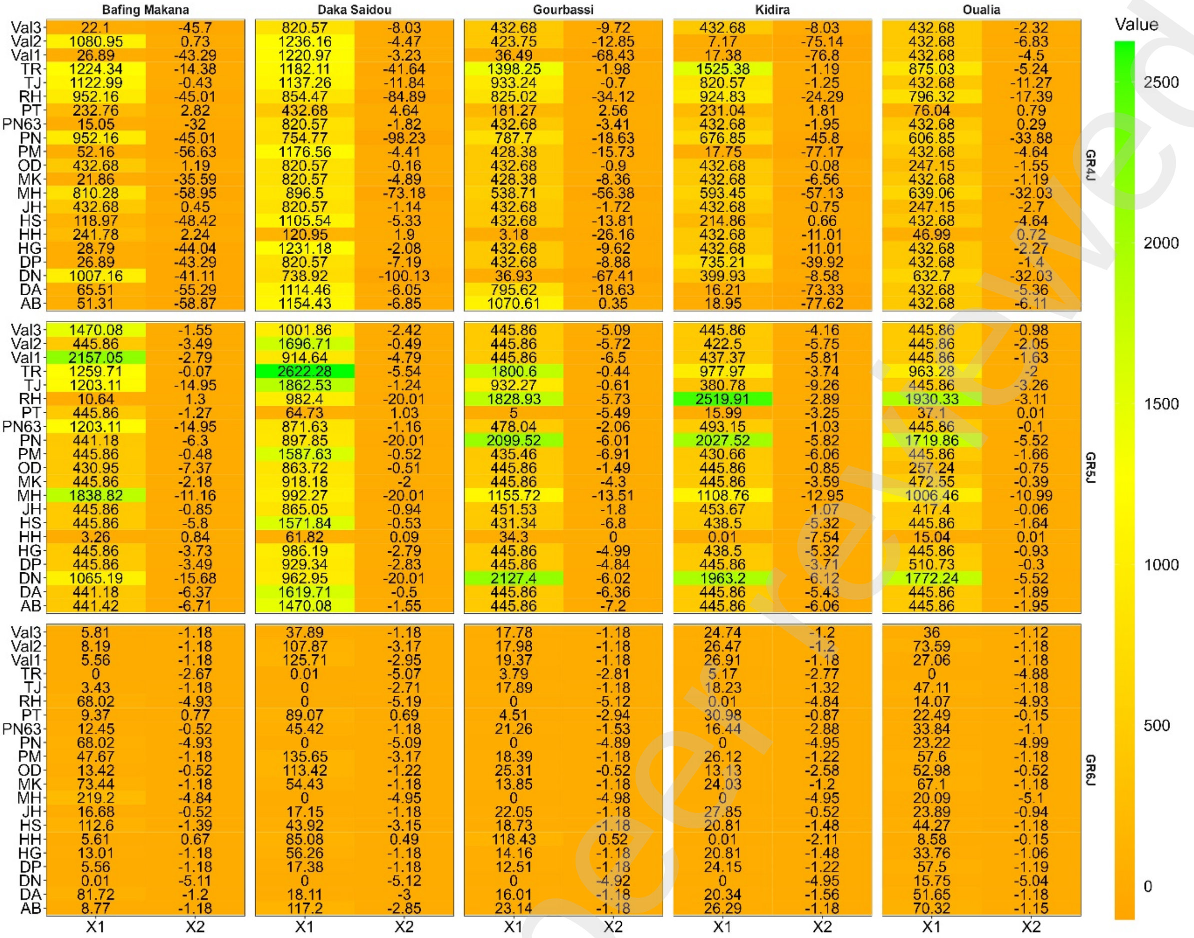

Figure 11: Influence of PET methods on model parameters X1 and X2 (read: DN Dalton, RH Rohwer, MH Mahringuer, PM Penman-Monteith, PN Penman (aerodynamic), TR Trabert, DA Droogers and Allen, AB Abtew, TJ Trajkovic, Val 1, 2, 3 Valiantzas 1, 2, 3, HS Hargreaves and Samani, PEN Penman (combinatory),HG,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

5. Conclusion

This paper aims to evaluate the sensitivity of global hydrological models to evapotranspiration estimating methods in the Senegal River Basin by using observed and reanalysis data over the period 1984-1995. The results show that all three GR models at daily time step can be validly used in the Senegal River basin for flow simulation. However, if we are interested in average flows and floods, the GR4J and GR5J models may be preferred. For low-flow simulation, however, the GR6J model is more robust. The results also highlight the fact that GR models are sensitive to basin size, so the larger the basin size, the poorer their performance. Thus, all three models perform less well in simulating flows in the Oualia basin, the main Bakoye station.

Observed and reanalysis data are used to calculate daily PET values according to 21 methods. Combinatory methods and temperature-based methods are the best. However, the aerodynamic methods underestimate PET and some temperature and radiation-based methods (Heydari and Haydari 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 of 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 (mean station KGE in calibration: 0.87 for GR4J, 0.84 for GR5J and 0.86 for GR6J, and in validation 0.76, 0.63 and 0.70) has the same or even better performance than the Penman-Monteith method (mean station KGE in calibration: 0.85 for GR4J, 0.83 for GR5J and 0.86 for GR6J and in validation 0.71, 0.63 and 0.66) and integrates only temperature data, which are easier to obtain and have fewer uncertainties. This method could also be used to study the impact of climate change on water resources in the context of west Africa.

Author contributions

Conceptualization, P.M.N, A.B, A.D; Data curation, P.M.N, O.G; Formal analysis, P.M.N, A.B, A.D, A.O, O.G; Investigation, P.M.N, A.B; Methodology, P.M.N, AB, O.G; Project administration, A.B, P.M.N, A.D, A.O; Software, P.M.N, O.G; Supervision, A.B, A.D, A.O; Validation, P.M.N, A.B, A.D, A.O, O.G; Roles/Writing - original draft, P.M.N, A.B; and Writing - review & editing, P.M.N, A.B, A.D, A.O.

Declaration of Competing Interest

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

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