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# Hydrological modeling with physics-based models in the oueme basin: Issues and perspectives for simulation optimization

René Bodjrènou [a,b,*], Luc Ollivier Sintondji [b], Françoise Comandan [b]

[a] *Laboratory of Applied Hydrology, INE-BENIN*
[b] *Laboratory of Hydraulics and Water Control, INE-BENIN*

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ABSTRACT

*Study region:* Oueme Basin, threatened by climate change and upstream energy projects, is limited by the quality of the adapted meteorological data through the assessment of their impacts with some models.
*Study focus:* This study focuses on the ParFlow-CLM model and describes its ability to simulate the water balances with good (observation data) and bad (observation transformed and reanalysis corrected and uncorrected data) meteorological forcing.
*New hydrological insights for the region:* The model correctly simulates all the terms of water balance, mainly evaporation and water table depth (WTD) with KGE always higher than 0.70. It is less sensitive to temperature, shortwave (SW), and longwave (LW) forcing. With those three variables, ParFlow-CLM simulates none significative difference in water balance terms using the reanalysis forcings on which we note an overestimation of temperature and an underestimation of LW. The same results are obtained with the other so-called bad meteorological forcings. On the other hand, the precipitation of the latter significantly influences the water balance. The annual water balance and especially evapotranspiration shows 683 ± 70 mm for observations versus 753 ± 63 mm and 662 ± 44 mm for ERA5 and MERRA2 respectively. The corrections applied on these variables seem to work better on MERRA2 (734 mm or 51 mm difference with observations) compared to ERA5 (760 mm or 77 mm difference with observations). The temperate, SW, LW variables of the reanalyses can be used for hydrological simulations with ParFlow-CLM and probably with other physics-based models over the Beninese basins but the precipitation of these must be corrected before use.

## 1. Introduction

Hydrological studies are crucial for the quantification and management of available water resources on a watershed scale. Many different hydrological models used in previous studies aimed at solving short or long-term problems within a basin. In West Africa, many of such studies are usually based on global models for several reasons, including the unsatisfactory quality of observation data and their irregular distribution in time and space (Dembélé et al., 2020). This is the case for the Sudanian zone of Benin. Within this

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*Abbreviations:* WTD :, Water Table Depth; LW :, Longwave radiation; SW :, Shortwave radiation; CLM :, Community Land Model; AMMA-CATCH :, Analyse Multidisciplinaire de la Mousson Africaine - Couplage de l'Atmosphère Tropicale et du Cycle Hydrologique; KGE :, Kling Gupta efficiency; NASH :, Nash-Sutcliffe Efficiency; RMSE :, Root Mean Square Error.

* Correspondence to: National Water Institute, University of Abomey-Calavi, Cotonou P.O. Box 536, Benin.
*E-mail address:* renebodjrenou@gmail.com (R. Bodjrènou).

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zone lies the Oueme basin, the largest basin in Benin. The basin has seen an increase in the number of studies evaluating the rainfall-flow relationship using rural engineering models in recent years (Kodja et al., 2018; Nounangnonhou et al., 2018) and other global models such as Hydrologiska Byråns Vattenbalansavdelning (HBV), Hydrologic Modeling System (HEC-HMS), Hydrological Model based on the Least Action Principle (HyMoLAP) (Biao, 2017; Houngue, 2020).

The region is characterized by complex hydrological processes, which limits the use of majority of these models (Giertz et al., 2010). First, they are limited to the study of surface water resources, and do not account for the entire hydrological cycle. This does not help to robustly identify the causes of the poor estimation of flows. Consequently, it is difficult to formulate tangible recommendations to decision makers in this region. Second, the parameters used in these models are generally adjusted to a given period and do not always account for the present-day realities of the environment. Moreover, these parameters evolve due to anthropogenic factors which modifies surface conditions and hydrodynamic characteristics of the soil. They can also evolve due to climatic factors causing the decrease of water masses and the lowering of the water table. These changes are often not accounted for in the models, negatively affecting the quality of simulations over their validation periods and/or other periods (Biao et al., 2016). In addition, the Oueme basin crosses all three of Benin's climatic zones, namely the sub-equatorial zone, which has two rainy seasons; the Sudano-Guinean zone and the Sudanian zone, which has only one rainy season (Bodjrènou et al., 2021). The use of a global model in this basin is therefore a poor option because of this climatic diversity, to which is added the strong variation in vegetation cover depending on whether one is in the north or south of the basin (Bodjrènou et al., 2023).

For these reasons, recent research on the functioning of the Oueme basin hydrosystem advocates the use of physically-based models. These include the study of Hector et al. (2018) who proposed to use the ParFlow model which is a critical zone model based on Richard's equation for 3D saturated and unsaturated subsurface transfers and the kinematic wave equation for surface flow. It is coupled to Community Land Model (CLM) which is a soil-vegetation-atmosphere transfer model, to calculate the energy balance and evapotranspiration fluxes (Kollet and Maxwell, 2005, 2008). Hector et al. (2018), highlighted the strong ability of the model to simulate water and energy fluxes and soil water stock (streamflow, evapotranspiration, soil moisture, WTD, and water storage) in the Sudanian zone. The study used data from the "Analyse Multidisciplinaire de la Mousson Africaine - Couplage de l'Atmosphère Tropicale et du Cycle Hydrologique" (AMMA-CATCH) Observatory, both for model inputs and for the evaluation of its outputs. Two constraints limit the evaluation of the hydrological behavior of the entire Oueme basin in this study. Firstly, it did not show long-term changes in water balance fluxes. One of the main reasons is that qualified data for these high temporal resolution hydrological simulations in this basin are only available in the early 2000 s. The second constraint is that the AMMA-CATCH observation, which is the best monitored network in Benin, is limited to the northern part of the basin (Galle et al., 2018).

An alternative for the use of this and other distributed models is to resort to reanalyses, which also have their shortcomings in describing the climate of this environment (Dembélé et al., 2020; Grenier et al., 2020; Bodjrènou et al., 2021). Bodjrènou et al. (2021), after a comparative study of two high temporal resolution reanalyses, identified ERA5 compared to MERRA2 as the most suitable to describe the climate of this environment. However, we do not know if it is this reanalysis that allows us to make better simulations on the Benin basins. Also, we do not know if the correction of the variables that they present are essential to optimize the simulations of the terms of the water balance on this basin. Moreover, it is difficult to systematically identify that all the variables of MERRA2 (the least good reanalysis) are bad in terms of simulation of the water balance. At the end of their study, Bodjrènou et al. (2021) recommend the use of bias correction to improve on the shortcomings of the reanalysis in the representation of the region's climate, but they do not mention their advantages or disadvantages over the simulations. Ardoin-Bardin et al. (2006) and Dembélé et al. (2020) showed the presence of holes in the time series has a knock-on effect on the perfect evaluation of ground-based reanalysis/satellite products. Additionally, Danso et al. (2019) showed that dust carried by strong winds settles on sensors and measuring instruments in the West African region, affects the quality of soil data. Therefore, the importance of data correction must be further explored and techniques appropriate to this region must be well thought out.

According to Dembélé et al. (2020), studies comparing reanalyses and satellite data with a model should advocate the use of a hydrological model whose sensitivity to forcings is known to draw consistent conclusions. In this case, it is essential to ensure that Parflow-CLM is capable of simulating water fluxes in Oueme basin and to know its sensitivity to different forcings before using it. Early sensitivity studies of the Parflow model by Herzog et al. (2021) were based on soil hydrodynamic parameters. Currently, it is unclear how to detect the impact of model forcings with biased and unbiased meteorological variables. On the other hand, the prioritized list of variables is not yet sufficiently clarified over the region and especially with this model. It is therefore unclear which variables to focus on for bias correction (Koutsouris et al., 2017). Given the above, this study proposes to: a) light on shortcoming of the reanalyses ERA5 and MERRA2 by relying on their precipitation, temperature, Short wave radiation (SW) and Long Wave radiation (LW) variable; b) evaluate the sensitivity of PARFLOW-CLM with a good and bad meteorological forcing; c) investigate the importance of applying some bias correction techniques to the reanalysis input data on the output of the ParFlow-CLM model.

This paper is organized as following: Section 2 describes the methodology of the study, Section 3 describes the results obtained according to the specific objectives, namely the reanalyses performances in describing the climate of the region, the performance and sensitivity of the models, the comparison of the reanalyses, and the effect of the bias corrections; Section 4 presents the well-documented discussion of the results before the conclusion summarized in Section 5.

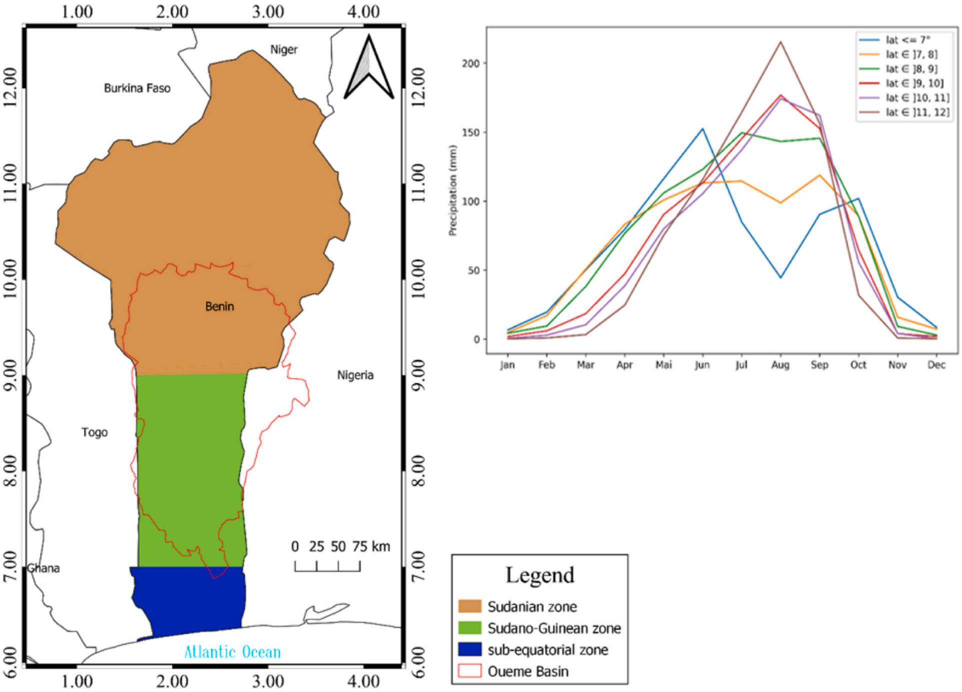

**Fig. 1.** Study area.

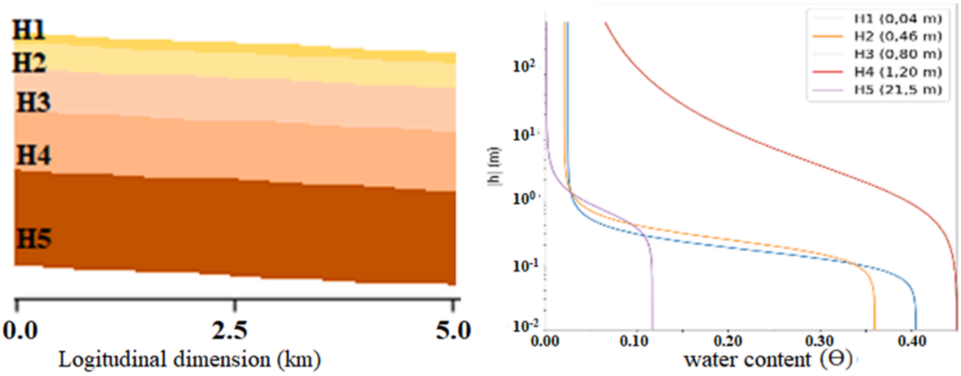

**Fig. 2.** Typology of slopes and schematic of the inflow retention curve. *The thickness of each layer numbered H1 to H5 is in brackets on the van Genuchten curve (right curve).*

## 2. Methodology

### 2.1. Study area and watershed typology

### 2.1.1. Study area

Benin is a small West African country bordered by the Atlantic Ocean to the south, Nigeria to the east, Togo to the west, and Burkina Faso and Niger to the north (Fig. 1). The Oueme basin is located in the interior of this country. It has climatic and topographical characteristics that vary greatly with latitude (Bodjrènou et al., 2021; Amou et al., 2022). Climatically, the Oueme basin shares the country's three climatic zones, namely the two rainy seasons in the south, one rainy season in the north and the transition region considered between 7° and 9° latitude, which are determined by the West African rainfall database (Bodjrènou et al., 2021). With this diversity, it is not appropriate to consider the use of global hydrological models in the basin.

### 2.1.2. Watershed typology

The study was carried out on a typical watershed at the Nalohou site which is an uncultivated area of the AMMA-CATCH observatory (Oueme upper). In situ observations and documented reports of the hydro-geomorphological characteristics such as vegetation,

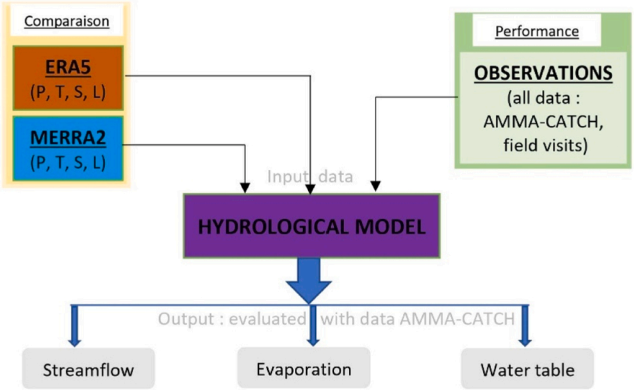

**Fig. 3.** Conceptualization of the study. *P, T, S and L represent precipitation, temperature, shortwave and longwave radiation, respectively.*

slope, friction coefficient, porosity, hydraulic conductivity, and soil layer profile are used. Information obtained from interviews conducted with resource persons were also used.

To reduce the computation time, the basin is represented in a 2D slope of 50 pixels of 100 m x 100 m (corresponding to 50 km in longitudinal dimension) and 24 m depth. The hydrodynamic characteristics considered in this study are homogeneous along each longitudinal layer. Before simulating the water balance terms with the ParFlow-CLM model (Kollet and Maxwell, 2005, 2008), the consistency of the introduced values was analyzed with the Van Genuchten (1980) curves (Fig. 2).

## 2.2. Hydrometeorological datasets

The hydrometeorological dataset includes the forcings that are used as inputs to the ParFlow-CLM model. It also includes the in-situ measurements that are used to evaluate the outputs of the model. The forcing data are prescribed with observations data (with and without transformation) comes from a point station on AMMA-CATCH observatory and the MERRA2 and ERA5 reanalyses (with and without bias corrections) selected on their grid closer to the observational station. ERA5 come from the European Center for Medium-Range Weather Forecasts (Hersbach et al., 2020), implemented by the Copernicus Climate Change Service, and MERRA2 from National Aeronautics and Space Administration (Gelaro et al., 2017). All those data are at hourly time step, except for the WTD data measured in situ, which are at daily time step.

All the other meteorological data necessary to simulate water balance with PARFLOW-CLM model (wind speed, pressure, specific humidity) come from the AMMA-CATCH observatory. In addition, in-situ measurements are needed to evaluate the model's outputs. These are streamflow, evapotranspiration and WTD. The streamflow measurements come from an ara-pont hydrometric station located at 1.6639°E and 9.7622°N. The evapotranspiration measurements are taken from a 2 m-flux tower located in the Nalohou watershed (2.6125°E and 9.7448°E). For the assessment of the WTD, we use measurements from a piezometric station located at a depth of 20 m, at an altitude of 452.792 m, and located 190 m from the river.

Recall that only the variables precipitation, temperature, LW and SW are used in this study. Their use depends on the objective pursued (see details in appendix). To evaluate the performance of the model, we use in-situ measurements of the four variables. For the study of the model sensitivity, we transformed the in-situ data based on the shortcomings of the reanalyses (Bodjrènou et al., 2021). The transformations consist of increasing SW by $20 w/m^2$ and precipitation by 25% (noted Prec1). The model sensitivity is also investigated with temperature decreased by 2 °C, LW by $10 w/m^2$, and precipitation by 25% (noted Prec2). The comparison of the reanalyses is performed using the four variables simultaneously and selecting them individually. The effect of the bias corrections was also investigated for all the variables of reanalyses corrected with techniques described in Section 2.4.

## 2.3. Conceptualization of the study

Fig. 3 conceptualizes the different simulations performed to achieve the objectives. The first simulation used in-situ measurements as inputs. This provides a basis to evaluate the capacity of the model to simulate the different terms of the water balance. The model's sensitivity is also assessed using the same data, which have undergone transformations. The second set of simulations used either ERA5 or MERRA2 as inputs. Both reanalyse products are first used as forcings in individual simulations. They are then bias corrected and also used in another set of simulations.

## 2.4. Bias correction techniques

The bias correction was performed over a period of 11 years from 2005 to 2015 and was based mainly on two methods, namely, the correction of the average of the series and the correction of the interannual trend. These two techniques were applied successively on the time series at an hourly time step for temperature, short and long wave radiation, and precipitation.

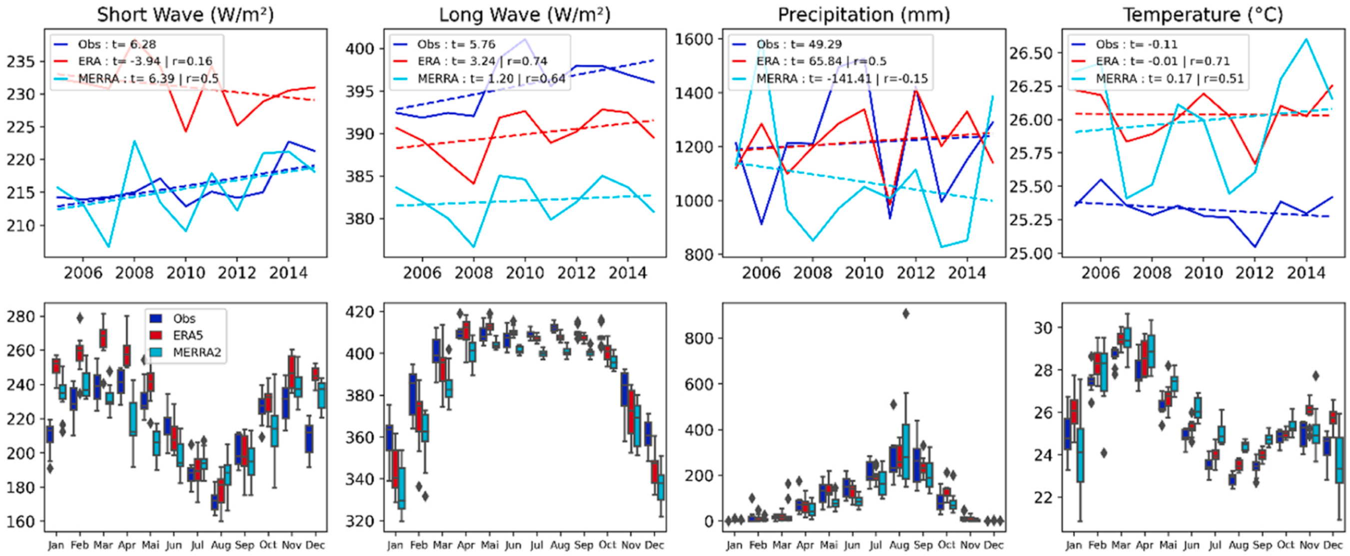

**Fig. 4.** Reanalyses performance on an annual (1st row) and monthly ($2^{sd}$ row) scale. *t corresponds to the interannual trend and r to the Pearson correlation.*

The first technique, also called the simple correction or delta method, consists of determining a correction factor obtained by the ratio of the average of the two series (observation vs. reanalysis). The importance of this bias correction technique in hydrological modeling is well established (Fang et al., 2015). It has helped to maintain consistency between the uncorrected and corrected series. Eq. 1 presents the mathematical formula applied for this bias correction.

For the trend correction, a weighted decrease or increase was applied depending on whether the trend of the simulations was higher than the trend of the observations or vice versa (Eq. 2). It assumes that the description of the climate of this study environment gradually improves over time thanks to the increasing installation of observation stations and their good monitoring (N'Tcha M'Po et al., 2017; Galle et al., 2018).

$$\mathrm{D_{cor}} = \mathrm{C} * \mathrm{D_{sim}} \tag{1}$$

With $\mathrm{D_{cor}}$, $\mathrm{D_{sim}}$ the corrected and simulated data and C the correction factor determined by the ratio of the mean between the observation and the simulation.

$$\mathrm{D_{cor}} = \mathrm{D_{sim}} \pm \Delta\mathrm{T} \tag{2}$$

With ΔT the difference between observed and simulated trend, normalized with the sample size. For any negative value, $\mathrm{D_{cor}}$ is set to zero.

### 2.5. Evaluation of the model results

The evaluation of the model output is performed over the whole simulation period (2005–2015) after three years of spinup. It is based on several metrics that allowed us to understand the overall behavior of the simulations compared to the in-situ data (over- or underestimation). The RMSE, defined by root mean square error (Eq. 3) provides information on the dispersion of the values (Chai and Oceanic, 2015). The Kling Gupta efficiency, KGE (Gupta et al., 2009) and the Nash-Sutcliffe Efficiency (Nash) are also used. The KGE (Eq. 4) provides an aggregated view of the correlation (r), mean (μ), and standard deviation (σ) ratios between the simulation and observations. However, it is often difficult to identify the component responsible for a low KGE value. To overcome this problem, Gupta et al. (2009) and Knoben et al. (2019) suggested decomposing the KGE submetrics and/or accompanying them with other evaluators. Therefore, we presented the correlations between observations and simulations in this study.

The Nash (Eq. 5) is a standardized criterion that aims to express the proportion of the variance in the observations explained by the simulations by comparing it to a reference estimator that is the mean of the observed streamflow (Nash and Sutcliffe, 1970). As with the KGE, the closer the Nash is to 1, the better the simulation.

These estimators were measured at different time scales (annual, monthly, daily) with some distinction between dry and rainy seasons. The mathematical formulas for each of these estimators are presented below.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(D_{obs} - D_{sim})^2} \tag{3}$$

With $\mathrm{D_{obs}}$: the observation data, $\mathrm{D_{sim}}$: the simulations and N the sample size

$$\mathrm{KGE} = 1 - \sqrt{(\mathrm{r}-1)^2 + \left(\frac{\sigma_{sim}}{\sigma_{obs}} - 1\right)^2 + \left(\frac{\mu_{sim}}{\mu_{obs}} - 1\right)^2} \tag{4}$$

With: $\sigma_{sim}$, $\mu_{sim}$: Standard deviation and mean of simulations, σ_obs, μ_obs: Standard deviation and mean of observations

$$Nash = 1 - \frac{\sum_{i=1}^{N}(Q_{obs,i} - Q_{sim,i})^2}{\sum_{i=1}^{N}(Q_{obs,i} - \overline{Q_{obs}})^2} \tag{5}$$

$Q_{obs,i}$ and $Q_{sim,i}$ are the observed and simulated values at the considered time step. $\overline{Q_{obs}}$ is the average of observed values.

## 3. Results

### 3.1. Reanalyses performances on precipitation, temperature, SW and LW

Fig. 4 shows the interannual evolution with indication of correlation and trend on the first hand and the evolution on monthly scale of precipitation, temperature, SW and LW. The in-situ meteorological data from the observatory helped to determine that the ERA5 and MERRA2 reanalyses underestimated the annual mean LW and overestimated the annual mean temperature over the basin. The SW is better simulated on MERRA2 with a strong correlation (0.5) and trends closer to the observations compared to ERA5 which has a poorer correlation and trend. For the other variables, MERRA2 is less good at the annual scale. At the monthly scale, we note that both reanalyses underestimate the LW in almost all months. With the exception of December and January where MERRA2 underestimates

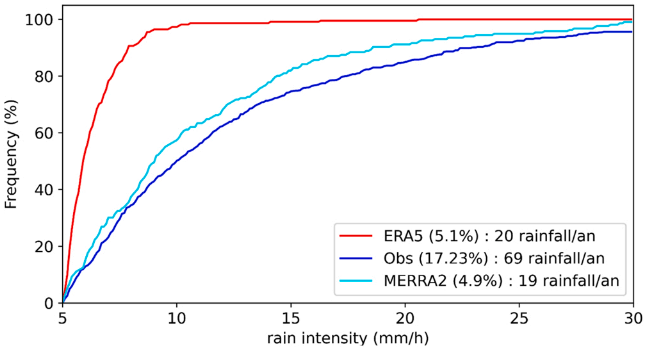

**Fig. 5.** Reanalyses performance on precipitation distribution greater than 5 mm $h^1$. *The values in brackets represent the ratio between the number of rainfall over 5 mm/h and the number of rainfall (over zero) in the observations.*

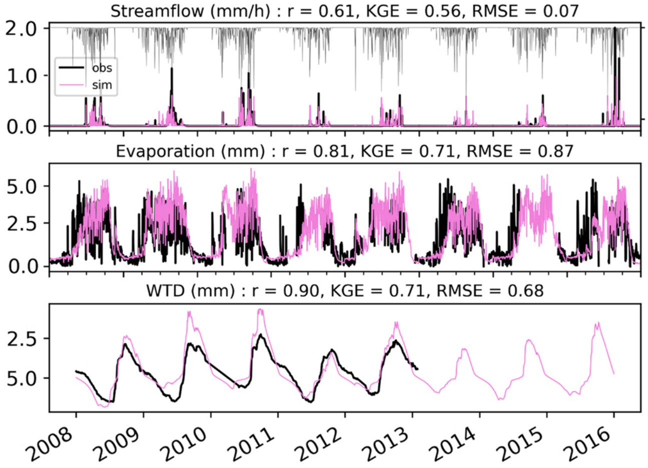

**Fig. 6.** Parflow-CLM performance at the daily scale between 2008 and 2015.

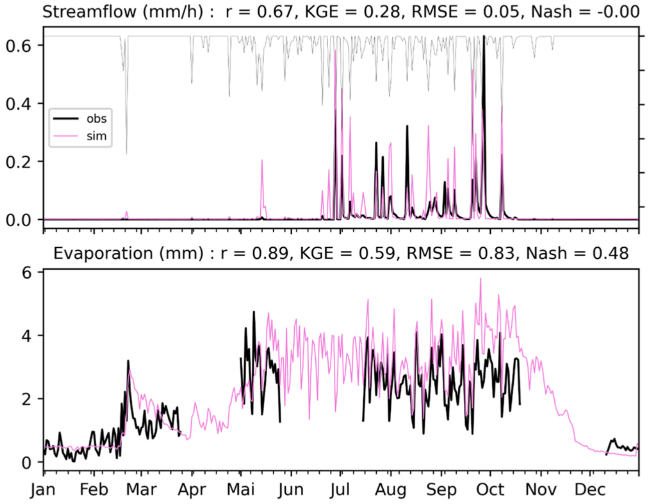

**Fig. 7.** Parflow-CLM performance on streamflow and evaporation in 2012.

the mean temperature, both reanalyses overestimate the monthly mean temperature for all months.

On the precipitation distribution (Fig. 5), it shows that the annual number of rainfall events greater than or equal to 5 mm $h^1$ in both reanalyses is about three times less than the rainfall events greater than or equal to 5 mm $h^1$ in the observations (20 and 19

**Table 1**
PARFLOW-CLM sensitivity on water balance at annual scale (2005–2015). *[a] shows a significant difference between the highlighted variable and the observations, in contrast to [b] which shows no difference. P, T, LW, and SW denote observed precipitation, temperature, longwave, and shortwave radiation, respectively.*

| | Obs | 1.25 x P | 0.75 x P | T – 2 | LW – 10 | SW + 20 |
|---|---|---|---|---|---|---|
| Streamflow (mm) | 475 ± 249 | 684 ± 307 [a] | 241 ± 142 [a] | 494 ± 253 [b] | 459 ± 240 [b] | 425 ± 228 [b] |
| Evaporation (mm) | 601 ± 187 | 696 ± 200 [b] | 532 ± 211 [b] | 582 ± 183 [b] | 617 ± 196 [b] | 651 ± 208 [b] |
| Water storage (mm) | 138 ± 329 | 138 ± 397 [b] | 137 ± 260 [b] | 139 ± 333 [b] | 138 ± 330 [b] | 138 ± 328 [b] |

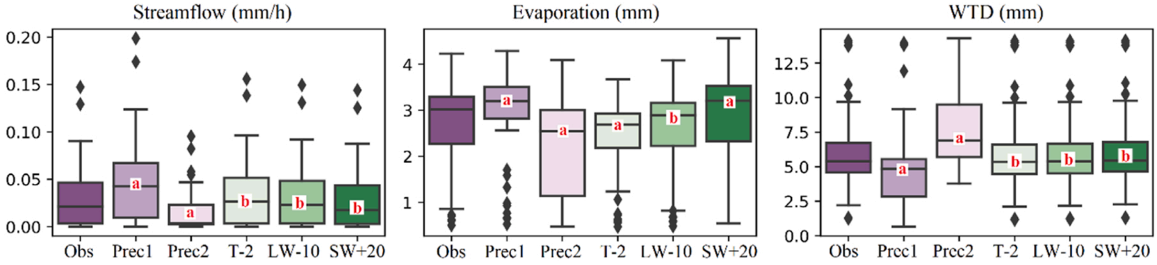

**Fig. 8.** Monthly averages of streamflow, evaporation and WTD for transformed and untransformed data.

respectively for ERA5 and MERRA2 against 69 for the observations). Compared to ERA5, MERRA2 has a better distribution of rainfall events greater than 5 mm h$^1$ (Fig. 5). While the latter has rainfall events greater than 25 mm h$^1$, rainfall events in ERA5 are practically 100% less than 10 mm h$^1$.

### 3.2. *Performance of the ParFlow-CLM model*

Fig. 6 presents the performance of the Parflow-CLM model in simulating the different terms of the water balance. The outputs of this model were compared on a daily time scale with the in-situ measurements from the Nalohou watershed. The best performances of the model are noted in the simulation of evapotranspiration and WTD. The amplitudes and variabilities of the simulations agree moderately well with the observations, which leads to the best correlation (always above 0.80) and KGE scores (always above 0.70).

The comparison of fluxes shows that on the streamflow, the model globally overestimates the observations with a small error (RMSE=0.07). The correlation between observed and simulated streamflow is lower (r = 0.61) than that for the Evaporation and the WTD.

Zooming in on 2012 (Fig. 7), it is seen that the model overestimates the streamflow, especially in October to April which represents the dry season. During this period, the streamflow is often non-zero in the simulations, in contrary to the observations where the streamflow is practically zero. It also seen that the variability of the simulated evaporation during this period is generally lower than the observation. The case is similar during the rainy season, leading to a high root mean square error (RMSE = 0.83).

### 3.3. *Model sensitivity analysis with transformed data*

Sensitivity analysis based on the shortcomings of the transformed data shows that the ParFlow-CLM model is more sensitive to the poor forcing of precipitation than to other variables. A difference of 25% (less) precipitation induces significant impacts (at the 5% threshold) on the water balance and mainly on the first order streamflow followed by evaporation (Table 1). A 25% increase in precipitation induced a 44% increase in streamflow and a 16% increase in evaporation. In contrast, a 25% decrease in precipitation reduced streamflow by 51% and evaporation by 11%. There was no effect on the water storage when precipitation is increased or decreased by 25%.

Similar results are obtained during the rainy season, especially with respect to streamflow (Fig. 8). It can be seen that while the average streamflow observed are about 0.031 mm h$^1$ over the entire period, there is a significant increase on Prec1 (0.048 mm h$^1$) and a significant decrease on Prec2 (0.016 mm h$^1$). Only the changes in precipitation also have a significant effect on the WTD. But on evaporation, it is only LW that has no significant difference. The transformation of precipitation, temperature and SW showed significant differences.

At the daily scale (not presented), there is a decrease in the KGE between the simulated WTD with the transformed precipitation (KGE less than 0.60) compared to the actual observations (KGE = 0.71). The same is seen for the streamflow, with a decrease of the KGE between the streamflow with observed data (KGE=0.56) compared to simulated streamflow (0.21 for Prec1 and 0.32 for Prec2). For the transformation of the other studied variables, only small variations are noticed for the first and second order evaporation and streamflow respectively. These variations are however not significant.

*Prec1 for precipitation increased by 25%, Prec2 for precipitation decreased by 25%. T, LW, and SW denote observed temperature, longwave, and shortwave radiation, respectively. Statistical tests indicate a significant difference (red letter 'a') or a non-significant difference (red*

**Table 2**
Performance of reanalyses corrected (ERA5 *, MERRA2 *) and not corrected (ERA5, MERRA2) on daily scale.

| | Obs | ERA5 | MERRA2 | ERA5 * | MERRA2 * |
|---|---|---|---|---|---|
| **streamflow** | | | | | |
| Cor | 61 | 23 | 10 | 24 | 13 |
| KGE | 56 | 11 | 2 | 13 | 3 |
| RMSE | 7 | 9 | 10 | 9 | 10 |
| Nash | 33 | -6 | -56 | -6 | -56 |
| **Evaporation** | | | | | |
| | Obs | ERA5 | MERRA2 | ERA5 * | MERRA2 * |
| Cor | 81 | 73 | 67 | 73 | 74 |
| KGE | 71 | 67 | 66 | 71 | 73 |
| RMSE | 87 | 99 | 103 | 93 | 92 |
| Nash | 50 | 35 | 29 | 43 | 43 |
| **WTD** | | | | | |
| | Obs | ERA5 | MERRA2 | ERA5 * | MERRA2 * |
| Cor | 90 | 89 | 86 | 89 | 86 |
| KGE | 71 | 86 | 59 | 87 | 58 |
| RMSE | 68 | 65 | 185 | 63 | 191 |
| Nash | 65 | 68 | -159 | 70 | -176 |

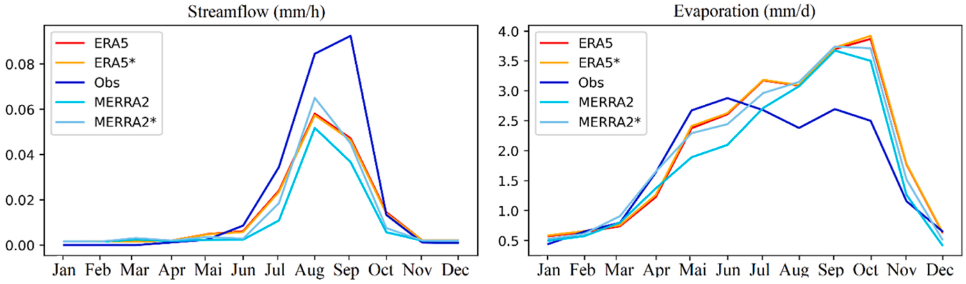

**Fig. 9.** Performance on seasonal scale simulations of streamflow and evaporation. *ERA5 * and MERRA2 * correspond to ERA5 corrected and MERRA2 corrected respectively.*

*letter ’b’).*

### 3.4. *Performance of the ERA5 and MERA2 reanalyses and effect of bias corrections*

Firstly, the outputs of the model simulations forced with ERA5, MERRA2 variables take individually are compared to the simulations of in-situ measurements. From this comparison (not presented), it is finding no significant difference on the simulations made with a temperature, SW and LW of ERA5 compared to the simulation made with the same in-situ data variable. LW of the ERA5 reanalysis improved the simulation of evapotranspiration. The same is true for the MERRA2 on which its LW has improved the simulation of evaporation. For the precipitation, the difference is clearly significant with both ERA5 and MERRA2. Regarding the comparative study of the two reanalyses, also with variables taken individually, we are not able to assert in a systematic way the simulation potential of the water balance terms of ERA5 vs. MERRA2. We note, however, that precipitation, LW and temperature in the ERA5 reanalysis appear to have better KGE scores on evapotranspiration. On the other hand, the simulation carried out with the SW of the MERRA2 reanalysis also seems to have slightly better performances than the simulations carried out with the SW of the ERA5 reanalysis (not presented).

Secondly, we compare globally all data (uncorrected and corrected) from ERA5 vs. MERRA2. We note in daily scale (Table 2) that ERA5 is better than MERRA2 at simulating the different terms of the water balance, which is likely due to its precipitation being closer to the observations. Overall, the corrections applied to the reanalyses improved the simulations and the performance indicators, particularly the KGE. This is reflected in the ERA5 correction that increases the measured KGE on streamflow (from 11 to 13) and the MERRA2 reanalysis correction that increases the measured KGE on evapotranspiration (from 66 to 73). We also find that the simulations improved primarily during the rainy season, but with a phase shift in the peak on streamflow and Evaporation (Fig. 9). The phase shift of about one month on streamflow (peak observed in August for reanalyses instead of September for observations) is likely related to the underestimation of precipitation by the reanalyse products during the first half of the year. The corrections applied significantly improve the performance of the MERRA2 reanalysis to simulate the streamflow that was underestimated in the rain season (Fig. 9).

Third, the effect of bias correction of the individual variables precipitation, temperature, LW and SW of reanalyses is analyzed in detail. The corrections applied to these variables do not show a significant improvement. We found that the uncorrected MERRA2

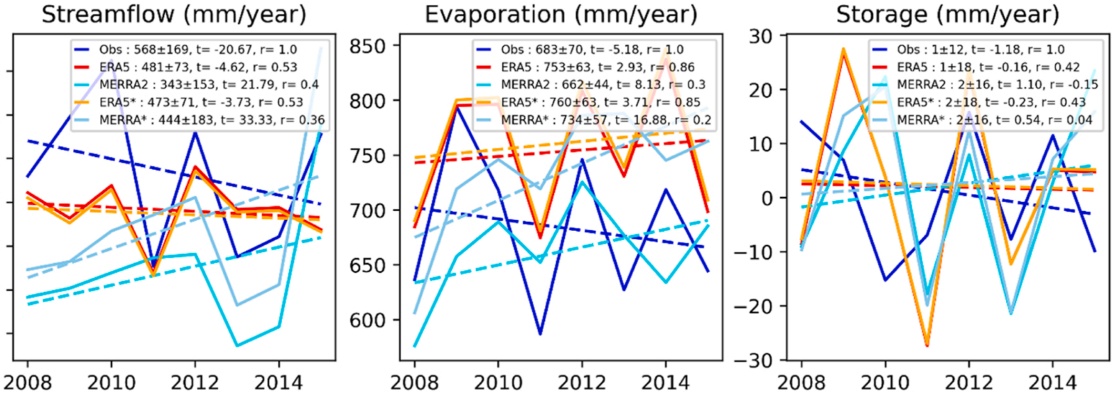

**Fig. 10.** Influence of precipitation corrections on balance sheet terms between 2008 and 2015. *ERA5 * and MERRA2 * correspond to ERA5 corrected and MERRA2 corrected respectively. t corresponds to the interannual trend and r to the Pearson correlation.*

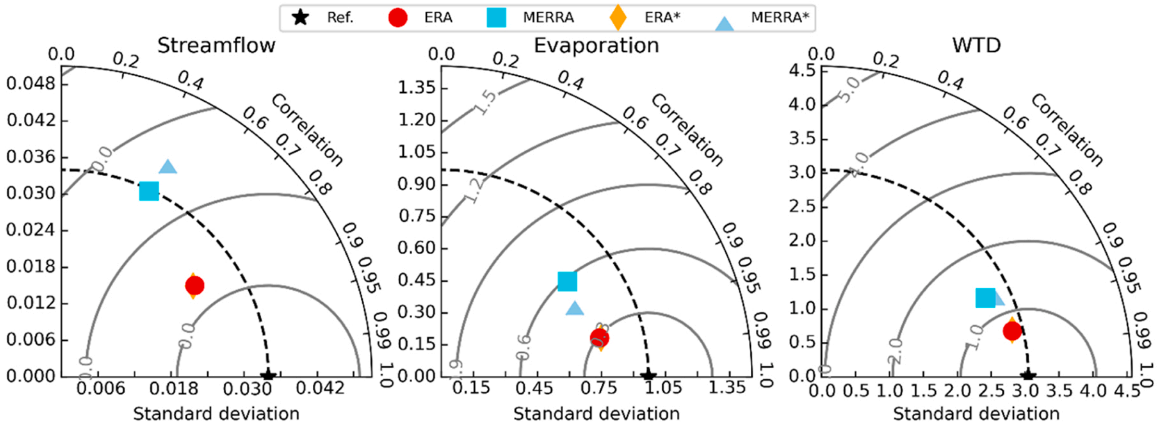

**Fig. 11.** Effect of precipitation correction on rainy season simulations. *ERA5 * and MERRA2 * correspond to ERA5 corrected and MERRA2 corrected respectively. Ref. equal to reference.*

sometimes produced better simulations of the water balance terms than the corrected version. The corrections applied to some variables sometimes degraded the RMSE and sometimes the KGE and therefore weakened the performance of the model. This is the case for the corrected LW of ERA5 which increased the biases with the observations by almost 4% (RMSE goes from 0.87 to 0.84) and the decrease of the KGE (from 0.74 to 0.71).

At the annual scale, the ERA5 reanalysis precipitation correction tends to degrade the annual mean streamflow (Fig. 10). With the observations, we note a difference of 87 mm/year on uncorrected ERA5 against 95 mm/year on corrected ERA5. The same is true for the correction effect which seems to reduce the performance of the WTD. On the other hand, the bias corrections applied to the MERRA2 reanalysis precipitation bring the annual reanalysis totals closer to the observations, likely because the reanalysis precipitation is moderately worse than the ERA5 reanalysis. Its also shows that the mean WTD of the streamflow with corrected MERRA2 (343 mm/yr) is worse than the mean WTD of the ERA5 uncorrected (481 mm/yr) and corrected (473 mm/yr). However, it observed that MERRA2 has a standard deviation of annual streamflow (153 mm/yr) closer to the observed standard deviation (169 mm/yr), which is likely due to the good distribution of precipitation in MERRA2.

At the seasonal scale and especially in the rainy season (Fig. 11), the correction applied to the ERA5 precipitation did not improve its ability to simulate the water balance terms, which is also likely because the mean of the series is equal to that found in the observations. The analysis performed with MERRA2 precipitation, which has an opposite trend to the observations and a totally different mean, shows that the correction techniques on the reanalysis precipitation brought their variation on the streamflow closer and improved the correlation of the evaporation and the WTD.

## 4. Discussion

Comparison studies of the reanalyses with the point station data show that ERA5 better describes the climate of the environment (better correlation, mean and trend) on all variables except SW on which MERRA2 is better. These results may be related to the coarser spatial resolution of MERRA2 than ERA5. These results are consistent with those of Grenier et al. (2020) over Benin showing that the performance of ERA5 (spatial resolution 0.25° x 0.25°) is better than the CFSR reanalysis, which has a resolution of 0.3122° x 0.3125°. The comparison of the reanalyses with the station point data can therefore be affected by the distance between the station and the chosen pixel point.

It is also clear that there is diversity in performance. Not all MERRA2 variables compared to ERA5 are systematically the worst. These results are consistent with the studies of Grenier et al. (2020) who found that in the month of April, the minimum temperature is better simulated in CFSR on the station of Natitingou (synoptic station near our study area) compared to ERA5. In contrast, the latter is worse for the maximum temperature and precipitation on the same station and in the same month.

Our results based on comparisons of model outputs show that simulations with SW, LW and temperature forcing taken individually confirm that there is no significant difference on any of the reanalyses vs. observations, probably because the model is less sensitive to these variables. These results are similar to those obtained with transformed observation data: no significant difference with transformed vs. untransformed SW, LW and temperature data.

Our analyses show that the ParFlow-CLM model performs well in simulating the different water balance terms. The results of this study support the findings of Jabot-Robert (2013), Hector et al. (2018) and Herzog et al. (2021) who have already evaluated and found that Parflow-CLM is performing well and exploitable model for water and energy flow simulations in the Upper Oueme basin. The best simulations are observed for evapotranspiration and water table depth. This could be explained by the homogeneity of the vegetation in this basin, which leads to a homogeneous transpiration of the plants in time and from one point of the watershed to another. Similarly, this homogeneity could lead to the same pumping of the water table by the vegetation over the entire basin, which implies that the simulated water table depths are very consistent with the observed water table depths over time. This was also attempted by Li et al. (2007) when they evaluated the hydrologic impact of land use change using a hydrologic model. They indicated that deforestation can increase the streamflow rate by up to 44% and even the annual streamflow by up to 65%. Therefore, keeping the basin homogeneous throughout the study period (without deforestation of any portion) would be equivalent to having the same streamflow rate under the same climate. Unfortunately, even if the study area was left undeveloped and unchanged by humans, certain natural transformations such as the presence of termites can alter soil properties (Dosso and Kone, 2016). As a result, they can alter streamflow. In addition, the terrain is not flat and therefore our 2D simulations cannot correctly interpret the realities of the environment, hence the poor performance of the model on streamflow simulation.

Model sensitivity studies show that transformations of temperature, longwave radiation (LW) and shortwave radiation (SW) data do not have significant effects on water balance simulations. In contrast, rainfall transformations have significant impacts on the simulations. These results can be explained by the studies of Vissin and Sintondji (2011) who reported that rainfall has the largest influence on tropical environments among all climate variables. The transformation of temperature, LW and Sw variables and mainly the decrease of the former by 2 °C influenced the evaporations in the first order. This result is similar to the outcome studies of Houngué et al. (2019) who show that when temperature increases, evaporation increases significantly, and that the variation of the latter is induced by almost 50% by the variation of temperature.

In opposed to simulations performed with SW, LW and temperature variables in the reanalyses, the simulations performed with rainfall from the reanalyses show poor performance vs. observations; this can be explained not only by the climate under which the work is performed but also that the models are more sensitive to rainfall (Vissin and Sintondji, 2011; Fang et al., 2015). These results can also be explained by the fact that observational data are derived from a point measurement station while reanalyses encompass information on large spatial scales, and thus aggregate information over the area covered by the scale (Bodjrènou et al., 2021).

We note in this study that simulations performed with the SW MERRA2 also appear to perform slightly better than simulations performed with the SW ERA5, particularly on evaporations. This result can be linked to the better correlation of the SW MERRA2 with respect to the observations which amounts to 0.50 compared to the correlation of the SW ERA5 with respect to the observations which amounts to 0.16. The results of this study show that it is difficult to identify the best reanalysis by taking the temperature and radiation variables individually. This result matches with those of Dembélé et al. (2020) who did not find potentially better products when they evaluated seventeen rainfall and temperature products over West Africa based on modeling.

Our results also show that bias correction on some variables such as longwave radiation has negative impacts on evaporation simulation. This result is consistent with studies by Koutsouris et al. (2017) who concluded at the end of their study on the hydrological impact of bias corrections tend to have a negative impact on streamflow simulations.

## 5. Conclusion

This study analyzed the issues related to the use of meteorological forcings from the ERA5 and MERRA2 reanalyses (corrected or not) to simulate the water balance terms of the Oueme basin. The analysis was based on the ParFlow-CLM model after verification of its potential and its sensitivity to temperature, rainfall, LW and SW variables. It can be concluded that the Parflow-CLM model is very efficient and recommendable for hydrological impact studies in the Oueme basin. The analysis of its sensitivity with the transformed variables and those of the reanalyses allows us to conclude that the Parflow-CLM model is more sensitive to rainfall than to the other variables. The good simulations observed on a few occasions with the temperature, SW or LW of the reanalyses and the degradation of the simulations observed on a few occasions when they are corrected allow us to conclude that these variables do not require corrections. They can be used directly in the hydrological models to simulate the water balance terms of the Oueme basin without being subjected to bias correction techniques. On the other hand, the meteorological forcing of the reanalysis rainfall was found to degrade the simulations and the bias correction techniques applied here are not sufficient to recommend their use in the models. The corrections applied to MERRA2 rainfall showed positive effects on the simulation of water balance terms while the effects are not as good on the ERA5 correction. In addition to the correction techniques used here, this study provides an incentive to experiment with other

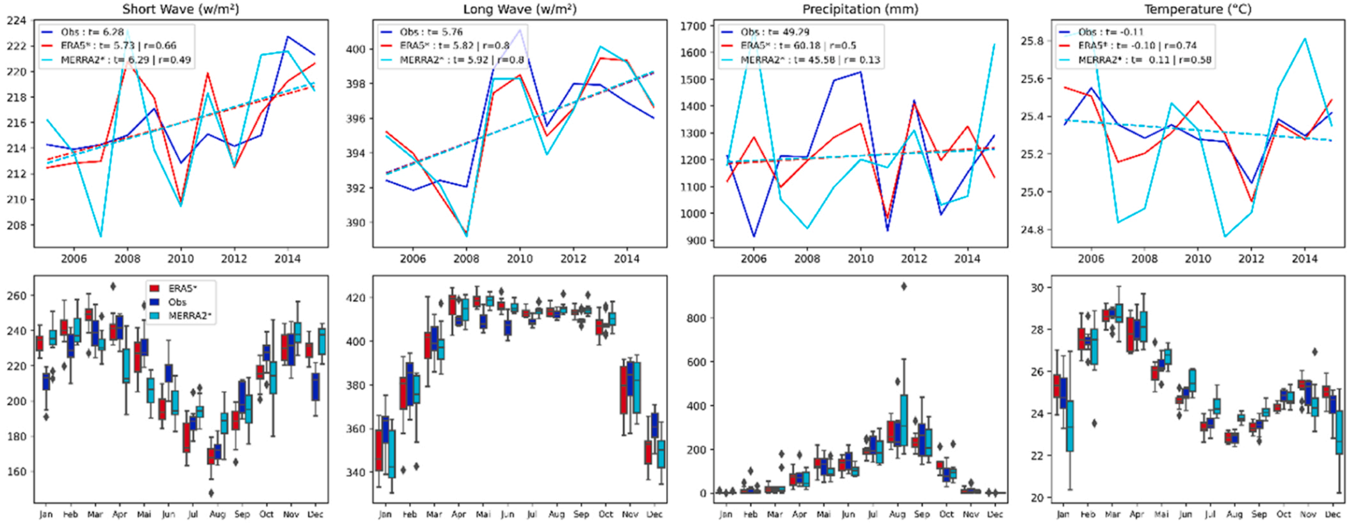

**Fig. A1.** Reanalyse corrected. *t corresponds to the interannual trend and r to the Pearson correlation.*

**Table A1**
The different combinations of data sets for the simulations. * = corrected.

| No | Pluie | Temp | LW | SW | Autres | Objectifs |
|---|---|---|---|---|---|---|
| 01 | Obs | Obs | Obs | Obs | Obs | Performance |
| 02 | Obs + 25% | Obs | Obs | Obs | Obs | Sensibility |
| 03 | Obs − 25% | Obs | Obs | Obs | Obs | Sensibility |
| 04 | Obs | Obs_-2° | Obs | Obs | Obs | Sensibility |
| 05 | Obs | Obs | Obs − 10 W/m$^2$ | Obs | Obs | Sensibility |
| 06 | Obs | Obs | Obs | Obs + 20 W/m$^2$ | Obs | Sensibility |
| 07 | ERA | ERA | ERA | ERA | Obs | Comparison |
| 08 | MERRA | MERRA | MERRA | MERRA | Obs | Comparison |
| 09 | ERA | Obs | Obs | Obs | Obs | Comparison |
| 10 | Obs | ERA | Obs | Obs | Obs | Comparison |
| 11 | Obs | Obs | ERA | Obs | Obs | Comparison |
| 12 | Obs | Obs | Obs | ERA | Obs | Comparison |
| 13 | MERRA2 | Obs | Obs | Obs | Obs | Comparison |
| 14 | Obs | MERRA2 | Obs | Obs | Obs | Comparison |
| 15 | Obs | Obs | MERRA2 | Obs | Obs | Comparison |
| 16 | Obs | Obs | Obs | MERRA2 | Obs | Comparison |
| 17 | ERA* | ERA* | ERA* | ERA* | Obs | Correction |
| 18 | ERA* | Obs | Obs | Obs | Obs | Correction |
| 19 | Obs | ERA* | Obs | Obs | Obs | Correction |
| 20 | Obs | Obs | ERA* | Obs | Obs | Correction |
| 21 | Obs | Obs | Obs | ERA* | Obs | Correction |

**Table A2**
Physical properties of soil.

| Horizon (m) | Ks (m/h) | Porosity | Perm. Relative | | Saturation of the soil | | | |
|---|---|---|---|---|---|---|---|---|
| | | | Alpha | N | Alpha | N | Sres | Ssat |
| H1 (0–0.04) | 0.45 | 0.45 | 6.948 | 3.2 | 6.948 | 3.2 | 0.055 | 0.9 |
| H2 (0.04–0.5) | 0.40 | 0.40 | 4.848 | 3.1 | 4.848 | 3.1 | 0.052 | 0.9 |
| H3 (0.5–1.3) | 0.42 | 0.50 | 0.77 | 1.4 | 0.77 | 1.4 | 0.053 | 0.9 |
| H4 (1.3–2.5) | 0. 42 | 0.50 | 0.77 | 1.4 | 0.77 | 1.4 | 0.053 | 0.9 |
| H5 (2.5–21) | 0.045 | 0.13 | 1.77 | 2.76 | 1.77 | 2.76 | 0.01 | 0.9 |

bias correction techniques on precipitation reanalyses prior to their use in hydrological models. Corrections that retain the same precipitation distributions and monthly totals should be sufficient interest to improve the quality of the ERA5 precipitation reanalysis.

## 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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## Appendix A

See Fig. A1, Tables A1 and A2.

## References

Amou, M., Sambieni, K., Avossè, A.D., Bodjrènou, R., Comandan, F., 2022. Short paper about the influence of climate variability on water availability in the Oueme delta (Southern Benin). Geo Eco Trop. 46 (2), 343–348. ⟨https://geoecotrop.be/uploads/publications/pub_462_14.pdf⟩.

Ardoin-Bardin, S., Dezetter, A., Servat, E., Dieulin, C., Casenave, L., Niel, H., Paturel, J.E., Mahé, G., 2006. Application de scénarii climatiques en modélisation hydrologique: Utilisation des sorties GCM. IAHS-AISH Publ. 308, 436–441. 〈https://horizon.documentation.ird.fr/exl-doc/pleins_textes/divers15-07/010042355.pdf〉.

Biao, E.I., 2017. Assessing the impacts of climate change on river discharge dynamics in Oueme River basin (Benin, West Africa. Hydrology 4 (4). https://doi.org/10.3390/hydrology4040047.

Biao, E.I., Alamou, E.A., Afouda, A., 2016. Improving rainfall–runoff modelling through the control of uncertainties under increasing climate variability in the Ouémé River basin (Benin, West Africa). Hydrol. Sci. J. 61 (16), 2902–2915. https://doi.org/10.1080/02626667.2016.1164315.

Bodjrènou, R.; Cohard, J.M.; Hector, B.; Lawin, E.A.; Chagnaud, G.; Danso, D.K.; M'po N'tcha, Y.; Badou, F.D.; Ahamidé, B. (2021). Climate Change from 1980 to present and performance of ERA5 and MERRA2 datasets for hydrological modelling purposes in Benin: Lessons learnt. In Proceedings of the First OZCAR TERENO International Conference, Strasbourg, France, 5–7 October 2021; p. 19. Available online: 〈https://ozcartereno2020.sciencesconf.org/〉.

Bodjrènou, R., Comandan, F., Danso, D.K., 2023. Assessment of current and future land use and land cover in the oueme basin for hydrological studies. Sustainability 2023 (15), 2245. https://doi.org/10.3390/su15032245.

Chai, T., Oceanic, N. (2015). Root mean square error (RMSE) or mean absolute error (MAE)? – Arguments against avoiding RMSE in the literature. January 2014. https://doi.org/10.5194/gmd-7–1247-2014.

Danso, D.K., Anquetin, S., Diedhiou, A., Lavaysse, C., Kobea, A., Touré, N.E., 2019. Spatio-temporal variability of cloud cover types in West Africa with satellite-based and reanalysis data. Q. J. R. Meteorol. Soc. 145 (725), 3715–3731. https://doi.org/10.1002/qj.3651.

Dembélé, M., Schaefli, B., Van de Giesen, N., Mariéthoz, G., 2020. Suitability of 17 gridded rainfall and temperature datasets for large-scale hydrological modelling in West Africa. Hydrol. Earth Syst. Sci. 24, 5379–5406. https://doi.org/10.5194/hess-24-5379-2020.

Dosso, K., Kone, F., 2016. Influence de l'activité des termites sur les propriétés du sol dans la région de Lamto (Côte d'Ivoire): mesure de la vitesse d'infiltration de l'eau et de la quantité de matière organique en conditions expérimentales. J. Appl. Biosci. 105 (1), 10203. https://doi.org/10.4314/jab.v105i1.16.

Fang, G.H., Yang, J., Chen, Y.N., Zammit, C., 2015. Comparing bias correction methods in downscaling meteorological variables for a hydrologic impact study in an arid area in China. Hydrol. Earth Syst. Sci. 19 (6), 2547–2559. https://doi.org/10.5194/hess-19-2547-2015.

Galle, S., Grippa, M., Peugeot, C., Moussa, I.B., Cappelaere, B., Demarty, J., Mougin, E., Panthou, G., Adjomayi, P., Agbossou, E.K., Ba, A., Boucher, M., Cohard, J.-M., Descloitres, M., Descroix, L., Diawara, M., Dossou, M., Favreau, G., Gangneron, F., Wilcox, C., 2018. AMMA-CATCH, a critical zone observatory in West Africa Monitoring a Region in Transition. Vadose Zone J. 17 (1), 180062 https://doi.org/10.2136/vzj2018.03.0062.

Giertz, S., Hiepe, C., Steup, G., Sintondji, L.O., Diekkrüger, B. (2010). Hydrological processes and soil degradation in Benin. Impacts of Global Change on the Hydrological Cycle in West and Northwest Africa, 168–197.

Grenier, P., Mailloux, C., Akpinfa, É., Agbazo, M.N., Chaumont, D., Rousseau, Y. (2020). Atlas climatique du Bénin. https://doi.org/10.13140/RG.2.2.27862.37443.

Gupta, H.V., Kling, H., Yilmaz, K.K., Martinez, F.M., 2009. Decomposition of the mean squared error and NSE performance criteria: implications for improving hydrological modelling. J. Hydrol. 377 (1), 80–91. https://doi.org/10.1016/j.jhydrol.2009.08.003.

Hector, B., Cohard, J.M., Séguis, L., Galle, S., Peugeot, C., 2018. Hydrological functioning of western African inland valleys explored with a critical zone model. Hydrol. Earth Syst. Sci. 22 (11), 5867–5888. https://doi.org/10.5194/hess-22-5867-2018.

Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz-Sabater, J., Nicolas, J., Peubey, C., Radu, R., Schepers, D., Simmons, A., Soci, C., Abdalla, S., Abellan, X., Balsamo, G., Bechtold, P., Biavati, G., Bidlot, J., Bonavita, M., Thépaut, J., 2020. The ERA5 global reanalysis. Q. J. R. Meteorol. Soc. 146 (730), 1999–2049. https://doi.org/10.1002/qj.3803.

Herzog, A., Hector, B., Cohard, J.M., Vouillamoz, J.M., Lawson, F.M.A., Peugeot, C., de Graaf, I., 2021. A parametric sensitivity analysis for prioritizing regolith knowledge needs for modeling water transfers in the West African critical zone. Vadose Zone J., March 1–22. https://doi.org/10.1002/vzj2.20163.

Houngue, R. (2020). Climate change impacts on hydrodynamic functioning of Oueme Delta (Benin). Ph.D. Thesis, University of Abomey-Calavi, Bénin. [Google Scholar].

Houngue, R., Lawin, A.E., Moumouni, S., Afouda, A.A., 2019. Change in climate extremes and pan evaporation influencing factors over Ouémé Delta in Bénin. Climate 7 (1). https://doi.org/10.3390/cli7010002.

Jabot-Robert, D. (2013). Caractérisation et modélisation de la dynamique de l'évapotranspiration en Afrique Soudanienne en zone de socle: interaction entre les aquifères et la végétation. Ph.D. Thesis, LTHE - University of Grenoble Alpes, France 〈https://theses.hal.science/tel-00849151/〉.

Knoben, W.J.M., Freer, J.E., Woods, R.A., 2019. Technical note: Inherent benchmark or not? Comparing Nash-Sutcliffe and Kling-Gupta efficiency scores. Hydrol. Earth Syst. Sci. Discuss. 1–7. https://doi.org/10.5194/hess-23-4323-2019.

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). Prepr., March 18. https://doi.org/10.20944/preprints201803.0090.v1.

Kollet, S.J., Maxwell, R.M., 2005. Integrated surface-groundwater flow modeling: A free-surface overland flow boundary condition in a parallel groundwater flow model. Adv. Water Resour. 29 (7), 945–958. https://doi.org/10.1016/j.advwatres.2005.08.006.

Kollet, S.J., Maxwell, R.M., 2008. Capturing the influence of groundwater dynamics on land surface processes using an integrated, distributed watershed model. Water Resour. Res. 44 (2), 1–18. https://doi.org/10.1029/2007WR006004.

Koutsouris, A.J., Seibert, J., Lyon, S.W., 2017. Utilization of global precipitation datasets in data limited regions: A case study of Kilombero Valley, Tanzania. Atmosphere 8 (12). https://doi.org/10.3390/atmos8120246.

Li, K.Y., Coe, M.T., Ramankutty, N., De Jong, C.R., 2007. Modeling the hydrological impact of land-use change in West Africa. J. Hydrol. 258–268. https://doi.org/10.1016/j.jhydrol.2007.01.038.

Nash, J.E., Sutcliffe, J.V., 1970. River flow forecasting through conceptual models part I — A discussion of principles. J. Hydrol. 10 (3), 282–290. https://doi.org/10.1016/0022-1694(70)90255-6.

Nounangnonhou, T.C., Fifatin, F.X.N., Lokonon, B.E., Acakpovi, A., Sanya, E.A., 2018. Modelling and prediction of Ouémé (Bénin) river flows by 2040 based on GR2M approach. LARHYSS J. 2521–9782 (33), 71–91. P-ISSN 1112-3680/E-ISSN. 〈http://larhyss.net/ojs/index.php/larhyss/article/view/567/579〉.

Van Genuchten, M.T., 1980. A closed form equation for predicting the hydraulic conductivity of unsaturated soils. Soil Sci. Soc. Am. J. 892–898, 44. https://doi.org/10.2136/sssaj1980.03615995004400050002x.

Vissin, E.W., Sintondji, L.O. (2011). Changement climatique et vulnérabilité des ressources en eau dans le bassin du zou a Atchérigbe. Revue de géographie du lardymes, université de Lomé, 1993–3134, 123–131.