

Testing sensitivity of BILAN and GR2M models to climate conditions in the Gambia River Basin

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Abstract: This study investigates the performance of two lumped hydrological models, BILAN and GR2M, in simulating runoff across six catchments in the Gambia River Basin (Senegal) over a 30-year period employing a 7-year sliding window under different climatic conditions. The results revealed differences in overall performance and variable sensitivity of the models to hydrological conditions and calibration period lengths, stemming from their different structure and complexity. In particular, the BILAN model, which is based on a more complex set of parameters, showed better overall results in simulating dry conditions, while the GR2M model had superior performance in wet conditions. The study emphasized the importance of the length of the calibration period on model performance and on the reduction of uncertainty in the results. Extended calibration periods for both models narrowed the range of the Kling-Gupta Efficiency (KGE) values and reduced the loss of performance during the parameter transfer from calibration to validation. For the BILAN model, a longer calibration period also significantly reduced the variability of performance metric values. Conversely, for the GR2M model, the variability rate did not decrease with the length of the calibration periods. Testing both models under variable conditions underscored the crucial role of comprehending model structure, hydrological sensitivity, and calibration strategy effects on simulation accuracy and uncertainty for reliable results.

Keywords: Rainfall-runoff model; BILAN; GR2M; Lumped models; The Gambia River Basin; Crash test.

INTRODUCTION

Understanding the drivers of uncertainty in hydrological modelling is of critical concern for delivering reliable predictions of the hydrological impacts of climate change, extreme events, disasters, and water resource management (Beven, 2018). Over the last decades, the estimation of modelling uncertainty has been the subject of numerous studies, investigating the factors affecting the uncertainty, as well as the methods of its assessment (Ancil et al., 2004; Andréassian et al., 2009; Hanel et al., 2012; Refsgaard and Madsen, 2013; Yapo et al., 1996). Improved understanding of uncertainty in hydrological modelling is essential for enhancing the accuracy and reliability of predictions, which can subsequently inform effective decision-making in water resources management.

Numerous studies have investigated various aspects of uncertainty in hydrological modelling, ranging from the role of parameters calibrated on historical data to predict runoff (Seibert, 2003; Vaze et al., 2010) to the effects of using contrasting calibration periods on model performance (Seibert, 2003). Seibert (2003) reported a performance loss when calibrating the HBV model in four Swedish catchments using periods with lower runoff peaks validated on higher peaks. Vaze et al. (2010) further explored this issue, testing four hydrological models in 61 Australian catchments, and found that models calibrated under wetter circumstances performed worse during dry seasons. Other studies have focused on specific hydrological processes, such as snow dynamics and soil moisture processes. Merz et al. (2011), for instance, found that the parameters

controlling these processes depend significantly on the hydro-climatological conditions of the calibration period, leading to notable biases in high flows, especially in snow-affected catchments. Coron et al. (2012) introduced the Generalized Split-Sample Test (GSST) and calibrated three rainfall-runoff models over a set of 216 catchments in southeast Australia. They discovered an (over) underestimation of average runoff volumes during parameter transfer over a wetter (drier) climate than the validation and vice versa.

Climate change presents a substantial challenge for hydrological modelling, as concurrent changes in precipitation patterns, rise of air temperatures, and changes in seasonality of hydrological processes have significant implications for model performance and uncertainty estimation. Multiple studies have investigated the impact of climate change on hydrological modelling predictions, providing insights into model behavior under changing climatic conditions (Berthet et al., 2020; Bodian et al., 2018; Vormoor et al., 2018). Understanding sensitivity of models to the climate conditions is of specific importance in regions exposed to intense effects of climate change, such as the West African basins (Roudier et al., 2014). For instance, Bodian et al. (2018) calibrated the GR4J model on two main West African Senegalese river basins using six GCMs and two RCP scenarios, predicting a decrease in annual streamflow for both basins under different RCP scenarios. Vormoor et al. (2018) reported a general performance loss due to the transfer of calibrated parameters to independent validation periods in five Norwegian catchments with mixed snowmelt/rainfall regimes. Berthet et al. (2020) proposed a crash-testing framework to

assess the quality of hydrological forecasts in an extrapolation context, revealing challenges in uncertainty quantification when forecasting high flows and a significant drop in reliability across catchments and lead times.

Despite the progress made in understanding uncertainty in hydrological modelling, considerable gaps in knowledge persist. Many studies have reported a decrease in model performance after transferring calibrated parameter sets between climatologically contrasting periods (Merz et al., 2011; Vaze et al., 2010; Wilby, 2005), indicating importance of the uncertainty associated with parameter estimation. Additionally, the existing literature has not thoroughly explored the effects of varying calibration period lengths and their influence on model performance. There is a need for further research to provide more comparable results across a diverse range of cases, which will contribute to a better quantification of model robustness and parameter transferability.

Understanding the relationship between the length of the calibration period and the model performance can provide valuable insights into the optimal calibration strategies for hydrological models under different climatic conditions. Moreover, there is a lack of comprehensive studies examining the portability of optimized parameters from calibration to validation, particularly in the context of changing climatic conditions. Investigating the transferability of optimized parameters can help hydrologists develop more reliable and accurate models for predicting future hydrological behaviour. Finally, many studies have focused on specific geographical regions, leaving considerable scope for research in other, less-studied areas. The investigation of hydrological modelling uncertainties in underrepresented regions can reveal novel findings on hydrological regimes and provide valuable information for local water resource management.

This research aims to address the following research questions: (a) How are models sensitive to climate conditions, and specifically, how well do they simulate dry/wet periods? (b) How does the length of the simulation period affect the calibration performance? (c) How portable are the optimized parameters from calibration to validation?

To answer these questions, this study performed a crash test of two hydrological models, BILAN and GR2M, under varying calibration and validation conditions. The Gambia River Basin was selected as the study area, providing the necessary complexity of physiographic conditions and serving as an example of a region highly vulnerable to climate change, where the appropriate design of hydrological models is important for defining sustainable water management strategies.

MATERIAL AND METHODS

Study area

The Gambia River Basin is a semi-arid region in West Africa, covering three countries: Guinea, Senegal, and Gambia. The study area (Figure 1) was selected for this research due to a mix of its unique characteristics, and also a lack of previous studies in the region. The basin spans over 77,100 km², making up approximately 25% of the surrounding Senegal River Basin (Degeorges et al., 2007). The Gambia River Basin is a region facing the effects of climate change, environmental transition, and human impact. Despite its dense woodland, the area is experiencing recurrent droughts, floods, deforestation, bush fires, overuse of land resources, and overgrazing (Bodian et al., 2018), which have contributed to the degradation of the environmental conditions and have impacts on runoff regime and its rising vulnerability to extreme events. Relatively sparse

network of hydrometeorological monitoring affects the approach to hydrological modelling, selection of modelling tools and models parametrization.

Hydrometeorological data

This study used monthly observed climate data, including rainfall and temperature, as well as streamflow data. Monthly rainfall and temperature data were obtained from the National Agency of Civil Aviation and Meteorology (ANACIM) and include information from seven rainfall stations and three temperature measurement stations. Tables 1, 2, and 3 provide a summary of the hydrographic network and climate data used in the study. The areal distribution of precipitation and temperature values across the Gambia River Basin was calculated using the weighted Thiessen polygon method, with precipitation data derived from seven rain gauge stations (Fongolimby, Goudiry, Kedougou, Kidira, Salemata, Saraya, and Tambacounda) and temperature data collected from three stations (Goudiry, Kedougou, and Tambacounda). The area of each polygon was calculated, and weights were assigned based on the ratio of the polygon area to the total area of the basin.

The potential evapotranspiration (PET), as a substantial input for hydrological modelling was calculated using the Oudin method (Oudin et al., 2010, Eq. (1)). While there are various methods to estimate PET, including the FAO-56 Penman Monteith method, they require extensive range of climate data, unavailable in the study area. The method proposed by Oudin et al. (2010), on the other hand, proved robust PET estimates even with limited data inputs (Flores et al., 2021; Kodja et al., 2020), making it suitable for application in regions with limited availability of climate data observations.

$$PET(i) = \begin{cases} \frac{0.408 \cdot Re \cdot (T(i) + 5)}{100} & \text{if } T(i) + 5 > 0 \\ 0 & \text{if } T(i) + 5 \leq 0 \end{cases}, \quad (1)$$

where Re is extraterrestrial radiation [MJ, m⁻² d⁻¹] and T the air temperature (°C), and

$$Re(i) = \frac{24.60}{\pi} \cdot G_{sc} \cdot dr [\omega s \cdot \sin \phi \cdot \sin \delta + \cos \phi \cdot \cos \delta \cdot \sin \omega s], \quad (2)$$

where G_{sc} is a solar constant (0.082 MJ, m⁻² min⁻¹), and dr is the inverse relative distance Earth-Sun, defined as

$$dr = 1 + 0.033 \cdot \cos\left(\frac{2\pi}{365}J\right), \quad (3)$$

and where J is number of the day in the year, δ is the solar declination, calculated as

$$\delta = 0.409 \cdot \sin\left(\frac{2\pi}{365}J - 1.39\right), \quad (4)$$

and where ωs the sunset hour angle and ϕ the catchment latitude, expressed in [rad].

Calibration approach

In this study the "crash test" methodology for model calibration, proposed for models in changing climatic conditions (Andréassian et al., 2009; Coron et al., 2012) was applied. Specifically, the Generalized Split-Sample Test (GSST) methodology, as proposed by Coron et al. (2012) and validated

Table 1. Annual precipitation in the study area (Data: ANACIM).

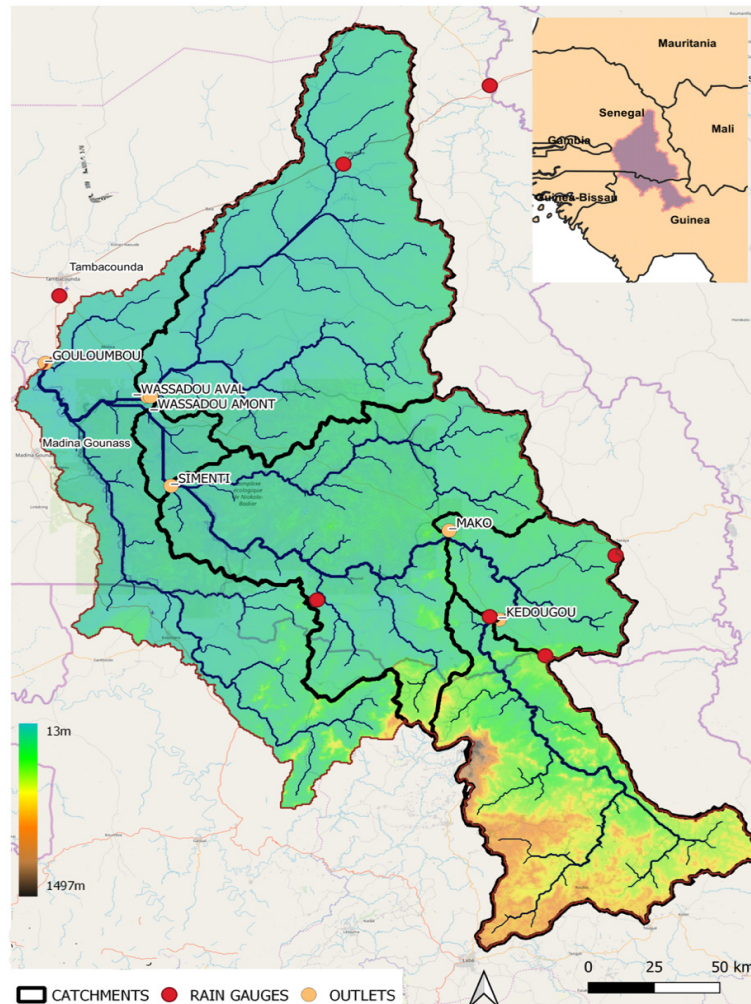
Rain Gauge	Lat	Lon	Altitude [m]	Rainfall [mm]	Observation period	Gaps (%)
Fongolimby	12.42	-12.02	399	854	1990–2017	0
Goudiry	14.18	-12.71	59	656	1960–2017	19
Kedougou	12.56	-12.71	121	1200	1960–2017	0
Kidira	14.46	-12.21	35	577	1990–2017	0
Salemata	12.62	-12.8	84	808	1990–2017	0
Saraya	12.78	-11.78	184	960	1990–2017	0
Tambacounda	13.71	-13.68	52	752	1990–2017	0

Table 2. Mean annual temperatures at gauging stations (Data: ANACIM).

Stations	Lat	Lon	Altitude [m]	Temperature [°C]	Observation period	Gaps (%)
Goudiry	14.18	-12.71	59	26.3	1991–2017	0
Kedougou	12.56	-12.21	121	28.6	1960–2017	0
Tambacounda	13.71	-13.68	52	28.8	1960–2017	0

Table 3. Main characteristics of the hydrographic network of the Gambia river upstream from Gouloumbou.

Catchments	Length [km]	Altitude max [m]	Altitude min [m]
Kedougou	243.00	1125.00	105.00
Mako	328.00	1125.00	75.00
Simenti	503.00	1125.00	10.00
Wassadou amont	559.00	1125.00	5.00
Gouloumbou	658.00	1125.00	0.00

**Fig. 1.** Map of the study area of the Gambia River Basin with gauging and meteorological stations.

by Vormoor et al. (2018) was applied including the following steps:

- Evaluate the extent of the time series and select a calibration period.
- Determine the hydrological year and derive drought based on climate variables such as rainfall, temperature, and runoff.
- Quantify dry years or periods with lower temperature as the 20th percentile, and wet years or periods with higher temperature as the 80th percentile.

The GSST methodology balances the validation performances to evaluate whether they vary significantly when climatic characteristics differ between calibration and validation periods. The GSST scheme consists in the division of the time series into sub-periods (SP) of the same length and conducting calibration and validation tests for all possible configurations. A sliding window of the selected length is used to define the sub-periods, with the window moving by one year between two periods to allow for overlapping of the sub-periods. The sub-periods are then categorized according to hydroclimatic characteristics to test the sensitivity of the models to the climate conditions (Table 4). For each calibration sub-period, the optimized parameter set is used to perform all possible validation tests on the independent sub-periods.

The validation sub-periods that overlap with the calibration sub-period are excluded to ensure strict independence of calibration and validation conditions. It's crucial to note that Dry Years and Wet Years are distinct and never overlap. Figure 2 provides a visual representation of the GSST methodology. The process is designed to evaluate the model's performance under different climatic conditions and ensure robustness in changing climatic conditions.

The 5-year moving window scheme, adapted from Coron et al. (2012) and Vormoor et al. (2018), is a generalized version of the calibration approach described earlier (Figure 2). In this scheme, the sub-period (SP_n) where calibration is performed, and the parameter set (Ω_n) are defined as follows:

SP_n refers to the sub-period during which the calibration is performed.

Ω_n denotes the optimized parameter set obtained from the calibration process for SP_n.

This scheme provides a systematic and comprehensive way to evaluate the model's performance under different climatic conditions and ensures the robustness of the model in changing climatic conditions. By using a moving window, the calibration and validation tests are performed on different sub-periods, providing a more thorough evaluation of the model's performance.

Hydrological Models

The study employs two well-established lumped hydrological models, BILAN and GR2M, which have been extensively used in various hydrological investigations (Bodian et al., 2018; Hanel et al., 2012; Vizina et al., 2015). These models have been selected based on their ability to effectively capture the hydrological processes in the study area and provide reliable results. The GR2M model, developed by the French National Institute for Agricultural Research (INRAE), is characterized by its simplicity and requires only two adjustable parameters: a capacity parameter (X1) and an exchange coefficient (X2) (Mouelhi et al., 2006). Due to its simplicity, the GR2M has been widely applied in various environments to study the hydrological response and has proven to be a robust tool for simulating river discharge (Bodian et al., 2018). In contrast, the BILAN model provides a more comprehensive representation of the hydrological system, with up to seven tuning variables (Hanel et al., 2012, Table 5).

The BILAN model has been successfully applied to complex hydrological systems and has demonstrated its ability to accurately represent the water balance components, including runoff, evapotranspiration, and storage changes (Vizina et al., 2015). By employing both the BILAN and GR2M models, this study aims to provide a comparative evaluation of their performance and demonstrate the applicability of these models in hydrological modelling. The application of these two models enabled a robust evaluation of the proposed methodology, as they have been tested and validated in a variety of hydrological settings.

Table 4. Definition of the sub-period categories.

Sub-period Category	Code	Sliding window length [years]	Description
Precipitation-Dry	PD	2–7	Periods with low precipitation, ranked in the lower 20th percentile.
Temperature-Low	TL	2–7	Periods with low temperatures, ranked in the lower 20th percentile.
Runoff-Dry	RD	2–7	Periods with low runoff, coinciding with dry weather conditions.
Precipitation-Wet	PW	2–7	Periods with higher precipitation, ranked in the 80th percentile.
Temperature-High	TH	2–7	Periods with high temperatures, ranked in the upper 80th percentile.
Runoff-Wet	RW	2–7	Periods with high runoff, coinciding with wet weather conditions.

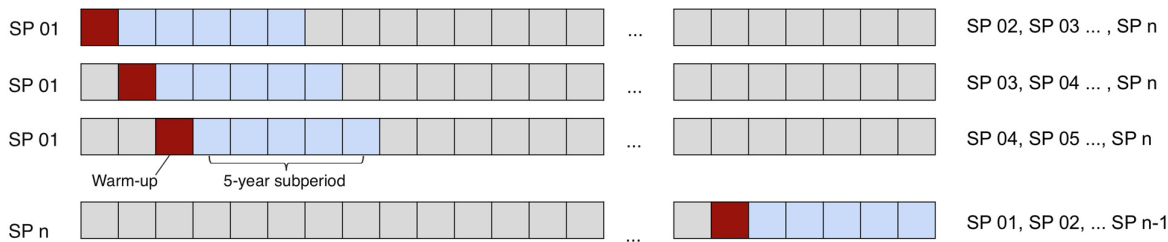


Fig. 2. Generation of calibration sub-periods using a 5-year sliding window based on the principles of the split-sample test and the differential split-sample test.

Table 5. The BILAN model parameters.

Parameter	Description
Spa	Capacity of soil moisture storage [mm]
Dgm	Temperature/snow melting factor
Dgw	Factor for calculating the quantity of liquid water available on the land surface under winter conditions
Alf	Parameter controlling outflow from direct runoff storage or parameter of rainfall-runoff equation for direct runoff
Soc	Parameter controlling the distribution of percolation into direct runoff and groundwater recharge under summer conditions or into interflow and groundwater recharge under summer conditions
Mec	Parameter controlling the distribution of percolation into direct runoff and groundwater recharge under snow melting conditions or into interflow and groundwater recharge under snow melting conditions
Wic	Parameter controlling the distribution of percolation into interflow and groundwater recharge under winter conditions
Grd	Parameter controlling outflow from groundwater storage (base flow)

Calibration method

The calibration of the BILAN and GR2M models was carried out using monthly time series of rainfall, runoff, and potential evapotranspiration as input data. A year of warming period and the Kling-Gupta efficiency (KGE) were used as the objective function. For the BILAN model, the calibration process involved adjusting the parameters controlling the capacity of soil moisture storage [mm] Spa (100, 2000), the parameter controlling the baseflow, Grd (0.001, 1), and the parameter controlling the direct runoff, Alf (0.00001, 0.003). These parameters have a significant impact on the simulation of runoff and depend on the geographical conditions. In a West African context of seasons without snow cover, only two seasons are forming the scope of runoff processes - a longer dry season and a shorter rainy season. Other BILAN parameters are left at their default values.

The GR2M model has only two parameters: X1, which controls the production store capacity, and X2, which controls the exchange coefficient. The calibration of the GR2M model was automated by iteratively adjusting the parameter values until the minimum value of the selected objective function was achieved.

Evaluation of model performance

Several performance measures can be used to evaluate the similarity between the observed and simulated discharge, including the Kling-Gupta efficiency (KGE), the Nash-Sutcliffe efficiency (NSE), coefficient of determination (R^2), percent bias (PBIAS), and the root mean square error (RMSE). These measures provide a comprehensive evaluation of the model's ability to reproduce basin discharge and allow for an assessment of hydrological model's performance under different conditions. The Kling-Gupta Efficiency metrics (Kling et al., 2012) is calculated as:

$$KGE = 1 - \sqrt{(r - 1)^2 + (\alpha - 1)^2 + (\beta - 1)^2}, \quad (5)$$

where r = Pearson correlation coefficient between the observed and simulated values, α = ratio of the standard deviation of the simulated values to the observed values, and β = ratio of the mean simulated values to the mean observed values.

The Nash-Sutcliffe Efficiency criterion (Nash and Sutcliffe, 1970), is calculated as:

$$NSE = 1 - \frac{\sum_{i=1}^n (Q_{obs,i} - Q_{sim,i})^2}{\sum_{i=1}^n (Q_{obs,i} - \bar{Q}_{obs})^2}, \quad (6)$$

where: $Q_{obs,i}$ is the observed discharge at time i , $Q_{sim,i}$ is the simulated discharge at time i , $\bar{Q}_{obs}$ is the mean observed discharge over the simulation period, and n is the total number of observations.

To assess the transferability of the optimized parameters from the calibration period to an independent validation period, the performance losses are evaluated using the Model Robustness Criterion (MRC) proposed by Coron et al. (2012), defined as:

$$MRC_{C-V} = \frac{\epsilon_C}{\epsilon_V} - 1, \quad (7)$$

where epsilon is the performance criterion (in this case RMSE) to be maximized during the calibration.

The MRC is based on the theory (Vormoor et al., 2018) that the set of parameters optimized during the calibration period (the donor) is used to simulate the discharge in the independent validation period (the receiver). The MRC reflects the ability of the parameter set optimized in the calibration period to simulate the discharge, particularly high flows, in the validation period. The performance criterion used in this study is the root mean square error (RMSE), which is maximized during calibration. A null MRC-value indicates that the parameter set optimized in the calibration period performs equally well in the validation period. Negative MRC-values indicate a decrease in the suitability of the parameter set for the validation period, and the more negative the MRC, the less transferable the parameter set is. For example, an MRC-value of -0.2 would indicate a 20% performance loss. A positive MRC estimate, on the other hand, would mean that the parameter set from the calibration period performs better on the validation period (Vormoor et al., 2018).

For the assessment of model performance, we computed the KGE, NSE, and RMSE metrics. The complete results can be found in the Appendix (Table A2 and A3). KGE was employed as the primary metric for presenting the performance in results, given its integrative nature, which makes it less susceptible to outliers and extreme values compared to RMSE and NSE (Moriassi et al., 2007). This robustness is of critical importance in assessing the performance of hydrological models, particularly in sensitive environments where the extreme events such as floods or droughts can lead to significant outliers.

RESULTS

Calibration performance

To evaluate the calibration and validation performance, we employed the defined sub-periods with varying window lengths based on hydroclimatic characteristics, set according to the above-stated methodology.

The calibration results for both models deliver generally satisfactory results, with the Kling-Gupta efficiency (KGE) values ranging from 0.66 to 0.92 for the BILAN model and from 0.61 to 0.79 for the GR2M model. The distribution of the overall calibration performance based on the KGE values across six catchments in the Gambia River Basin is illustrated in the box plots shown in Figures 3–4.

The results indicate a declining calibration performance as the simulation period is extended, with an average drop in model performance for the BILAN and GR2M models of 0.0009% and 0.006%, respectively (Appendix, Table A2). Nevertheless, the validation performance of the GR2M model is fair to good, with the KGE values ranging from -0.17 to 0.63 . The KGE values of the BILAN model range between -6.34 and 0.76 throughout the validation period. These results demonstrate that the BILAN model outperforms the GR2M model in terms of calibration

accuracy, with median KGE values for both models close to 0.8 . The validation indicates that the performance of the two models is comparable in the mean KGE values and response to calibration period length. However, substantial differences in the performance metrics variability were obtained (Figures 5–6).

The average KGE metric values for the calibration periods indicate an overall higher performance of the BILAN model for all sub-period lengths. The mean KGE values in the overall assessment of the BILAN model are decreasing with the longer

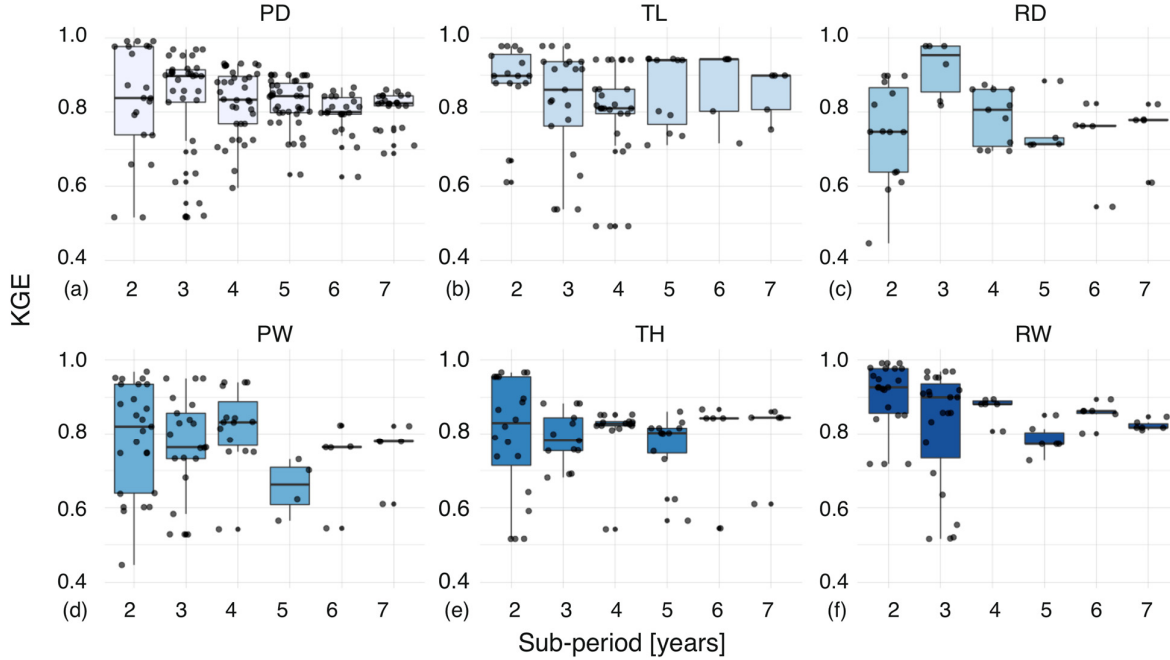


Fig. 3. Calibration performance of the BILAN model for the defined sub-periods and variable length of time window: (a) Precipitation-Dry, (b) Temperature-Low, (c) Runoff-Dry, (d) Precipitation-Wet, (e) Temperature-High, (f) Runoff-Wet.

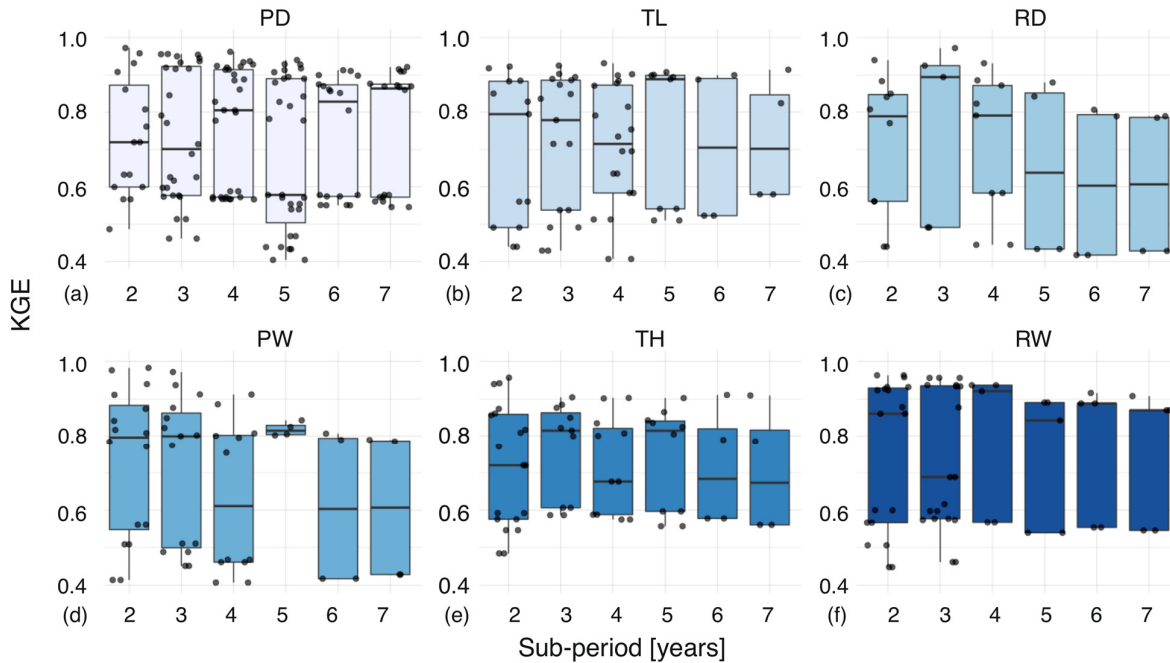


Fig. 4. Calibration performance of the GR2M model for the defined sub-periods and variable length of time window: (a) Precipitation-Dry, (b) Temperature-Low, (c) Runoff-Dry, (d) Precipitation-Wet, (e) Temperature-High, (f) Runoff-Wet.

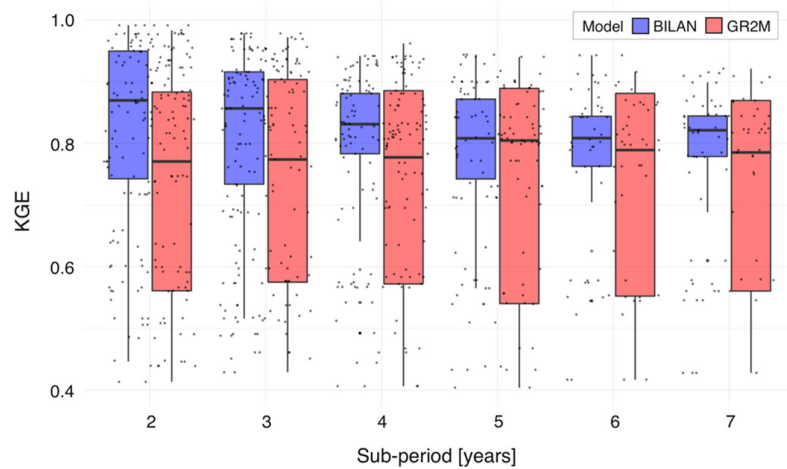


Fig. 5. Overall calibration performance of the models without the distinction of climate variable.

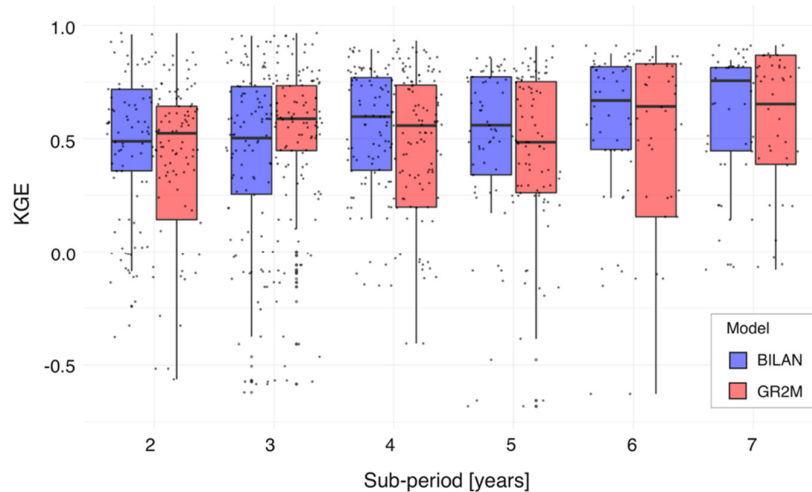


Fig. 6. Overall validation results of the models without the distinction of climate variable. A sliding window of 2–7 year long sub-period is used, with a one-year warming period always considered.

sub-periods, though they stay in the acceptable range of values over 0.8 for all variants. Important is the apparent tendency of decrease of performance variability with the rising length of the calibration sub-periods. Despite the slightly lower mean KGE values, the substantial decrease of the volatility of the BILAN model performance is a sign that longer calibration periods may reduce the modelling uncertainty and better fit to the nature of the simulated processes (Figure 5).

The results for the GR2M model calibration performance display different patterns. The average KGE values are overall slightly lower than for the BILAN model. However, the patterns of the model's volatility performance are diverging. Variability of the KGE values for the GR2M model is higher than for BILAN in all variants. Most importantly, it does not indicate any significant decrease with the length of the calibration period (Figure 6). Thus, for the GR2M, the length of the calibration period has no significant effect on reduction of modelling uncertainty.

The validation results for both models show a positive response to increasing length of the sub-period used. In particular, the BILAN model shows an increase in model performance at the mean KGE values. Meanwhile, the volatility of the values, aggregated from different sub-periods remains at a balanced level for all lengths of the validation period window (Figure 6).

The GR2M model achieves a comparable performance for the KGE metric. However, as in the case of calibration, there is a significantly higher variability of the obtained values, which slightly increases with the length of the validation period.

The results indicate that the BILAN model performs better in calibration than in validation, but with declining calibration performance and increasing validation performance as the simulation duration expands. On the other hand, the GR2M model performs better in calibration than validation, with relatively stable KGE values as the simulation duration expands. The overall median calibration performance for both models is around 0.8, while the median validation performance is around 0.5. The BILAN model replicates the high flow rates very well but underestimates the low flow rates, while the GR2M model tends to underestimate high flow rates and exaggerate low flow rates.

Comparison of measured and simulated monthly runoff over the study period shows that the two models achieve a very good agreement in the basic aspects of the description of the hydrological regime (Figure 7). The seasonal rhythm is correctly expressed and a close agreement is achieved in the low flow period, as well as in the timing of the peak and the shape of the hydrographs. Simulated maximum discharge values for the annual peaks are almost always slightly lower than the observed ones.

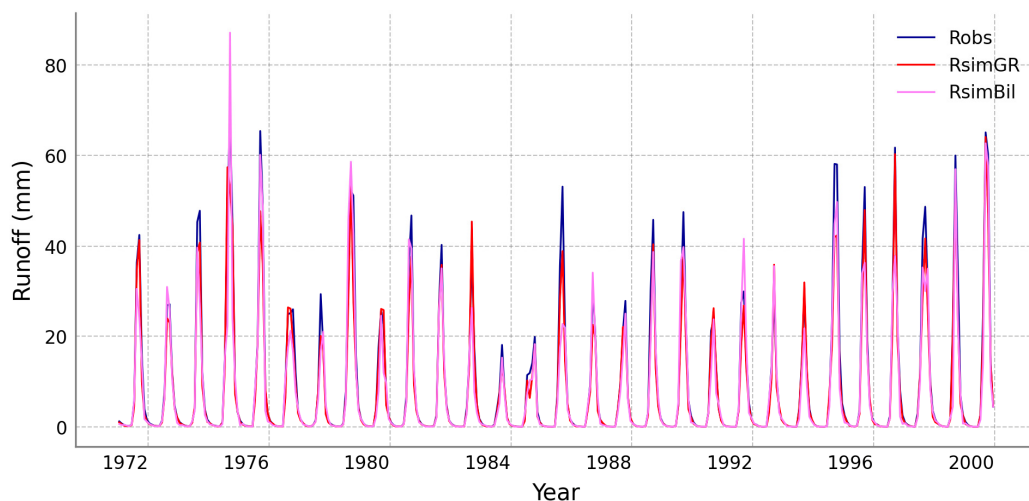


Fig. 7. Hydrograph of the observed runoff (Robs) and runoff simulated by the GR2M (RsimGR) and BILAN (RsimBil) models at the Gouloumbou (basin outlet).

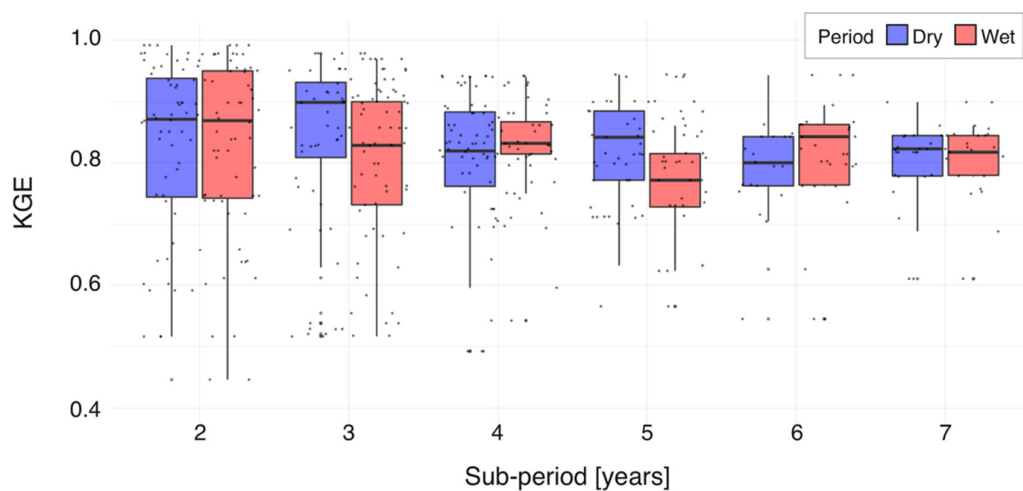


Fig. 8. Impact of drought on calibration performance of BILAN model. A sliding window from $k = 2$ (representing a 2-year sub-period) to $k = 7$ (representing a 7-year sub-period) is used, with a one-year warming period always considered.

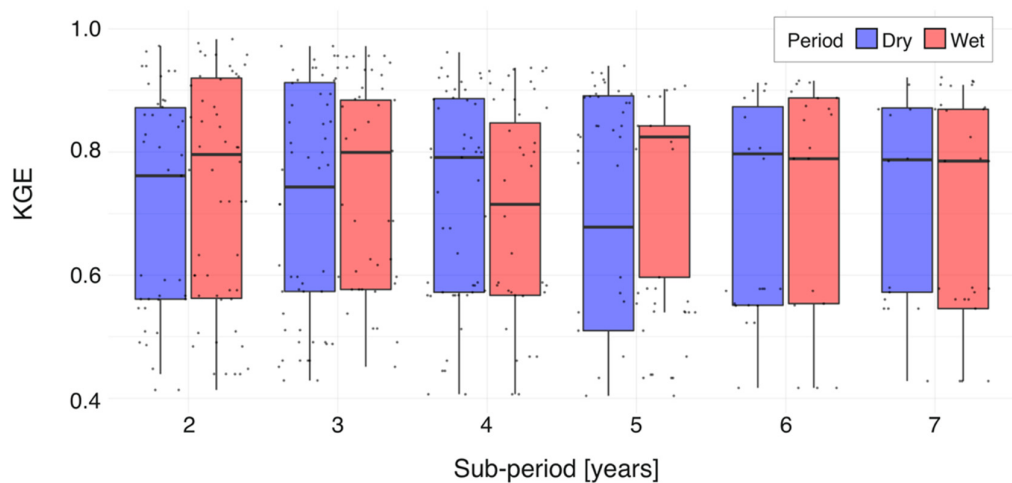


Fig. 9. Impact of drought on calibration performance of GR2M model. A sliding window from $k = 2$ (representing a 2-year sub-period) to $k = 7$ (representing a 7-year sub-period) is used, with a one-year warming period always considered.

Impact of drought type on model performance

Calibration results show that the BILAN model predicts dry years better for shorter time series and wet years better for longer time series. Nevertheless, during validation, this model in opposite simulates dry periods more accurately than wet ones.

The dry season results for the BILAN model show a very slight decrease in model performance with increasing length of the simulated period (Figure 8). At the same time, a significant decrease in the variability of the transformation values with increasing period length is also evident in this case. Meanwhile, for the variability of KGE values, there is no significant difference between the wet periods.

The BILAN model mimics better drier years for shorter time series and wetter years for longer time series, but it simulates better drier periods than wetter periods.

In contrast, the GR2M calibration results indicate that wet periods are replicated more accurately than dry periods during calibration and validation (Figure 9). The median of calibration performances for dry and wet periods for BILAN are respectively (0.85 and 0.6) and GR2M (0.7 and 0.8). However, there is a significant difference between the two models, with the GR2M model showing a significantly higher variance of the performance values for both the dry and wet periods (Figure 9).

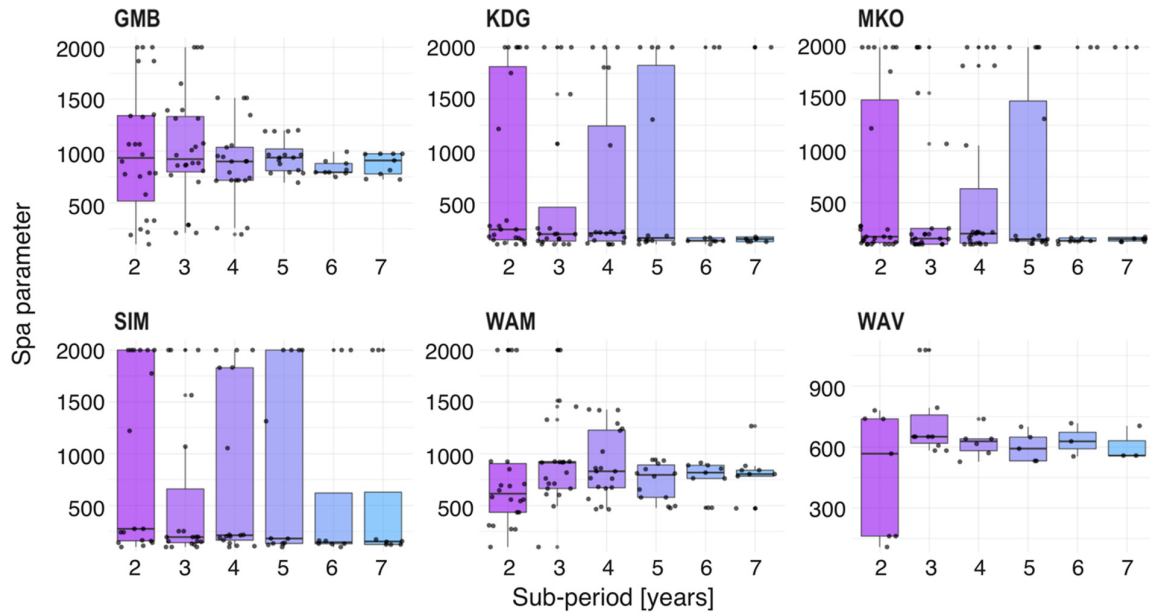


Fig. 10. Spa Parameter Distribution (a–f). The distribution of the BILAN model's Spa parameter across (a) Gouloumbou, (b) Kedougou, (c) Mako, (d) Simenti, (e) Wassadou Amont, and (f) Wassadou Aval. K being the subperiods.

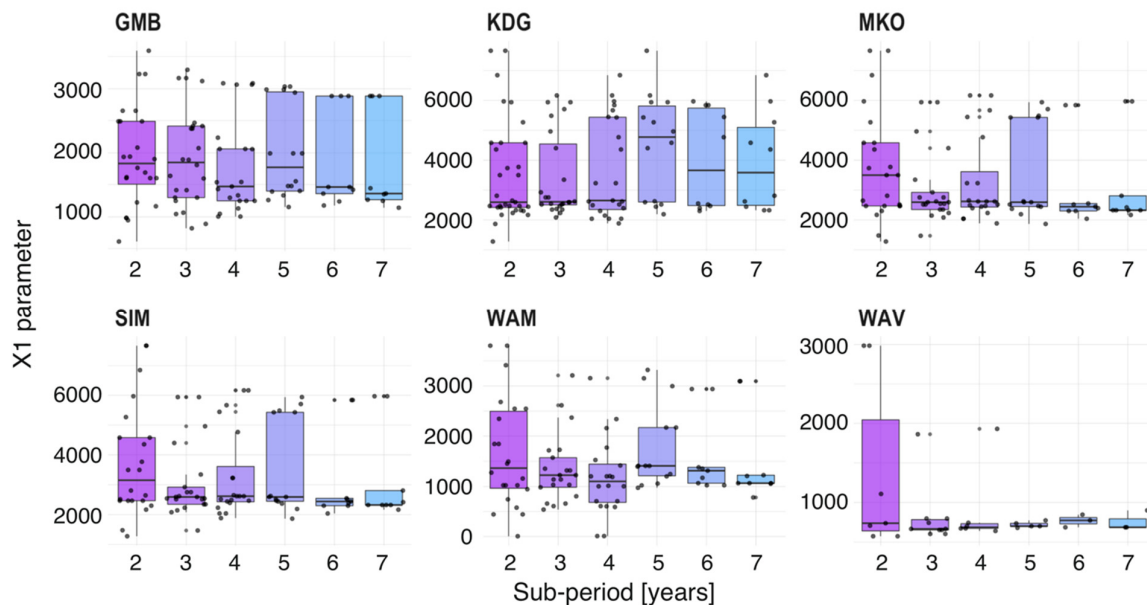


Fig. 11. X1 Parameter distribution (a–f). The distribution of the GR2M model's X1 parameter across (a) Gouloumbou, (b) Kedougou, (c) Mako, (d) Simenti, (e) Wassadou Amont, and (f) Wassadou Aval. K being the subperiods.

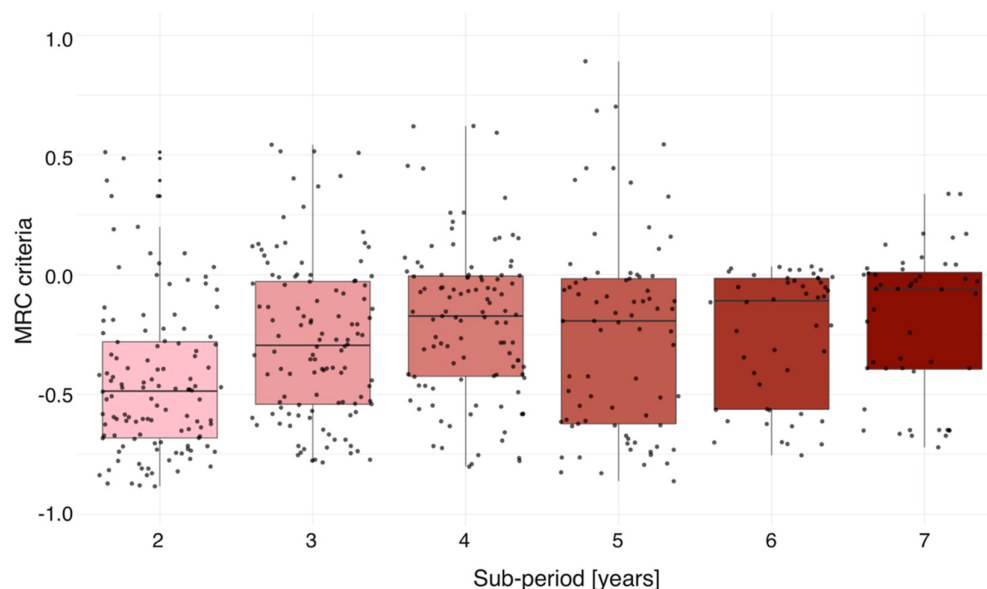


Fig. 12. Overall performance loss of the BILAN model from calibration to validation using the MRC with RMSE as the performance criterion. A sliding window from $k = 2$ (representing a 2-year sub-period) to $k = 7$ (representing a 7-year sub-period) is used, with a one-year warming period always considered.

Parameters transferability

Distribution of the optimized parameters

During the calibration of the BILAN model, the values of Spa and Grd parameters were observed to drop, indicating changes in their behavior. The maximum Spa value for the Gouloumbou catchment was around 1000, while for the Kedougou, Mako, and Simenti catchments, it was less than 500, and approximately 600 for the Wassadou-Amont and Wassadou-Aval catchments (Figure 10). The highest Grd value was approximately 0.6 for Kedougou, Mako, and Simenti, while the lowest value was around 0.1 for Gouloumbou, Wassadou-Amont, and Wassadou-Val. The Alf parameter ranged between 0.001 and 0.003. The optimized parameters for the BILAN model are summarized in the appendix.

Calibration of GR2M parameters displayed different patterns of distribution in basins. Specifically, the values of X1 parameter in GMB and KDG subcatchments is not displaying decrease of volatility with the length of calibration period (Figure 11).

Parameters transferability: The MRC criterion

Globally, both the BILAN and GR2M models exhibit a performance loss from calibration to validation of around 25% for all time periods, regardless of climatic conditions. The boxplots (Figure 12) illustrate the performance of the BILAN model in accordance with the MRC criteria based on the Root Mean Square Error (RMSE).

Nonetheless, as the span of the simulation time rises, the performance loss diminishes. For the BILAN model, performance losses vary from -50% for 2-year sub-periods to -8% for 7-year sub-periods, but for the GR2M model, performance losses range from -50% to -20% .

DISCUSSION

The primary objective of this study was to investigate the robustness and performance of two widely used lumped hydrological models BILAN and GR2M for assessing their performance and sensitivity to climate conditions in the Gambia

River Basin in Western Africa. This basin is representing a region, highly vulnerable by climate change, but also suffering from a lack of hydrological data and reliable hydrological predictions (Roudier et al., 2014). The knowledge of potential limitations of hydrological models, used for predictions in such vulnerable areas is important for understanding uncertainties of simulations and the potential effects on their use in definition of water resources management strategies.

The use of lumped conceptual models was determined by the structure, nature and availability of data for model setup. In complex areas with sparse input data sources, such as are the West African basins, the use of lumped models presents an approach with reasonable balance between efficiency, performance and limitations based on the simplified representation of hydrological processes (Anctil et al., 2004; Andréassian et al., 2009; Refsgaard and Madsen, 2013).

The results of the application of the BILAN and GR2M models in Gambia River Basin exhibit comparable overall performance of both models. However, they exhibited a significantly different sensitivity to the climate and hydrological conditions; while the BILAN model demonstrates superior performance in dry conditions, the GR2M model excels in wet conditions.

Specifically, the BILAN model showed better simulation of dry years (median KGE = 0.85) than wet years (median KGE=0.6) but tended to underestimate low flows. In contrast, the GR2M model displayed better performance during calibration of wet years (median KGE = 0.8) compared to dry years (median KGE = 0.7), with a potential to underestimate high flows or overestimate low flows. Such limitations of hydrological models in performance of simulations in significantly dry or wet conditions have also been identified in case of other lumped models, even for simulations using long (10–20 years) calibration periods (Coron et al., 2012; Slezziak et al., 2018; Vaze et al., 2010).

Both models displayed the same trend of diminishing loss of performance with the rising length of the simulation period, however with different efficiency. In the case of 2-year period, which has been the shortest tested, the loss for both models was equally reaching -50% . However, for a 7-year period the BILAN model

performed significantly better, reaching a loss of -8%, while the loss of GR2M model was about -20%. The performance loss observed during the transfer of parameters from the calibration to the validation period has significant effect into the resilience of hydrological models and reveals a decrease in accuracy when optimized parameters are applied to an independent validation period (Brigode et al., 2013).

The findings of this study are consistent with concerns raised by Coron et al. (2012) and Vormoor et al. (2018) regarding the limitations of the GSST and sliding window methodologies. Coron et al. (2012) identify issues with the temporal transferability of hydrological model parameters, noting that models may not maintain their accuracy when faced with different climatic conditions, thus calling for dynamic recalibration. Vormoor et al. (2018) take this further by showing how model parameters can be unstable under different flood seasonality conditions, suggesting that a single calibration may not be sufficient for different seasonal patterns.

While the GSST methodology is widely used, it has its drawbacks, particularly in terms of how data are partitioned for calibration and validation.

CONCLUSIONS

Testing the BILAN and GR2M hydrological models in the Gambia River Basin over a 30-year period, with varying calibration periods, highlights the importance of understanding model structure, hydrological sensitivity, and calibration strategy effects on simulation accuracy and uncertainty for reliable results, particularly under diverse climate conditions. Both models showed acceptable calibration results, while BILAN demonstrated slightly superior overall accuracy in standard performance metrics. The study showed that the different model structure and complexity translates to different sensitivity to hydrological conditions and to the length of model calibration. The results indicate that extending the calibration period leads to a reduction in the range of Kling-Gupta Efficiency (KGE) values and reduces the loss of performance during the transition from the calibration to the validation phase. This finding is particularly pronounced for the BILAN model, which shows its slightly better performance in the study basin compared to GR2M.

The sensitivity of the calibration under different drought scenarios revealed that the BILAN model outperformed GR2M in dry periods, while GR2M was more accurate in wet years. This indicates a distinct sensitivity of the models to the extremes of dry and wet conditions, as well as to significant temperature variations. The application of calibrated parameters to independent validation periods resulted in a decrease in the average performance of the models, ranging from -5% to -25%. Furthermore, the study highlights the different sensitivities of the two models to different hydrological conditions. The BILAN model shows improved accuracy in dry periods but tends to underestimate low flows, while the GR2M model, which is more effective in wet years, often overestimates low flows.

The simulations underscored the critical importance of the appropriate length of a calibration period. The longer calibration period not only improves model performance but also reduces the uncertainty in simulation results, a trend more evident in the BILAN model. In practical applications, the GR2M model, with its simpler structure and fewer input parameters, is suitable for regions with limited data, especially in simulating water rich seasons. However, it is marked by higher uncertainty, which does not significantly reduce even with extended calibration periods. Conversely, the BILAN model, requiring a more comprehensive set of parameters, yields more reliable results in dry conditions

and benefits from reduced uncertainty with longer calibration.

Testing both models under variable conditions underscores the crucial role of comprehending model structure, hydrological sensitivity, and calibration strategy effects on simulation accuracy and uncertainty for reliable results, particularly in the context of practical applications such as modelling hydrological processes in regions affected by climate change.

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APPENDIX A CATCHMENT AND HYDROLOGICAL DATA**Table A1.** Catchments information from the Global Runoff Data Center.

Station ID	River	Station	Country	Latitude	Longitude	Area [sq. km]
1813200	GAMBIA	GOULOUMBOU	SN	13.47	-13.73	42000
1813780	GAMBIA	KEDOUGOU	SN	12.57	-12.18	7550
1813700	GAMBIA	MAKO	SN	12.87	-12.35	10450
1813500	GAMBIA	SIMENTI	SN	13.03	-13.30	20500
1813460	GAMBIA	WASSADOU AMONT	SN	13.35	-13.37	21200
1813450	GAMBIA	WASSADOU AVAL	SN	13.35	-13.38	33500

APPENDIX B CALIBRATION PERFORMANCE**Table A2.** Overall Calibration Performance of BILAN and GR2M models.

	BILAN	BILAN	BILAN	GR2M	GR2M	GR2M
K	KGE	NSE	RMSE	KGE	NSE	RMSE
2	0.83	0.72	8.98	0.73	0.71	11.72
3	0.83	0.69	10.29	0.73	0.70	11.49
4	0.83	0.70	11.66	0.76	0.72	11.25
5	0.83	0.71	15.50	0.68	0.64	17.61
6	0.80	0.64	13.94	0.74	0.69	12.45
7	0.81	0.67	13.69	0.74	0.69	12.60
2	0.79	0.66	20.30	0.66	0.64	21.58
3	0.77	0.62	21.15	0.67	0.65	20.80
4	0.82	0.74	17.93	0.64	0.61	22.31
5	0.66	0.53	13.19	0.82	0.85	6.61
6	0.73	0.65	21.73	0.61	0.58	24.09
7	0.75	0.66	20.48	0.61	0.59	23.03
2	0.74	0.62	21.42	0.65	0.64	20.66
3	0.92	0.87	10.76	0.75	0.74	17.81
4	0.79	0.69	18.77	0.71	0.69	18.01
5	0.75	0.69	20.39	0.65	0.63	21.93
6	0.73	0.65	21.73	0.61	0.58	24.09
7	0.75	0.66	20.48	0.61	0.59	23.03
2	0.91	0.82	8.22	0.76	0.73	11.56
3	0.82	0.66	10.25	0.73	0.70	11.22
4	0.87	0.77	9.85	0.79	0.74	10.42
5	0.78	0.62	13.33	0.74	0.69	11.71
6	0.86	0.73	11.10	0.76	0.71	11.74
7	0.82	0.68	12.67	0.75	0.69	12.20
2	0.73	0.50	12.94	0.72	0.71	11.54
3	0.79	0.65	14.44	0.76	0.74	12.19
4	0.81	0.69	16.88	0.72	0.69	16.07
5	0.77	0.63	15.32	0.74	0.72	12.42
6	0.79	0.66	16.58	0.71	0.69	15.18
7	0.80	0.66	15.77	0.70	0.67	14.97
2	0.89	0.80	12.12	0.70	0.68	17.24
3	0.82	0.70	16.29	0.72	0.70	17.50
4	0.80	0.66	18.00	0.71	0.68	17.80
5	0.86	0.77	14.02	0.73	0.71	17.35
6	0.87	0.79	13.47	0.71	0.68	18.03
7	0.85	0.74	16.50	0.72	0.69	18.33

Table A3. Overall Validation Performance of BILAN and GR2M models.

	BILAN	BILAN	BILAN	GR2M	GR2M	GR2M
K	KGE	NSE	RMSE	KGE	NSE	RMSE
2	-5.31	-43.92	24.89	0.47	0.58	14.72
3	0.30	-0.17	16.09	0.53	0.61	12.69
4	0.62	0.50	15.36	0.51	0.65	12.63
5	0.49	0.48	32.99	0.17	0.15	26.91
6	0.69	0.54	16.56	0.59	0.64	12.71
7	0.70	0.61	16.69	0.61	0.65	12.74
2	0.14	-1.85	28.33	0.23	0.35	28.41
3	0.35	0.44	43.52	0.16	0.15	32.14
4	0.34	0.49	46.50	-0.17	-0.31	40.82
5	0.42	0.50	22.96	0.34	0.35	13.46
6	0.29	0.42	55.50	0.12	0.03	34.98
7	0.24	0.37	59.41	0.03	-0.09	35.03
2	-1.43	-9.13	31.87	0.28	0.36	26.63
3	0.21	-0.18	19.33	0.55	0.65	19.65
4	0.57	0.56	32.87	0.19	0.07	29.22
5	0.36	0.41	48.42	-0.08	-0.26	39.99
6	0.29	0.42	55.50	0.12	0.03	34.98
7	0.24	0.37	59.41	0.03	-0.09	35.03
2	-2.91	-22.24	22.32	0.35	0.48	14.51
3	0.42	-0.02	14.90	0.54	0.65	11.87
4	0.74	0.68	13.57	0.43	0.65	11.94
5	0.67	0.55	16.75	0.50	0.61	12.69
6	0.74	0.65	14.44	0.63	0.67	11.66
7	0.72	0.60	15.82	0.64	0.66	12.00
2	-6.34	-72.81	24.12	0.39	0.44	15.50
3	0.44	0.35	17.28	0.47	0.45	15.79
4	0.46	0.28	22.45	0.44	0.53	18.25
5	0.62	0.52	20.20	0.45	0.55	14.89
6	0.71	0.58	20.04	0.50	0.54	16.62
7	0.67	0.61	19.88	0.47	0.51	16.42
2	-5.58	-38.91	29.70	0.45	0.59	19.03
3	0.37	0.11	19.49	0.53	0.63	18.62
4	0.64	0.56	25.22	0.38	0.43	22.45
5	0.73	0.61	17.85	0.63	0.71	15.87
6	0.76	0.66	16.68	0.52	0.64	17.46
7	0.72	0.66	21.21	0.61	0.64	18.36

APPENDIX C PARAMETERS TRANSFER

Table A4. BILAN model Optimized Parameters Spa, Grd and Alf.

	GOULOUMBOU			KEDOUGOU			MAKO		
K	Spa	Grd	Alf	Spa	Grd	Alf	Spa	Grd	Alf
2	773	0.0431	0.0025	227	0.4815	0.0003	179	0.5896	0.0002
3	968	0.0315	0.0026	177	0.5885	0.0002	163	0.6138	0.0002
4	858	0.0910	0.0024	150	0.5189	0.0001	150	0.5193	0.0001
5	860	0.0288	0.0028	987	0.4837	0.0001	988	0.4835	0.0001
6	861	0.0258	0.0028	132	0.5078	0.0001	131	0.5080	0.0001
7	824	0.0238	0.0028	139	0.5188	0.0001	138	0.5189	0.0001
2	1468	0.0414	0.0015	1380	0.4423	0.0001	1380	0.2940	0.0000
3	548	0.2447	0.0015	155	0.5957	0.0000	155	0.5958	0.0000
4	1192	0.0319	0.0021	1109	0.4127	0.0002	1109	0.4121	0.0002
5	1191	0.0258	0.0021	2000	0.3774	0.0001	2000	0.3768	0.0001
6	795	0.0244	0.0015	2000	0.3808	0.0000	2000	0.3800	0.0000
7	974	0.0218	0.0015	2000	0.3620	0.0000	2000	0.3609	0.0000
2	644	0.2904	0.0016	138	0.5651	0.0002	137	0.5651	0.0002
3	1039	0.1198	0.0020	374	0.4419	0.0007	374	0.4418	0.0007
4	893	0.0325	0.0026	681	0.4377	0.0008	684	0.4375	0.0008
5	878	0.0294	0.0026	130	0.5745	0.0001	130	0.5746	0.0001
6	902	0.0251	0.0027	128	0.5705	0.0000	128	0.5706	0.0000
7	909	0.0231	0.0028	171	0.5359	0.0003	171	0.5358	0.0003
2	1208	0.1059	0.0013	1950	0.3992	0.0001	1953	0.3100	0.0000
3	1038	0.0797	0.0013	1886	0.3262	0.0000	1889	0.3256	0.0000
4	829	0.1020	0.0011	1934	0.4646	0.0000	1940	0.4639	0.0000
5	1029	0.0270	0.0015	2000	0.3808	0.0000	2000	0.3800	0.0000
6	795	0.0244	0.0015	2000	0.3620	0.0000	2000	0.3609	0.0000
7	974	0.0218	0.0015	474	0.6239	0.0003	475	0.6240	0.0003
2	400	0.3506	0.0014	188	0.5786	0.0002	186	0.5743	0.0002
3	1073	0.0290	0.0023	203	0.5021	0.0004	202	0.5021	0.0004
4	902	0.0326	0.0027	134	0.4695	0.0000	134	0.4696	0.0000
5	913	0.0296	0.0030	159	0.5383	0.0003	159	0.5386	0.0003
6	787	0.0271	0.0028	125	0.5301	0.0000	124	0.5304	0.0000
7	726	0.0230	0.0027	123	0.3746	0.0006	123	0.3749	0.0006
2	1323	0.1057	0.0010	100	0.5188	0.0001	100	0.5192	0.0001
3	1313	0.0904	0.0010	138	0.5411	0.0002	138	0.5417	0.0002
4	488	0.1381	0.0009	123	0.4863	0.0000	127	0.4936	0.0001
5	972	0.0269	0.0016	132	0.5035	0.0000	132	0.5036	0.0000
6	795	0.0244	0.0015	151	0.5232	0.0002	150	0.5232	0.0002
7	974	0.0218	0.0015						

Table A5. BILAN model Optimized Parameters Spa, Grd and Alf.

	SIMENTI			WASSADOU - AMONT			WASSADOU - AVAL		
K	Spa	Grd	Alf	Spa	Grd	Alf	Spa	Grd	Alf
2	206	0.6954	0.0003	647	0.2510	0.0018	450	0.1131	0.0014
3	163	0.6142	0.0002	720	0.1850	0.0019	713	0.2221	0.0029
4	150	0.5195	0.0001	805	0.0319	0.0017	618	0.0315	0.0027
5	989	0.4834	0.0001	657	0.0916	0.0011	591	0.0282	0.0029
6	132	0.5082	0.0001	831	0.0273	0.0018	635	0.0255	0.0027
7	138	0.5189	0.0001	827	0.0251	0.0018	631	0.0234	0.0027
2	1381	0.4414	0.0001	1519	0.2222	0.0008			
3	155	0.5958	0.0000	914	0.0373	0.0021			
4	1109	0.4118	0.0002	991	0.2875	0.0009			
5	2000	0.3764	0.0001	578	0.5743	0.0007			
6	2000	0.3795	0.0000	479	0.0135	0.0005			
7	2000	0.3604	0.0000	473	0.0138	0.0005			
2	137	0.5650	0.0002	488	0.3739	0.0010			
3	374	0.4418	0.0007	1424	0.0373	0.0015			
4	686	0.4375	0.0008	1165	0.0284	0.0012			
5	130	0.5746	0.0001	919	0.0291	0.0020			
6	128	0.5706	0.0000	912	0.0265	0.0020			
7	173	0.5391	0.0003	1267	0.0243	0.0018			
2	1955	0.3983	0.0001	1040	0.2638	0.0005			
3	1891	0.3253	0.0000	1053	0.1591	0.0005			
4	1943	0.4636	0.0000	539	0.2051	0.0005			
6	2000	0.3795	0.0000	479	0.0135	0.0005			
7	2000	0.3604	0.0000	473	0.0138	0.0005			
2	476	0.6240	0.0003	515	0.3297	0.0008	503	0.0900	0.0021
3	186	0.5747	0.0002	805	0.2602	0.0016	740	0.2684	0.0029
4	202	0.5021	0.0004	860	0.0348	0.0015	640	0.0325	0.0030
5	134	0.4697	0.0000	941	0.0327	0.0017	531	0.0305	0.0030
6	159	0.5388	0.0003	761	0.0264	0.0017	628	0.0264	0.0030
7	124	0.5305	0.0000	803	0.0268	0.0019	558	0.0257	0.0030
2				645	0.0451	0.0020	423	0.0391	0.0019
3				789	0.0355	0.0018	793	0.0341	0.0018
4				944	0.0312	0.0018	699	0.0257	0.0022
5				816	0.0283	0.0017			
6				889	0.0265	0.0018			
7				841	0.0252	0.0017			

Table A6. GR2M Optimized Parameters: X1, X2.

	GOULOUMBOU		KEDOUGOU		MAKO		SIMENTI		WASSADOU - AMONT		WASSADOU - AVAL	
K	X1	X2	X1	X2	X1	X2	X1	X2	X1	X2	X1	X2
2	1477	0.8	5746	0.56	2535	1.04	2135	1.07	1800	0.71	1778	0.73
3	1570	0.8	5484	0.58	2267	1.03	2267	1.03	911	0.66	692	0.69
4	1422	0.8	5540	0.58	2380	1.03	2380	1.03	1268	0.71	937	0.72
5	1322	0.8	5618	0.57	3983	0.79	3983	0.79	2064	0.66	704	0.70
6	1398	0.8	5508	0.57	2323	1.03	2323	1.03	1215	0.71	809	0.70
7	1328	0.8	5265	0.59	2306	1.03	2306	1.03	1140	0.70	793	0.70
2	2011	0.8	5249	0.74	5249	0.74	5249	0.74	1611	0.66		
3	1358	0.8	2752	1.17	2752	1.17	2752	1.17	1317	0.88		
4	1766	0.8	4450	0.79	4450	0.79	4450	0.79	1523	0.60		
5	1990	0.8	5433	0.55	5433	0.54	5433	0.54	2172	0.66		
6	2885	0.8	5844	0.56	5844	0.56	5844	0.56	2938	0.63		
7	2885	0.8	5971	0.56	5971	0.55	5971	0.55	3093	0.62		
2	1483	0.8	2940	1.14	2940	1.14	2940	1.14	1881	0.87		
3	1314	0.8	2909	1.12	2909	1.12	2909	1.12	1289	0.77		
4	1280	0.9	3436	0.96	3436	0.96	3436	0.96	688	0.53		
5	1431	0.9	2569	1.16	2569	1.16	2569	1.16	1401	0.87		
6	1361	0.9	2547	1.15	2547	1.15	2547	1.15	1380	0.85		
7	1362	0.8	2807	1.11	2807	1.11	2807	1.11	781	0.62		
2	2228	0.8	2854	0.97	5746	0.57	5746	0.57	1390	0.51		
3	2475	0.8	3253	0.89	5313	0.57	5313	0.57	2477	0.64		
4	2735	0.8	2740	0.98	5462	0.58	5462	0.58	1775	0.48		
5	2737	0.8										
6	2885	0.8	2490	1.03	5844	0.56	5844	0.56	2938	0.63		
7	2885	0.8	2529	0.99	5971	0.55	5971	0.55	3093	0.62		
2	1299	0.78	3386	0.86	3386	0.86	3386	0.86	1771	0.63	806	0.72
3	1809	0.82	2498	0.99	2498	0.99	2498	0.99	1013	0.64	679	0.68
4	1249	0.8	2618	0.96	2618	0.96	2618	0.96	1200	0.66	672	0.67
5	1480	0.87	2592	1.0	2592	1.00	2592	1.00	1409	0.73	699	0.71
6	1176	0.8	2392	1.02	2392	1.02	2392	1.02	1064	0.69	685	0.69
7	1141	0.8	2322	1.04	2322	1.04	2322	1.04	1064	0.70	685	0.71
2	2714	0.8	2378	1.10	2378	1.10	2378	1.10	1627	0.75	1845	0.83
3	2813	0.79	2155	1.11	2155	1.11	2155	1.11	1168	0.73	1863	0.82
4	3074	0.79	2104	1.08	2104	1.08	2104	1.08	933	0.67		
5	2670	0.81	2315	1.06	2315	1.06	2315	1.06	1014	0.66		
6	2885	0.8	2298	1.08	2298	1.08	2298	1.08	1022	0.68	773	0.65
7	2885	0.8	2322	1.04	2322	1.04	2322	1.04	1054	0.67		