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Hydrological performance of the ERA5 reanalysis for flood modeling in Tunisia with the LISFLOOD and GR4J models

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ABSTRACT

Study region: This study is focused on 6 catchments in Tunisia, in North Africa, under a semi-arid climate where daily river discharge and precipitation observations are available between 1992 and 2006.
Study focus: The distributed hydrological model LISFLOOD has been compared with a lumped model, GR4J, to reproduce river runoff and floods, using observed rainfall interpolated from rain gauges and from the ERA5 reanalysis.
New hydrological insights for the region under study: LISFLOOD and GR4J with their default parameters have little skill in Tunisia, but when calibrated, both hydrological models provide similar performance to reproduce river discharge,
with a mean KGE of 0.65 for GR4J driven by observed rainfall, and 0.59 with ERA5, and similarly a mean KGE of 0.59 for LISFLOOD driven by observed rainfall and 0.48 with ERA5. All model simulations perform very similarly using either observed rainfall data from rain gauges interpolated over the basins or ERA5 rainfall, indicating its value as an alternative to observations in data-scarce areas such as Tunisia. The development of regional databases of river discharge observations in North Africa could allow the calibration of such hydrological models on a larger scale for operational flood modeling and forecasting.

1. Introduction

Floods are the most common natural hazard, as such, flood affected 23 % of the world's population during the 1995–2005 period with disproportionally high impacts on the poorest and most vulnerable countries, notably in Africa (Douglas et al., 2008; Jongman, 2018; Tramblay et al., 2020). Tunisia, like the rest of the Mediterranean countries, regularly experiences severe flooding caused by intense rainfall events, which result in significant material losses as well as casualties (Llasat et al., 2010). While these floods have severe consequences in terms of casualties and economic losses, an increase in the vulnerability to these episodes has been observed mainly attributed to urban development and land use change (Zahar et al., 2008; Fehri, 2014; Loudyi and Kantoush, 2020; Dahri and Abida, 2020).

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Flood-related losses can be mitigated through effective flood forecasting and early warning mechanisms that provide additional preparation time prior to a flood event (Thiemig et al., 2011; Cools et al., 2016), which allows the timely implementation of flood mitigating measures such as securing assets and evacuating people. In Europe, flood forecasting and early warning is primarily addressed at national and regional level through their own systems and tools, which are complemented at European scale since 2005 by the European Flood Awareness System, EFAS (Bartholmes et al., 2009; Thielen et al., 2009). EFAS is Europe's overarching flood forecasting and monitoring system operated since 2012 under the Copernicus Emergency Management Service. Its global extension, the Global Flood Awareness System, GloFAS (Alfieri et al., 2013; Harrigan et al., 2020), aims at providing such flood forecasting and monitoring capabilities at global scale using a similar setup to EFAS but using ERA5 (Hersbach et al., 2020). Based on the open source (https://ec-jrc.github.io/lisflood/) LISFLOOD model (Van Der Knijff et al., 2010), EFAS and GloFAS are supporting national and regional authorities responsible for flood risk management, with a wide range of constantly updated early flood forecast information for a fast and dynamic situational awareness on possible flood risks for the next 10 (EFAS) and 30 (GloFAS) days. In addition, EFAS also supports the EU Civil Protection Mechanism through providing daily an overview across Europe and neighboring countries on currently observed and forecasted flood events, for an improved and coordinated emergency response at European level.

Even though being a pan-European system, EFAS covers the northern part of Africa and produces daily hydrological predictions for riverine and flash floods, and hence might be suitable for supporting the Tunisian authorities with early flood risk information. However, the predictive capacity of EFAS, or GloFAS, for that particular area is unknown, as the lack of available hydrological data (river discharge and precipitation data, mostly) allows neither the calibration of LISFLOOD nor the validation of the current uncalibrated performance over those areas. Complicating matters, the Tunisian river basins are also relatively small, as the majority of Mediterranean basins (Merheb et al., 2016), compared to the spatial resolution of large-scale models, that could limit the model's capacity to correctly represent the dynamics of the hydrological response. Global hydrological models (GHMs) such as LISFLOOD are designed to be implemented in all the possible hydrological regimes by including a variety of relevant runoff generating processes (Archfield et al., 2015; Bierkens, 2015; Sood and Smakhtin, 2015; Trigg et al., 2016; Kauffeldt et al., 2016) but they still need to be evaluated at the basin scale to assess their accuracy. Since there are no in-situ observations of precipitation or river discharge in Tunisia currently available to the EFAS or GloFAS frameworks, there is a strong need to validate the hydrological simulations against observed discharge data to evaluate their current capacity to reproduce floods prior to using those for flood forecasting in an operational environment (Bernhofen et al., 2018; Trigg et al., 2016). A very important question would be to know how effective the model could be

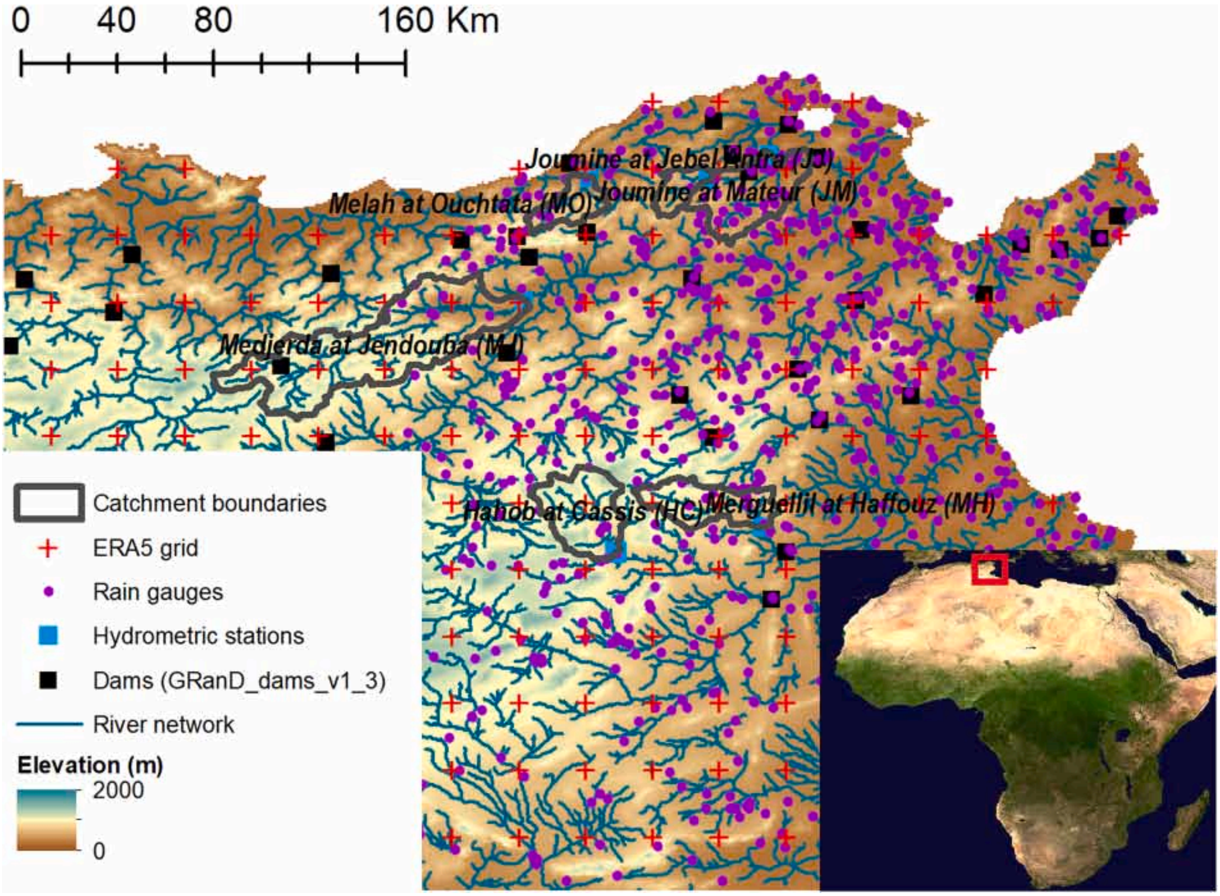

Fig. 1. Map of the selected Tunisian basins.

when driven by the recent ERA5 reanalysis in place of observed rainfall, since ERA5 has demonstrated good capabilities for hydrological modeling in different regions of the world and in particular semi-arid ones (Bandara et al., 2021; Bandhauer et al., 2022; Jiang et al., 2021; Reder and Rianna, 2021; Tarek et al., 2021).

In this context, the objective of the present study is to evaluate the feasibility of flood modeling in Tunisia using ERA5 rainfall as input, as a preliminary step towards the implementation of EFAS/GLOFAS in this region. This is done based on a set of 6 basins, comparing uncalibrated as well as calibrated simulations of the LISFLOOD distributed model and the GR4J lumped model (Perrin et al., 2003). These two models are compared herein to evaluate the sensitivity of the results to two different hydrological model structures. Both models are forced with observed precipitation and ERA5, to investigate the suitability of using a global reanalysis dataset providing precipitation and temperature in place of observations, an aspect which is of particular interest for hydrological modeling in data scarce areas. The questions addressed in the present study are: (i) What is the performance of the hydrological models to reproduce daily discharge dynamics with ERA5 compared to using observed precipitation? (ii) Are the hydrological models able to simulate the occurrence and the magnitude of high-flows?

2. Study area and datasets

For this study, six Tunisian catchments were selected (Fig. 1) based on catchment size, discharge data and rain gauge data availability as well as length of the hydrological record and data quality. The main characteristics of these catchments are summarized in Table 1. They are all located in Northern and central parts of Tunisia, with semi-arid conditions characterized by low annual rainfall and high evapotranspiration, that are typical of Mediterranean catchments of North Africa. There is a gradient in aridity from North to South, with the Hathob (HC) and Merguellil (MH) basins being the two most arid ones holding the largest proportion of zero flow days. There is a marked seasonality of precipitation and surface runoff, with a rainy season during winter months and a dry season spanning during summer months with high evapotranspiration rates. Consequently, all basins are intermittent, except basin 2, the Medjerda river (MJ), which is the only perennial river in Tunisia. Only two basins are impacted by dams: the Medjerda (MJ) spanning across Algeria and Tunisia, with the Ain Dalia dam in Algeria controlling 6 % of basin area, and the basin of Joumine at Mateur (JM), where the Joumine dam controls 40 % of basin area.

The discharge data used in this study was obtained from the SIEREM database (Dieulin et al., 2019). Although the available record starts in the 1950 s, most stations present limited and discontinuous discharge time series. Thus, the discharge data availability defined the study period, which runs from January 1991 to September 2006, the year 1991 being used for model spin-up. Despite a careful selection of the discharge dataset from the available stations in Tunisia, the discharge time series present some gaps, as it is often the case in data scarce areas. In particular the missing data represents up to 40 % of daily data in Joumine at Jebel Antra (JJ) and Melah at Ouchtata (MO). Thus, the evaluation is performed over a smaller number of years for these stations. It should be noted that the highest frequency of missing data is reported during summer and early autumn, the driest months of the year when runoff usually ceases.

Two different daily precipitation datasets were used to force the hydrological models: (i) precipitation observations from 960 rain gauges with data from 1975 to 2006 obtained from the database of the Direction Générale des Resources en Eau (DGRE) of Tunisia and (ii) the ERA5 precipitation product available from 1979 to present with a spatial resolution of 30 km. The rain gauge data used here was previously used to produce precipitation maps over Tunisia (Tramblay et al., 2019) and, therefore, was already quality checked. The precipitation observations were interpolated using Inverse Distance Weighting to generate a 5 km gridded daily precipitation dataset. The ERA5 rainfall was re-gridded to the same 5 km grid using a bilinear interpolation. Although the two hydrological models were implemented with the same rainfall inputs there are slight differences in the data processing to adapt it to the structure of each of the models. In the case of GR4J, the interpolated observed precipitation and ERA5 were averaged for each catchment to obtain its daily areal value. In contrast, for the LISFLOOD implementation, the model was run using the distributed rainfall at 5 km. In the particular

Table 1
Catchments characteristics.

Accronym	Name	Catchment area [km^2]	Mean altitude [m]	Mean annual precipitation [mm]	Mean annual potential evapotranspiration [mm]	Zero-flows [%]	Missing data [%]	Missing data 1992–2001 [%]	Missing data 2001–2006 [%]
JM	Joumine at Mateur	1096	194	633	1259	15 %	15 %	9 %	28 %
MJ	La Medjerda at Jendouba	2983	656	633	1209	0 %	13 %	17 %	7 %
MH	Merguellil at Haffouz Téléphérique	819	577	550	1332	28 %	1 %	1 %	1 %
HC	Hathob at Cassis Ain Saboun	973	828	570	1307	63 %	21 %	7 %	48 %
JJ	Joumine at Jebel Antra	227	311	633	1259	5 %	43 %	35 %	60 %
MO	Melah at Ouchtata	390	360	669	1236	13 %	46 %	39 %	60 %

case of the Medjerda (MJ) basin that originates in Algeria (40 % of catchment area), since no rain gauges in Algeria were available for this study, observed rainfall is only computed with rain gauges in Tunisia. A comparison of the observed and ERA5 rainfall over the basins is provided in Fig. 2. In terms of seasonal rainfall, ERA5 overestimate rainfall compared to observations (on average +15 %), in

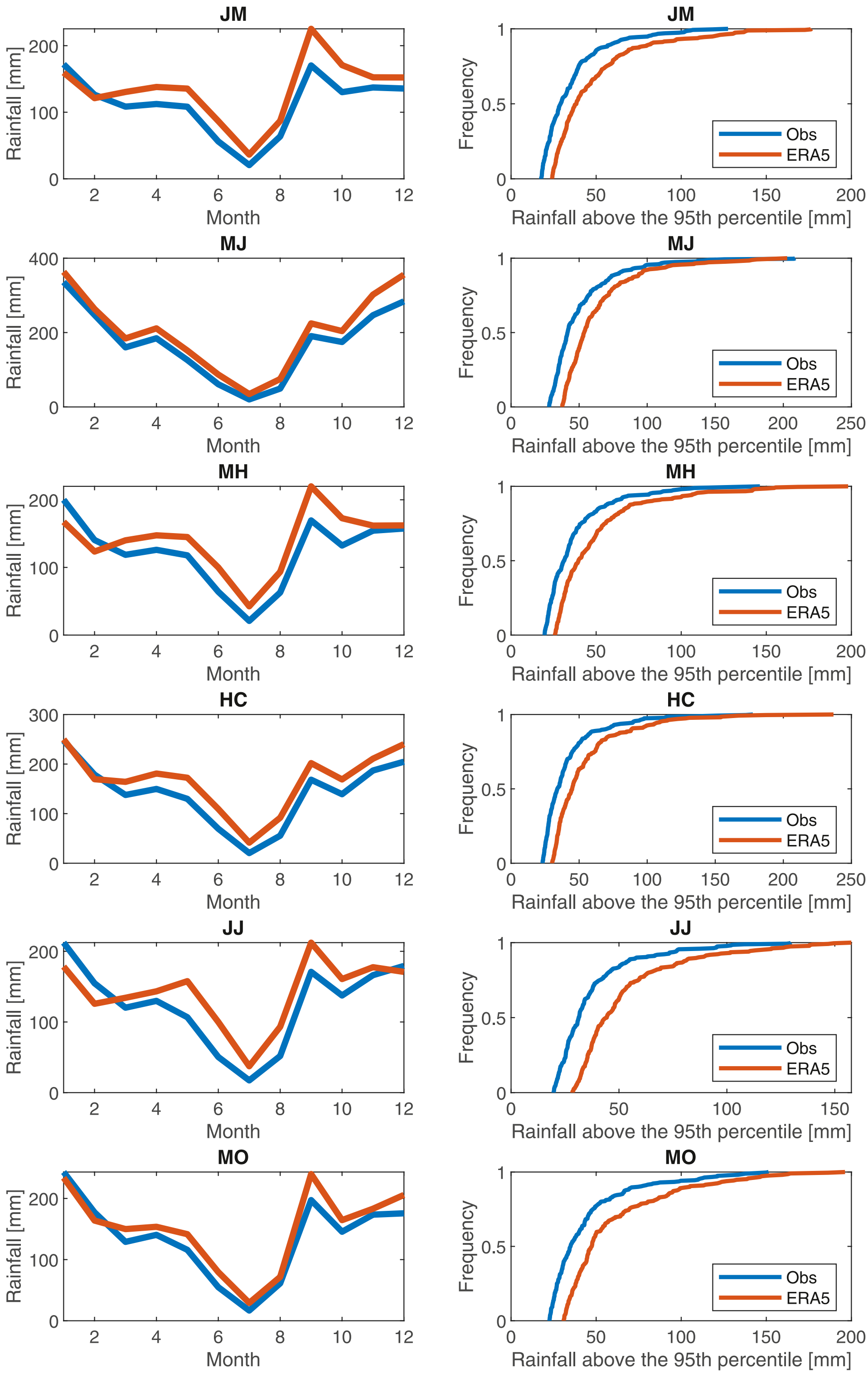

Fig. 2. Monthly rainfall (left) and cumulative distribution function of daily rainfall above the 95th percentile (right) for observed and ERA4 rainfall in each basin.

particular in September and May. In terms of extremes, rainfall events above the 95th percentile also display higher values for ERA5, + 33 % compared to rain gauges data. However, this comparison remains hampered by the lack of homogeneity of the rain gauge network, in terms of spatial but also temporal coverage due to missing data for some stations and time periods.

The temperature data used is the daily ERA5 temperature (Hersbach et al., 2020), in the absence of meteorological stations with data available. In the implementation of the GR4J model, it was used to calculate daily potential evapotranspiration (PET) through the Hargreaves formula (Hargreaves and Samani, 1985) with daily minimum and maximum temperatures that proved to be efficient in North Africa (Er-Raki et al., 2010). For LISFLOOD, the evapotranspiration inputs were calculated through the LISVAP model (Van Der Knijff, 2010) that rely on the Penman-Monteith formulation computed with ERA5 data. The updated documentation and source code of this model can be found with the current model documentation under https://ec-jrc.github.io/lisflood-lisvap/. Even if the two models do not share the same computation of PET, this should not influence the results given the very small influence of the PET formulation in water-limited regions such as Tunisia (Dakhlaoui et al., 2020).

3. Hydrological models

3.1. LISFLOOD

LISFLOOD is a spatially distributed rainfall-runoff and channel routing model (De Roo et al., 2000; Van Der Knijff et al., 2010). Given that LISFLOOD was originally developed to model large European rivers, it is based on raster files in order to simplify the management of large datasets. LISFLOOD requires a large number of static inputs that describe the physical properties of the catchments (e.g. land cover, leaf area index, channel and soil properties, etc.) and it is driven by the dynamic inputs which are the meteorological forcing, that is, the precipitation, temperature and potential evapotranspiration time series. As LISFLOOD is open source, its source code can be found with the updated model documentation and user guide under https://github.com/ec-jrc/lisflood-code.

The standard setup of LISFLOOD is made of three different components (i) a three-layer soil water balance, (ii) subsurface and groundwater flow and (iii) routing of surface runoff. One interesting characteristic of this model is that conceptualization is a hybrid between physically-based and conceptual model. On one hand, the processes involved in the soil module are reproduced by solving the corresponding governing equations as it is characteristic of the physically-based models. On the other hand, the groundwater and subsurface component is constituted by two sequential reservoirs, with a similar structure to those of the conceptual models. This standard setup of the model with split routing is used in this study. The processes are simulated cell-by-cell and include snow melting, interception, infiltration, preferential flow, groundwater flow, lateral flow and surface runoff.

The LISFLOOD setup as used in EFAS has 14 parameters left to determine through calibration. However, given the scope of the present study, the parameters related to snow melting, floodplains, lakes and reservoirs were excluded. Thus, the LISFLOOD structure presented above, leaves a total of 8 parameters to be determined through calibration.

1. Xinanjiang exponential (Xi) controls the infiltration capacity;
2. Power Preferential Flow (PF) determines which proportion of precipitation bypasses the soil and goes directly to the water table;
3. Upper Zone time constant (UZ), determines the residence time of the upper groundwater reservoir or fast response of the system;
4. Groundwater percolation (Perc), that is the maximum percolation rate from the upper to lower groundwater zone;
5. Lower groundwater Zone time constant (LZ), equivalent to the UZ, in this case controls the residence time of the lower reservoir and consequently, the slow response of the system;
6. Manning multiplier (Man) is applied to the manning roughness coefficient to fine-tune the timing of the channel routing;
7. Ground water Loss (GwLoss) parameter, the maximum loss rate out of lower groundwater zone;
8. Lower Zone threshold (LZThreshold) parameter, a threshold to stop outflow from lower groundwater zone to the channel.

3.2. GR4J

GR4J (Perrin et al., 2003) is a lumped conceptual rainfall runoff hydrological model. This model was chosen since it proved to be efficient to reproduce river discharge in different basins of Tunisia (Dakhlaoui et al., 2017, 2019), due to its simplicity, low data requirements and parsimonious structure. The conceptualization of the model is based on two sequential reservoirs that mimic the runoff generation processes at catchment scale. The first reservoir simulates the soil moisture budget from the input time series evaporation (E) and precipitation (P). The amount of moisture retained by the soil is controlled by the parameter X1, which is a threshold representing the maximum storage capacity of the soil reservoir (S). The water outgoing this reservoir is split in two flows: a fast flow representing the short-time response of the catchment and a slow flow, which represents the slow response of the system and goes into the second deposit. The fraction of flow going to the second reservoir is determined by the parameter X2, which is the groundwater exchange coefficient. As in the first reservoir, the second deposit has a threshold value that represents the maximum amount of water that can be held in it (R) and it's defined by the parameter X3. Finally, the routing time of both flows - fast and slow - is established by a unit hydrograph whose time base corresponds to the last parameter X4 (Table 3). In this way, the flow going into the second reservoir has a routing time equal to the unit hydrograph time base (UH1), whereas the routing time of the flow contributing directly to the streamflow is two times the unit hydrograph time base (UH2).

4. Methods

4.1. Model calibration strategies

In an initial run, the two models (LISFLOOD and GR4J) are set up with their default parametrization (ie. the default values of the model parameter for each model, in Table 2 for LISFLOOD and Table 3 for GR4J) and forced once with ERA5 and once with the interpolated/aggregated observed precipitation. The aim of this exercise is threefold: (1) to evaluate their capacity to reproduce the general hydrological conditions in an uncalibrated state, (2) to establish a baseline performance that allows us to assess the improvement brought through calibration, and (3) to compare the influence of the precipitation input on model performance.

After establishing a baseline performance both models are calibrated. For that, the input datasets are divided into nine years for calibration (January 1992 to August 2001) and five validation years (August 2001 to August 2006). The data in 1991 is used for the model warm-up and therefore not used to compute the scores. Since the LISFLOOD model code for calibration is based on the DEAP algorithm (Fortin et al., 2012; Maier et al., 2014; Hirpa et al., 2018), for consistency we applied the same algorithm for GR4J calibration so the results can be compared (see Hirpa et al., 2018 Section 3.1 for full details about the algorithm implementation). Hydrologic models are typically calibrated through the use of objective functions, the most common being the Nash-Sutcliffe efficiency criterion (Nash and Sutcliffe, 1970). However, given the potential limitations of this metric (Gupta et al., 2009; Kling et al., 2012) the Kling-Gupta efficiency score (KGE) is considered herein for model calibration, notably because the KGE is a linear combination of three components of the modeling error; the Pearson correlation coefficient, the bias ratio and variability ratio between observed (*Qo*) and simulated (*Qs*) runoff:

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

$$\text{with} r = \frac{cov \quad (Q_o - Q_s)}{\sigma^2_{Qo}\sigma^2_{Qs}}; \alpha = \frac{\sigma_{Qs}}{\sigma_{Qo}}; \beta = \frac{\overline{Q_s}}{\overline{Q_o}} \tag{2}$$

Consequently, the calibration was performed using the KGE as an objective function, proven to be efficient to reproduce peak flows and mean annual regime (Mizukami et al., 2019). For LISFLOOD, the parameter ranges are the same as applied in the calibration of EFAS. In the case of GR4J, the parameter range used during calibration and the initial run are those presented in Perrin et al. (2003).

4.2. Skill scores for high runoff events

The model's ability to reproduce flood events is evaluated by three skill scores, the Probability of Detection (POD), False Alarm Ratio (FAR) and Heidke Skill Score (HSS) (Wilks, 2019). To compute these scores, all events above the 95th percentile of daily discharge computed over the whole period have been extracted from observations and also model simulations. The 95th percentiles have been computed only for discharge value above 0.5 $m^3.s^{-1}$, to not bias the detection of high runoff events towards smaller values, since intermittent rivers frequently have zeros flow values. For each model simulation the thresholds (ie. the 95th percentiles) to extract the events are redefined, to avoid the effects of model bias on the detection of flood events. By doing so, this evaluation is fully consistent with the event detection done in EFAS and GloFAS (Bartholmes et al., 2009). As explained in Thielen et al. (2009), there are two main motivations to use this approach. First, the absence of detailed information about small scale river regulation (small dams, water uptakes for irrigation…) that cannot be modelled, inducing bias on simulated discharge. Second, the limited accuracy of meteorological measurements, notably precipitation, that could lead to large discrepancies between modelled and observed discharge.

$$POD = \frac{a}{(a+c)} \tag{3}$$

$$FAR = \frac{b}{(a+b)} \tag{4}$$

$$HSS = \frac{ad - bc}{((a+c)\bullet(c+d) + (a+b)\bullet}(b+d))/2 \tag{5}$$

Table 2
List of LISFLOOD calibration parameters including their default values and their ranges.

Parameter		Min	Max	Default
Xinanjiang	Xi	0.01	5	0.5
Power Preferential Flow	PF	0.5	8	4
Upper Zone Time Constant	UZ	0.01	40	10
Groundwater Percolation	Perc	0.01	2	0.8
Lower Zone Time Constant	LZ	40	1000	100
Manning Multiplier	Man	0.5	2	1
Groundwater loss	GwLoss	0	0.5	0
Lower-zone threshold	LZThreshold	0	30	10

Table 3
List of GR4J calibration parameters including their default values and their ranges.

Parameter		Min	Max	Default
Production storage capacity	X1	20	2000	350
Groundwater exchange coefficient	X2	-6	4	0
Routing storage capacity	X3	1	300	90
Time base of unit hydrograph	X4	0	5	1.7

where *a* is the hit rate (the events correctly modelled), *b* the false alarms (events modelled but not observed), *c* the missed events (observed events not modelled) and *d* the correct negative, that can be obtained from a contingency table. In addition to these scores, quantile-quantile plots, a graphical method for comparing two probability distributions by plotting their quantiles against each other, were used to compare the distributions of high runoff events to detect potential biases due to the rainfall input or the hydrological model.

4.3. Hydrological consistency of the simulations

Several studies have described a number of hydrological signatures that can be incorporated into the hydrologic modeling process to evaluate the hydrological consistency of the simulations, beyond the use of standard verification scores such those aforementioned. There are two main ways in which these hydrological signatures can be used to improve the hydrological consistency of the simulations: (1) to compare and identify the most adequate model structure for a given catchment or to evaluate the suitability of a single model and (2) to include them in the calibration process as a part of a multi-objective calibration approach (McMillan et al., 2017; McMillan, 2020; Gnann et al., 2021). In the present study, four hydrological signatures tailored to describe flood related processes have been used to compare the hydrological consistency of the simulations generated by LISFLOOD and GR4J with a focus on extremes. For

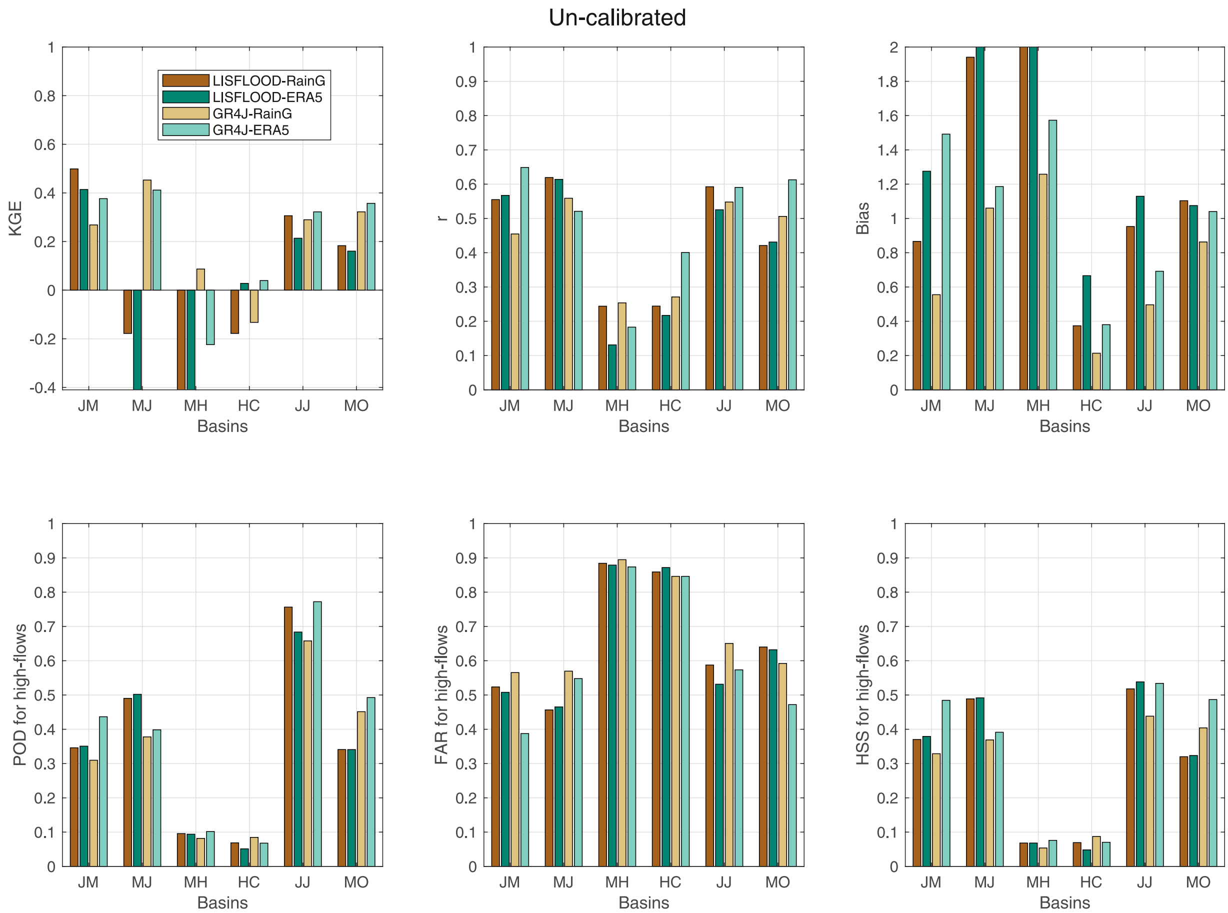

Fig. 3. Evaluation scores without model calibration (baseline performance), simulated by LISFLOOD and GR4J driven by observed rainfall (RainG) and ERA5 during 1992–2006.

this purpose, the toolbox presented in Gnann et al. (2021) has been used to compute hydrological signatures from daily discharge that describe several components of the hydrological response typical of these semi-arid basins:

1. The Richard-Baker Flashiness index (FI), that quantifies the response time of runoff after the onset of a rainfall event and the return to base flow conditions (Baker et al., 2004);
2. Peak distribution (PD), that shows whether the peak discharges are of equal height. It is computed as the slope between the 10th and 50th of a flow duration curve constructed by only considering hydrograph peaks (Euser et al., 2013);
3. Rising limb density (RLD), is a descriptor of the hydrograph shape and smoothness without consideration for the flow magnitude, thus describing the flashiness of the catchment response. It is computed as the ratio between the number of rising limbs and the total amount of timesteps the hydrograph is rising (Sawicz et al., 2011), so it is equivalent to the inverse of the mean time to peak;
4. Variability Index (VI), the standard deviation of the common logarithms of discharge determined at 10 % intervals from 10 % to 90 % of the cumulative frequency distribution (Estrany et al., 2010).

5. Results

5.1. Model performance without calibration

This first evaluation represents a benchmark, to test whether the models without calibration could be useful for hydrological modeling and notably the detection of high flow events during the full period with observed data. In general, the performance with uncalibrated models is not satisfactory and highly dependent on the basins (Fig. 3). For example, in Joumine at Mateur (JM), Joumine at Jbel Antra (JJ) or Melah (MO) basins, the simulations with LISFLOOD and GR4J produce KGE close or above 0.3, while for the other basins the performances are very low with KGE close to zero. Model bias, as shown on Fig. 3, is very strong with either an over or underestimation of runoff. Yet, for most simulations the KGE is larger than – 0.41, that is the value corresponding to a mean flow benchmark (Knoben et al., 2019). Nevertheless, the correlations between observed and simulated flows exceed 0.5 in 4 of the 6 basins, due to the strong streamflow seasonality typical of semi-arid basins. The weakest performances in terms of KGE and HSS are observed

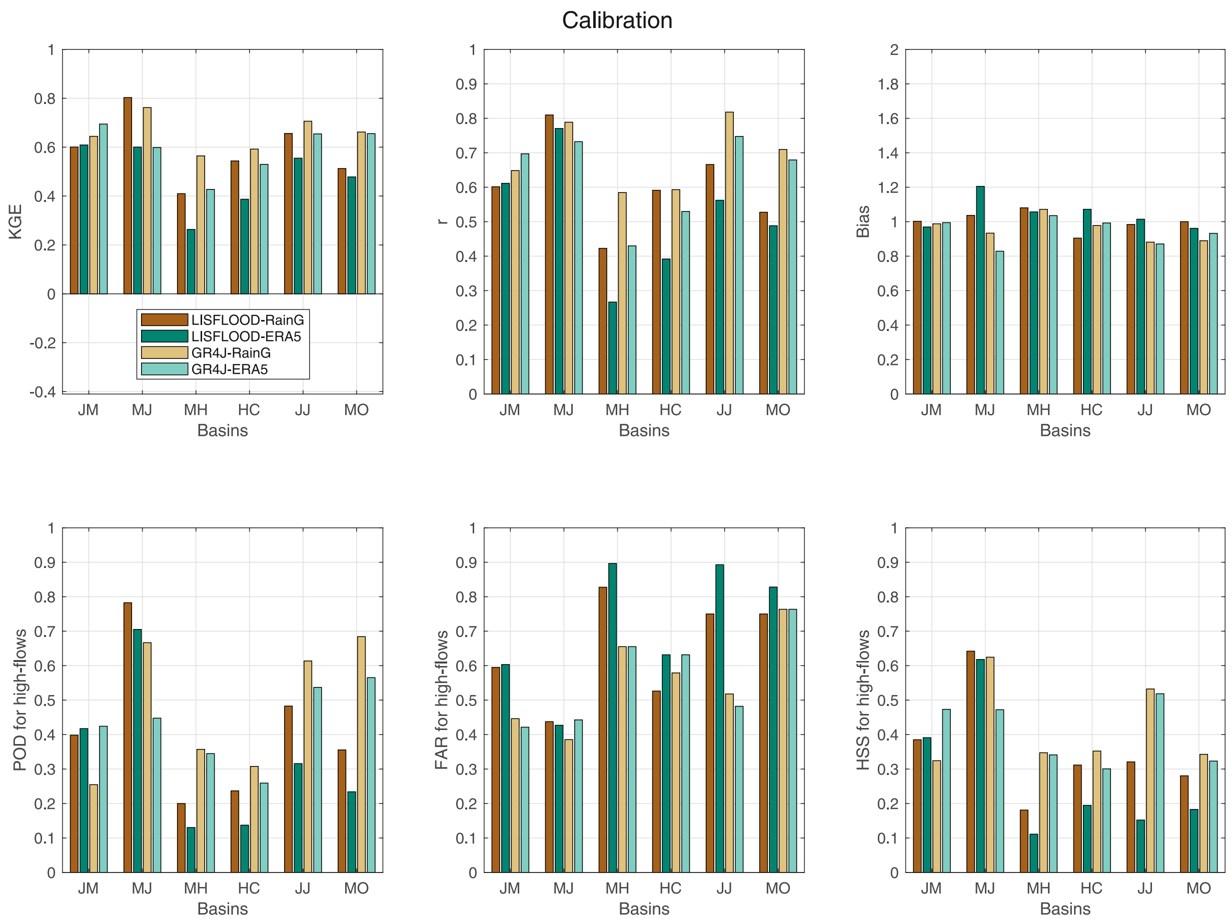

Fig. 4. Evaluation scores after model calibration.

for basins MH and HC,the most arid ones, with very low POD and high FAR. The POD scores can reach 0.5, especially for basins of Joumine at Mateur (JM), Medjerda (MJ), Joumine at Jebel Antra (JJ) and Melah (MO). Interestingly, for the smallest basin, Joumine at Jebel Antra (JJ), the POD is reaching values close to 0.8 with LISFLOOD driven by observed rainfall and GR4J driven by ERA5, proving that the un-calibrated setup is efficient to detect floods in this basin. No significant differences are observed between the LISFLOOD and GR4J models, nor between the use of observed precipitation or ERA5, with performance varying greatly from one catchment to another. When looking at the daily discharge values above the 95th percentile, all the simulations strongly underestimate the flow values (results not shown). These results indicate that the simulations without model calibration are strongly biased and cannot be used for flood event detection in most cases.

5.2. Model calibration and validation

After model calibration, as shown on Fig. 4, considering observed rainfall or ERA5, we obtained slightly better performances with GR4J driven by observed rainfall (mean KGE = 0.65) or ERA5 (mean KGE = 0.59), rather than with LISFLOOD driven by observed rainfall (mean KGE = 0.59) or ERA5 (mean KGE = 0.48). The highest KGE values are obtained in 4 out of 6 basins with the combination of GR4J with observed rainfall (MJ, MH, HC, JJ, MO). A similar difference between the two models' efficiency is obtained in terms of correlations. However, less differences are found between the two hydrological models for POD or HSS scores, indicating a similar performance to reproduce high runoff events. For instance, very similar POD scores are observed between LISFLOOD and GR4J driven by observations (mean POD of 0.41 and 0.45, respectively), or ERA5 (0.36 and 0.4, respectively). However, the FAR is very high for 3 basins (MH, JJ, MO) notably with LISFLOOD driven by ERA5, yielding low HSS scores. It should be noted that acceptable KGE scores do not warrant a good detection capability in terms of skills scores for flood detection, that are low for three basins out of six. In terms of flood magnitude, the quantile-quantile plots (Fig. 5) show that all models, once calibrated, are able to reproduce the distribution of daily discharge events above the 95th percentile, except for the Hathob (HC) and Melah (MO) basins. There are no striking differences between simulations with observed rainfall or ERA5, except for the Medjerda (MJ) basin where the best reproduction of threshold exceedances is obtained with LISFLOOD driven by observed rainfall, and Joumine at Jebel Antra (JJ) with the best simulations are those of LISFLOOD driven by observed rainfall or ERA5.

During the validation, we observed very strong differences among basins (Fig. 6). The mean KGE is equal to 0.32 with LISFLOOD

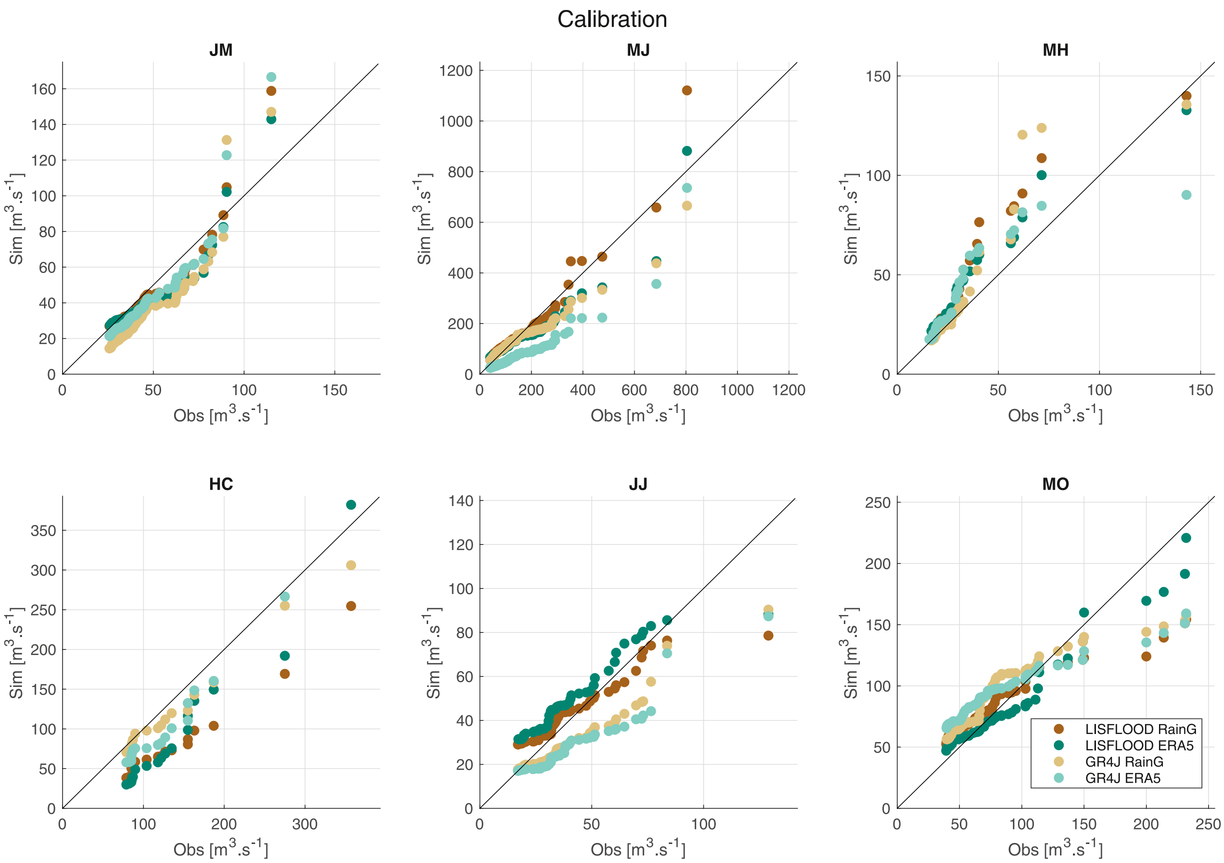

Fig. 5. Quantile-quantile plots of high-flow events simulated during calibration by LISFLOOD and GR4J driven by observed rainfall (RainG) and ERA5.

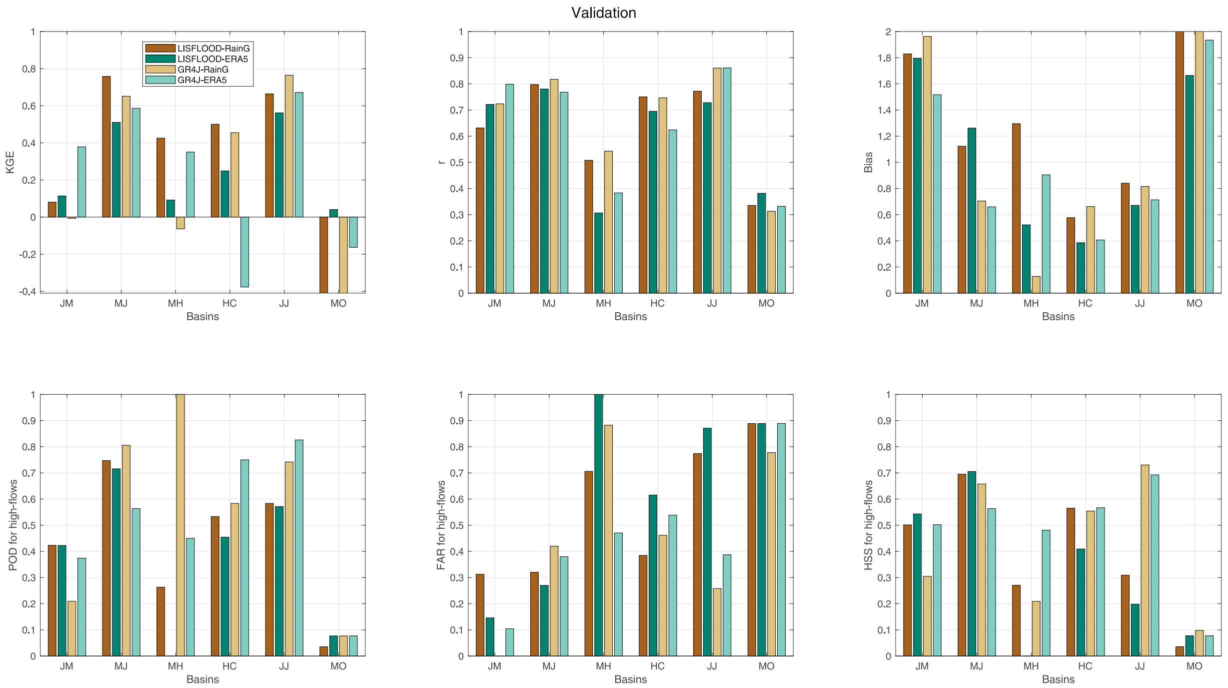

Fig. 6. Evaluation scores in validation.

and 0.2 with GR4J when using observed rainfall (0.26 and 0.24 with ERA5), but average performance could be misleading here due to the large differences between basins. It should be noted that these scores remain quite low, due to the short period of validation in a context of a strong interannual variability of precipitation and runoff in these semi-arid environments. Better performances are achieved in terms of POD with LISFLOOD (mean POD = 0.45 using observed rainfall and 0.4 with ERA5) than with GR4J (POD = 0.43 and 0.35, with observed rainfall or ERA5, respectively). On the contrary, the correlation between observed and simulated runoff remains above 0.5, except for the Melah (MO) basin. Overall, the only basin with acceptable performances in validation with the two

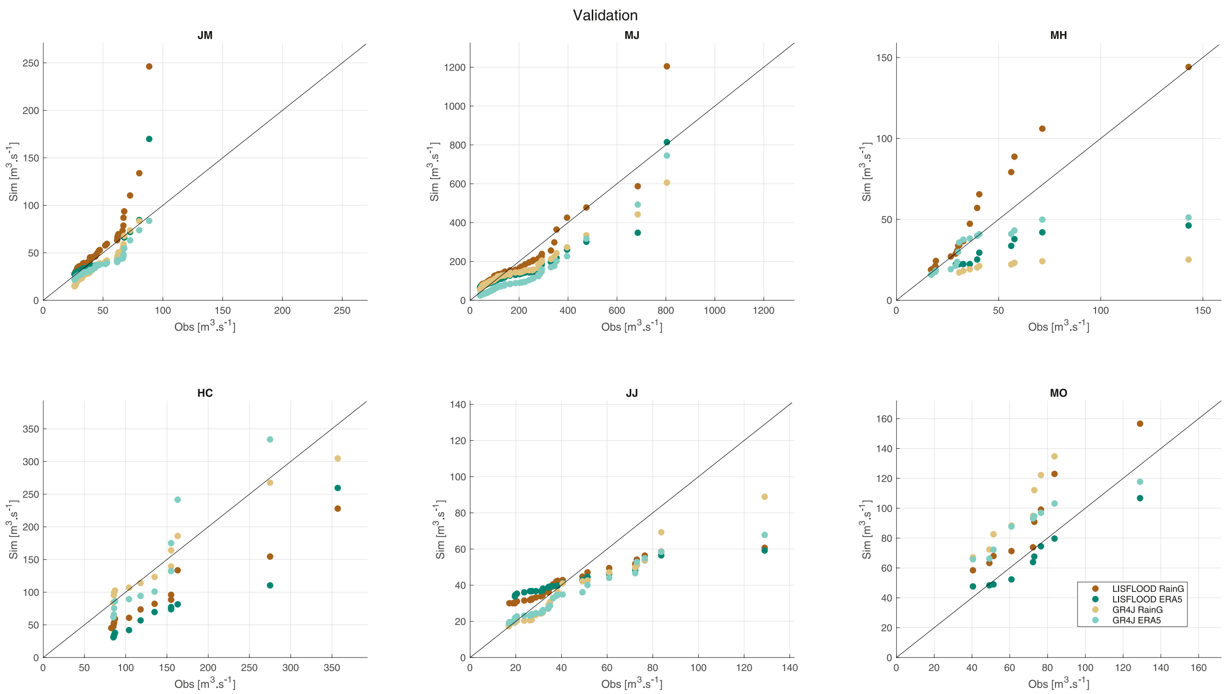

Fig. 7. Quantile-quantile plots of high-flow events simulated in validation by LISFLOOD and GR4J driven by observed rainfall (RainG) and ERA5.

hydrological models and rainfall inputs is the Medjerda (MJ), being the largest one in the sample considered herein. In the only basin with the presence of a dam significantly influencing river flow (Joumine at Mateur, JM), we note a relatively weak performance in terms of KGE, but performances similar to the other basins for the detection of floods. The hydrographs of the JM basin show the effect of dam regulation notably between 1998 and 2001 (as shown in Supplementary materials figures).

For the high-runoff events magnitude (Fig. 7), there are more differences between the different rainfall inputs during validation than calibration but overall, the quantile-quantile plots of Fig. 7 indicate that for most basins the runoff events above the 95th percentile are not well reproduced in validation. the best results are obtained for the Medjerda (MJ), with simulations driven by observed rainfall closer to observations than simulations driven by ERA5. The difference between the two hydrological models appears small here, suggesting that the rainfall input has the largest influence on the results.

5.3. Model ability to reproduce hydrological signatures

The hydrological signatures computed with observed daily discharge data reveal the difference in terms of runoff response across the basins (Fig. 8). For instance, the two signatures indicative of the flashiness response, the flashiness index and the rising limb density, are the highest for the two southernmost basins (Merguellil, MH, and Hathob, HC) that are the most arid and intermittent basins. This reveals that in these two basins the hydrograph shapes are less smooth than in northern Tunisia with shorter response time of runoff after a rainfall event, explaining the lower efficiency of hydrological models there. For the peak distribution, the values are rather homogeneous in the different basins, with the highest value for the smallest basin, Joumine at Jebel Antra (JJ). LISFLOOD and GR4J tend to underestimate the flashiness index and the rising limb density, when driven by observed or ERA5 rainfall (Fig. 8), but these differences to reproduce the different hydrological signatures are to a large extent dependent on the catchment characteristics. A distinct behavior is observed for the two most arid basins, with different reproduction of the signatures with different combinations of models and rainfall inputs. This is most notably the case for the flashiness Index and rising limb density in basins 3 and 4, the peak distribution in basin 3. The variability index is generally the worst reproduced signature in all the basins. On the contrary, the flashiness index and rising limb density signatures are best reproduced with mean absolute errors less than 0.5. Overall, no striking differences in the ability of LISFLOOD and GR4J to reproduce the hydrological signatures using observed or ERA5 rainfall is found. Focusing on the independent validation period it is shown in Fig. 8 that LISFLOOD driven by rain gauge data outperforms the same model driven by ERA5 for all signatures, whereas with GR4J, ERA5-driven simulations outperform those driven by observations in 3 out of 4 signatures.

6. Discussion

Hydrological modeling in Tunisia is challenging due to the data availability and data quality issues. As for many semi-arid regions, the performance of hydrological models is usually low, due to the strong interannual variability of runoff generation, but also the observational limitations in the context of a high spatial variability of rainfall inputs (McIntyre and Al-Qurashi, 2009). Notably, dryland hydrology is characterized by strong threshold effects that may require specific hydrological model structures (Cudennec

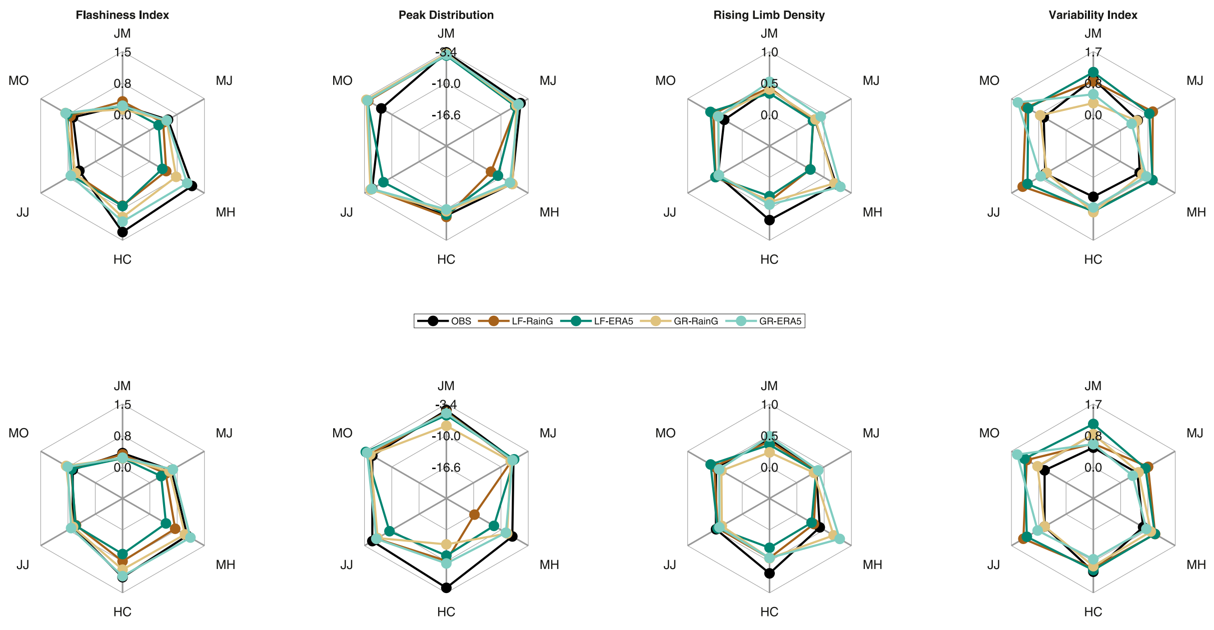

Fig. 8. Spider plots showing the observed and simulated hydrological signatures for each basin. FI: Flashiness index, PD: Peak Distribution, RLD: Rising Limb Density, VI: Variability Index. Upper row, the hydrological signatures in calibration, and lower row in validation.

et al., 2007; Wheater et al., 2007; Sumi et al., 2022) accounting for the non-linearity in the storage-discharge relationship (Jothityangkoon et al., 2001; Huang et al., 2016; Lahmers et al., 2019), the influence of the seasonal variability of vegetation cover on interception and soil crusting (Wheater et al., 2007, Bouvier et al., 2018), landscape variability and lateral redistribution processes that could reduce runoff volumes (Güntner and Bronstert, 2004) and transmission losses within the channel beds (Goodrich et al., 1997). Because of its conceptual nature, the GR4J model could not be easily modified to represent these processes. However, given the modular structure of LISFLOOD, the current model structure used in EFAS could be adapted to include the relevant processes following some field-based validation of the main components that would be required. An additional issue stems from the available data to perform a model evaluation as in the present work, with the daily time step of discharge data being suboptimal to analyze flood dynamics. Several studies observed a fast decay of soil saturation following rainfall events, indicating hourly time step data better suited for this type of analysis in semi-arid basins (El Khalki et al., 2020). This may be the cause for the low scores on flood detection (POD and HSS) in the present study. Most moderate to small flood events may last only a few hours and not span over days, therefore their detection using daily data is challenging. However, if daily data are already rare and difficult to obtain, instantaneous flow data are even rarer.

The conclusions of the present work, and others on the same topic, are a strong incentive for the development of river discharge databases at the national, regional and continental levels to foster the development of flood warning systems, such as EFAS or GloFAS. As shown in the present study, the rainfall provided by the ERA5 reanalysis could provide a reliable alternative in place of observed rain gauge data, provided that discharge data would be available for model calibration. There is indeed a crucial need for good quality river discharge data (Beven et al., 2020; Crochemore et al., 2020) that also cover a variety of different regions (Do et al., 2018; Tramblay et al., 2021), to be used for the validation of hydrological simulations with GHMs such as LISFLOOD. While about two-thirds of hydrological data from observational networks in developing countries are reported to be in declining conditions (Dixon et al., 2020), there are some ongoing initiatives for data rescue such as the World Meteorological Organization's Global Hydrometry Support Facility or the Global Flood Partnership (Alfieri et al., 2021), that is regrouping a community of both researchers and practitioners from various countries to develop modeling strategies to reduce flood risks. While it is obvious that it is not possible to adopt the same modeling strategy in data poor and data rich regions, where hydrological models can be calibrated with observations in a large number of basins, the present study illustrates the potential of using a GHM for flood risk management at catchment scale in a developing country. To overcome the limitations linked to the lack of discharge data for calibrating the models over large regions, the regionalization of the GHMs parameter could provide pre-determined parameter values adapted to ungauged basins in different regions (Beck et al., 2020; Ma et al., 2021). However, any regionalization attempt requires river discharge data quality on a large number of catchments to constitute a statistically significant group of "donor" basins from which we can transfer the parameters to ungauged basins. As recent studies suggest, these approaches could be applied on worldwide databases of basin properties taking benefits of the recent developments in machine learning techniques (Feng et al., 2021; Ma et al., 2021).

7. Summary and conclusions

In this study, two models with very different structures were compared to reproduce river runoff and floods for a set of Tunisian basins: The distributed LISFLOOD model, used in the EFAS and GloFAS, and the lumped GR4J model. The performance of the two hydrological models tested in ungauged basins was assessed through their application with default parameter values to mimic the absence of discharge data for calibration, showing little skill without calibration. The calibration process has been proven to greatly enhance the performance of the two hydrological models. The comparison of the performance of LISFLOOD and GR4J after calibration shows that both models have similar skill in determining whether a flood event will occur. Results also showed little effects of the precipitation input on the simulated discharge: the differences of the simulated quantiles of the observation-driven models and the ERA5-driven models are very similar. It should be noted that the different evaluation scores remained low, as is often the case in semi-arid and arid basins characterized by a strong variability of precipitation and runoff. In these basins, flood hydrographs have a reduced or no base flow contribution, and most of the streamflow is constituted by the direct surface runoff largely influenced by the infiltration capacity of the soil. The reproduction of the hydrological behavior of these rivers is still challenging, often requiring sub-daily data for model calibration and evaluation. Results of the present study demonstrate that ERA5 data could provide a valuable alternative to observed precipitation, as long as there is available river discharge data to calibrate the hydrological model parameters. This is especially important when the modeling results are intended to be used for water resources management at catchment or regional scales, rather than an assessment at global scale. As data availability conditions the modeling approach in Tunisia and in most developing countries, the main scientific question to address is no longer which model better represents the extreme flows, but rather which modeling strategy can best reproduce floods for a maximum number of basins, while requiring a minimum amount of data. In other words, the question to be answered in the future is how to apply such models regionally given the available data, to implement efficient regional flood warning and forecasting systems such as EFAS or GLOFAS.

CRediT authorship contribution statement

Elia Cantoni: Conceptualization, Data curation, Formal analysis, Methodology, Writing – original draft, Writing – review & editing. **Stefania Grimaldi:** Methodology, Writing – review & editing. **Peter Salamon:** Conceptualization, Methodology, Writing – review & editing. **Hamouda Dakhlaoui:** Methodology, Writing – review & editing. **Alain Dezetter:** Methodology, Writing – review & editing. **Vera Thiemig:** Conceptualization, Methodology, Writing – review & editing.

Declaration of Competing Interest

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

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.ejrh.2022.101169.

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