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Research papers

Regional flood frequency analysis in North Africa

Yves Tramblay[a,*], El Mahdi El Khalki[b], Abderrahmane Khedimallah[a,c], Mahrez Sadaoui[d], Lahcen Benaabidate[e], Tayeb Boulmaiz[f], Hamouda Boutaghane[g], Hamouda Dakhlaoui[h,i], Lahoucine Hanich[j], Wolfgang Ludwig[d], Mohamed Meddi[c], Mohamed Elmehdi Saidi[j], Gil Mahé[a]

[a] HSM (Univ. Montpellier, CNRS, IRD), Montpellier, France
[b] International Water Research Institute, Mohammed Vi Polytechnic University (UM6P), Benguerir, Morocco
[c] Water and Environmental Engineering Laboratory (LGEE), Higher National School of Hydraulics, Blida, Algeria
[d] Centre de Formation et de Recherche sur les Environnements Méditerranéens, CNRS, UMR 5110, Perpignan, France
[e] Laboratory of Functional Ecology and Environment Engineering, University of Sidi Mohamed Ben Abdellah, Fes, Morocco
[f] Materials, Energy Systems Technology and Environment Laboratory, University of Ghardaia, Ghardaia, Algeria
[g] Laboratory of Soil and Hydraulic, Badji Mokhtar Annaba University, Annaba, Algeria
[h] Laboratoire de Modélisation en Hydraulique et Environnement (LMHE), Ecole Nationale des Ingénieurs de Tunis (ENIT), Tunis, Tunisia
[i] Ecole Nationale d'Architecture et d'Urbanisme, Université de Carthage, Sidi Bou Said, Tunisia
[j] L3G Laboratory, Earth Sciences Department, Faculty of Sciences and Techniques, Cadi Ayyad University, Marrakech, 40000, Morocco

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ABSTRACT

The Maghreb countries located in North Africa are strongly impacted by floods, causing extended damage and numerous deaths. Until now, the lack of accessibility of river discharge data prevented regional studies on potential changes in flood hazards or the development of regional flood frequency estimation methods. A new database of daily river discharge data for 98 river basins located in Algeria, Morocco, and Tunisia, has been compiled, with an average of 36 years of complete records over the time period 1960–2018. A peaks-over-threshold sampling of flood events is considered first to detect trends in the annual frequency and the magnitude of floods. The trend analysis results revealed no significant changes in flood frequency or magnitude at the regional level, with only a few spurious trends due to isolated extreme or clustered events. An envelope curve relating maximum floods for a range of catchment areas in North Africa has been developed, for the first time in this region with such a large database. Then, regional estimation methods for flood quantiles were compared. The regional estimation from multiple catchment characteristics (including soil types, land use, elevation, and geology) was performed by comparing two multiple linear regression methods, Stepwise regression and Lasso regression, and a machine learning algorithm, Random Forests. Results indicate a better performance of the Lasso regression to estimate flood quantiles at ungauged locations, with mean absolute relative errors close to 50 % and relative bias close to 20 %. The most relevant catchment predictors identified by the regression models are the topographic wetness index, which provides better estimates than catchment area, but also altitude, mean annual rainfall, and soil bulk density. The results of this study could be useful to improve operational procedures for sizing hydraulic structures at ungauged sites.

1. Introduction

North Africa is a region severely affected by floods where there are twice as many fatalities related to floods in Algeria, Morocco, and Tunisia than in Spain, France, and Italy in the last decades, as reported by the International Disaster Database (https://www.emdat.be/). Nevertheless, it is also a region where there is little knowledge about floods, not only in terms of temporal trends but also in regional estimation methods, to contribute to the mitigation of the adverse effects of these episodes (Boutaghane et al., 2022; Loudyi et al., 2022). In particular, in a context of data scarcity and a low density of the hydrometeorological networks, it is of uttermost importance to develop

* Corresponding author at: ESPACE-DEV (Univ. Montpellier, IRD), Montpellier, France.
E-mail address: yves.tramblay@ird.fr (Y. Tramblay).

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reliable regional flood frequency methods to estimate flood quantiles at ungauged locations, for dams, bridges, and different types of infrastructure constructions, and also to protect people against destructive floods such as those recorded in Tlemcen and El Bayadh (Algeria) at the beginning of September 2023, which killed eight people, and those recorded in Libya on 11 September 2023, with several thousand fatalities. Table 1.

Flood frequency analysis is a widely applied methodology to estimate the return levels at different locations based on statistical distributions fitted to annual maximum discharge or peaks-over-threshold data (Stedinger, 1993; Pan et al., 2022), that can be expanded to ungauged locations to estimate flood quantiles regionally (GREHYS, 1996; Svensson and Jones, 2010). A great variety of regional methods have been developed, either using geographic proximity or catchment characteristics to estimate flood quantiles at a target location (Burn, 1990; Farquharson et al., 1992; Hosking and Wallis, 1993; Burn, 1997; Meigh et al., 1997; Ouarda et al., 2001; Pandey and Nguyen, 1999; Salinas et al., 2013; Wazneh et al., 2015; Desai and Ouarda, 2021). These approaches mostly rely on two steps (Ouarda et al., 2001), first the identification of homogeneous regions, that can be contiguous or not, based on catchment similarity, and second, the regional estimation using multiple regressions (Pandey and Nguyen, 1999; Svensson and Jones, 2010) or machine learning techniques (Shu and Burn, 2004; Desai and Ouarda, 2021) using catchment attributes. A popular method is the Index Flood (Dalrymple, 1960), which relies on regional distributions scaled by an index, usually taken as the mean annual flood. Yet, several studies have shown that this method is not optimal in semi-arid and arid regions (Salinas et al., 2013). While most of these well-established methods are now routinely used in many regions of the world, only few studies are providing guidelines about the application of these methods in North Africa, hampering their use for operational applications.

Several studies have reported stronger uncertainties in regional flood frequency analysis for semi-arid and arid regions, compared to more humid regions, mostly due to the very high spatial and temporal variability of flood events and their precipitation triggers, but also rather short records available in many countries (Farquharson et al., 1992; Salinas et al., 2013; Smith et al., 2015). Regional flood growth curves for arid regions are displaying flood distributions with a much heavier tail than in other climate zones, with the heaviness of the tail increasing with aridity, challenging a reliable estimation of the probabilistic model parameters to estimate flood return levels (Farquharson et al., 1992; Padi et al., 2011a; Zaman et al., 2012; Guo et al., 2014; Metzger et al., 2020). In North Africa, a small number of studies have applied flood frequency techniques, and even fewer regional flood frequency methods, mostly with a very limited number of stations (Farquharson et al., 1992; Abida and Ellouze, 2006, 2008; Ellouze and Abida, 2008; Chérif and Bargaoui, 2013; Zemzami et al., 2013; Zoglat et al., 2014; Benameur et al., 2017; Zkhiri et al., 2017; Meddi et al., 2017; El Alaoui El Fels et al., 2018; Karahacane et al., 2020; Saidi et al., 2020; Boumessenegh and Dridi, 2022). For instance, focusing on regional studies only, the seminal paper of Farquharson et al. (1992) about regional flood frequency in arid areas contains only 13 stations in Algeria, Morocco, and Tunisia and similarly, there are 8 stations in Padi et al. (2011) over the same countries. At the national or basin scales, Zhiri et al. (2017) considered 5 stations of the Tensift basin in southern Morocco, Ellouze and Abida (2008) 48 stations in Tunisia, and Meddi et al. (2017) 57 stations in northern Algeria. The three studies mentioned above considered the index flood method with geographically contiguous regions.

The objective of this study is first to check for trends in flood frequency or magnitude in the largest ever-built database of time series of river runoff in North Africa with long records, and second to test regional estimation methods for flood quantiles adapted to ungauged basins, for this area under a Mediterranean semi-arid climate. After the data collection presented in section 2, the methodology in terms of flood sampling, trend detection, local frequency analysis, and regional estimation methods for flood quantiles are presented. In section 3 are presented the results and discussion and in section 4, the conclusion and perspectives.

Table 1
Catchment properties.

Abbrev.	Description	Data source
CN	Curve Number	Ross et al., 2018 10.1038/sdata.2018.91
AWC	Available Water Capacity	
BD	Bulk density	Harmonized World Soil Database,
Clay	% Clay	Wieder et al., 2014
Gravel	% Gravel	https://doi.org/10.3334/ORNLDAAC/1247
Sand	% Sand	
Silt	% Silt	
GWd	Groundwater depth	McDonald et al., 2012
GWp	Groundwater productivity	https://doi.org/10.1088/1748-9326/7/2/024009
GWs	Groundwater storage	
MaAlt	Maximum altitude	Hydrosheds, Lehner et al., 2013
SLP	Mean slope	10.1002/hyp.9740
MeAlt	Mean altitude	
TWI	Topographic Wetness Index	Sørensen et al., 2006 10.5194/hess-10-101-2006
Forest	% Forest	
Urban	% Urban	ESA CCI LandCover
Crop	% Cropland	http://www.esa-landcover-cci.org/
CropIr	% Cropland irrigated	
Grass	% Grassland	
Shrub	% Shrubland	
Sparse	% Sparse	
Bare	% Bare land	
Area	Area	
P	Mean annual precipitation	CRU, Harris et al., 2020
T	Mean annual temperature	10.1038/s41597-020-0453-3
PET	Mean annual potential evapotranspiration	

2. Data collection

We compiled an unprecedented database of 98 catchments (Fig. 1) in North Africa that have at least 30 years of daily discharge records between 1960 and 2018, and we excluded years with more than 10 % of missing data. The minimum record length is 15 years, the mean record length is 36.5 years, and the median is 37 years. The median catchment area is 688 km^2, ranging from 27 km^2 to 7500 km^2 with only 7 basins larger than 3000 km^2. The mean annual precipitation is 539 mm/year, computed from the CRU database (Harris et al., 2020), ranging from 137 mm/year to 960 mm/year for the wettest areas, located in Northwestern Morocco and Eastern Algeria/Northwestern Tunisia. The mean annual evapotranspiration is high, on average 1316 mm, with a low variability between 1126 mm/year to 1793 mm/year, which characterizes these semi-arid basins. The aridity index (ie. the ratio of annual precipitation to potential evapotranspiration) is below 0.5 for 65 basins, indicating semi-arid conditions, and below 0.2 for 7 stations, corresponding to arid conditions. The 33 basins with an aridity index higher than 0.5, indicative of dry sub-humid conditions, are mostly located along the Atlantic or Mediterranean coastlines. The main criterion for the selection of basins was the absence of large dams or regulation structures that may affect the river discharge and flood regime. We used the Global Reservoir and Dam Database (GRanD) (Lehner et al., 2011) to exclude stations where large dams are present. However, this database is not a complete inventory of all dams and reservoirs in North Africa (Sadaoui et al., 2018). For this study, the dam identification approach already used by Sadaoui et al. (2018) has been extended to the whole Maghreb using satellite imagery to cover all the basins in North Africa. The approach is based on the manual digitalization of additional reservoirs that were not already included in the GRanD database. The identification of these reservoirs was made from Google Map satellite images visualized into the QGIS software. This approach enabled the

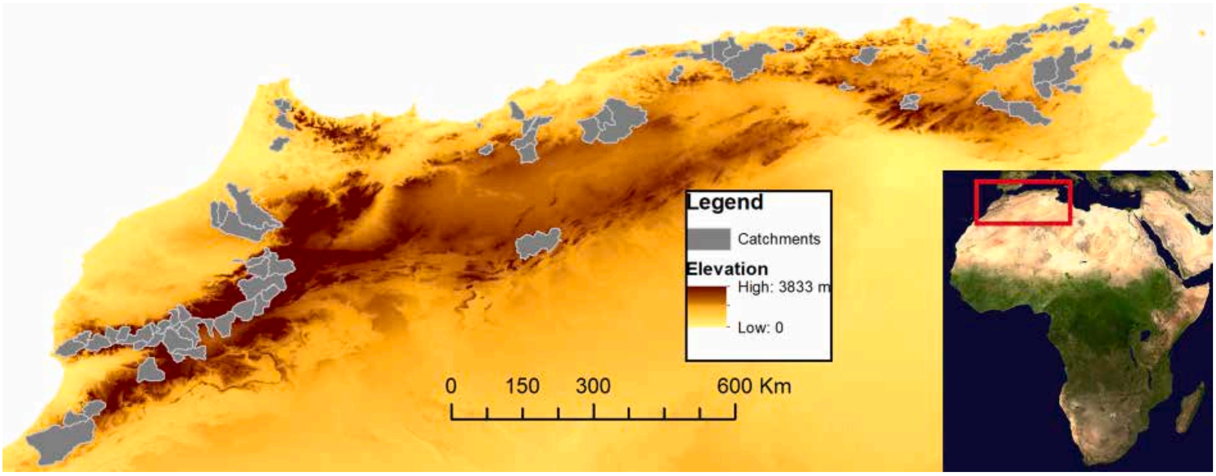

Fig. 1. Map of the 98 catchments selected located in North Africa.

identification of small hillside reservoirs and dams.

Several catchment attributes have been extracted from available databases, after the delineation of the catchment boundaries using the HydroShed digital elevation model with a 300 m spatial resolution (Lehner and Grill, 2013). All these attributes have been averaged to the catchment scale to obtain one attribute per basin. From the HYSOGs250m database (Ross et al., 2018), we extracted the Curve Number, which is an empirical dimensionless parameter indicating the runoff response characteristic of a drainage basin, with lower numbers indicating low runoff potential and larger numbers increased runoff potential. Soil data were extracted from the Harmonized World Soil Database (Wieder et al., 2014), to obtain soil characteristics such as the bulk density, available water capacity, and the proportion of clay, sand, and silt. Several quantitative attributes of the groundwater have also been retrieved, including groundwater depth, productivity, and storage (MacDonald et al., 2012). We also considered the Topographic Wetness Index (TWI), first introduced in the Topmodel formulation (Beven and Kirkby, 1979). The TWI is defined as ln(a/tan β), where tan β is the local slope of the ground surface and a is the upslope area. Basins with a large (small) upslope area receive a high (small) index value and are expected to have relatively higher (lower) water availability. Steep locations, such as mountain areas, have a small index value and are expected to be better drained than lowlands (Sørensen et al., 2006). In addition, several land use classes have also been extracted: forest, urban, cropland, grassland, shrubland, and sparse and bare areas (ESA, 2017). Finally, mean annual precipitation, temperature, and evapotranspiration have been computed from the CRU v4 dataset (Harris et al., 2020).

3. Methodology

3.1. Flood event sampling and trend analysis

We extracted flood events based on a peaks-over-threshold sampling, leading to an average number of one flood event per year. Indeed, as noted previously by several studies, the use of annual maximum flood can lead to a biased sample containing very low discharge values for dry years (Farquharson et al., 1992; Zaman et al., 2012; Tramblay et al., 2022). To ensure event independence, which is a prerequisite for applying flood frequency analysis methods, we conducted a declustering approach based on two rules, first a minimum of 3 days between two consecutive flood peaks, and second, between two consecutive peaks, the discharge must drop below 2/3 of the smallest peak (Lang et al., 1999; Tramblay et al., 2022).

Then, the presence of trends was tested by applying the Mann-Kendall test for trends (Mann, 1945) to the flood event magnitudes. To test trends on flood occurrence (ie. the number of floods per year), as an alternative to a Poisson regression since for most stations the data are over-dispersed with the variance exceeding the mean of flood counts, we applied a Negative binomial regression (Hilbe, 2011; Bhunya et al., 2013), framed as a Generalized Linear Model with time as a covariate. To assess whether there is a significant trend in the number of floods per year, a deviance test has been applied to compare the model with or without time as a covariate. For trend detection, we consider the 5 % significance level.

Finally, to avoid detecting spurious trends related either to the large number of repeated tests or possible cross-correlations between the different stations (Wilks, 2016), we implemented a False Discovery Rate procedure (Benjamini and Hochberg, 1995) to assess the field (or regional) significance of the trend results. The false discovery rate (FDR) procedure introduced by Benjamini and Hochberg (1995) is meant to identify a set of at-site significance tests by controlling the expected proportion of falsely rejected null hypotheses that are actually true. Several studies have shown that the FDR approach is robust to cross-correlations between locations and can work with any statistical test for which one can generate a p value (Wilks, 2016). The FDR method is applied to the Mann-Kendall test results to check if the trends are regionally significant. The detected trends are regionally significant if at least one local null hypothesis is rejected according to the global (or regional) significance level, α_{global} (Wilks, 2016). For consistency with the local trend analysis, the global significance level is also set to 5 % in the FDR procedure.

3.2. Local frequency analysis

The Generalized Pareto (GP) distribution (Pickands, 1975) is fitted to the peaks over threshold flood series for each station. The cumulative distribution function of the GP distribution is:

$$F(x) = 1 - exp\left[-\frac{x - q0}{\alpha}\right] for \kappa = 0 \quad (1)$$

$$F(x) = 1 - \left[1 - \kappa\frac{x - q0}{\alpha}\right]^{-1/\kappa} for \kappa \neq 0 \quad (2)$$

where x is the data, α is the scale parameter, κ is the shape parameter and q0 the threshold.

The Maximum likelihood (ML) estimation method for the GP parameter is widely used, but several studies have reported some limitations of the ML estimation approach in the context of short records and arid areas (Metzger et al., 2020). For this reason, two estimation approaches deemed more robust for the model parameters have been compared: the L-Moments (Hosking and Wallis, 1987) method (LMOM) and the Generalized Maximum Likelihood (GML) method. The GML relies on a prior for the shape parameter to avoid unrealistic values (Martins and Stedinger, 2000, 2001, El Adlouni et al., 2007). The prior for κ has a beta distribution (with shape parameters $\alpha = 3$ and $\beta = 6$) with a mode at -0.1, and the shape parameter values are in the range $[-0.5, +0.5]$. As recommended by Martins and Stedinger (2000), the distribution of the prior distribution has been reevaluated using the regional flood information available in the present study. To do so, the values of the shape parameters obtained with the L-Moments approach have been compared to the prior distribution provided by Martins and Stedinger (2001) to assess its validity in the study area.

To compare the different GP parameter estimation methods, the confidence intervals for the computed quantiles are obtained from a parametric bootstrap, which should be preferred for small to moderate sample sizes (Kyselý, 2008). To assess the uncertainty extent, a normalized uncertainty range is defined as the ratio of the difference between the 97.5 % and the 2.5 % bounds to the estimated return level (Metzger et al., 2020).

3.3. Regional estimation of flood quantiles

We use multiple linear regression (MLR), which is the most common technique in RFFA (Pandey and Nguyen, 1999) to estimate flood quantiles from catchment characteristics. In the present work, several catchment predictors are considered, that may introduce multi-collinearity, causing the regression coefficients to be unreliable with a high variance. The consequence would be a poor performance of the model for new data, which would be a problem when such a model is tailored for ungauged basins. Therefore, we use two variable selection techniques, stepwise regression and Lasso regularization. Stepwise regression is a method for adding and removing predictors from a linear model, based on their statistical significance in explaining the response variable. The method begins with an initial model and uses forward and backward stepwise regression to determine a final model. At each step, the function searches for predictors to add or remove in the model based on the value of the sum of squared errors and the p-value of an F-statistic to test models with and without a potential term at each step. Lasso is a regularization technique that includes a penalty term that constrain the size of the estimated coefficients (Tibshirani, 1996). It is a useful method to reduce the number of predictors and provide shrinkage estimates with lower predictive errors than ordinary least squares. The method relies on the estimation of λ, a non-negative regularization parameter. As λ increases, the number of predictors considered decreases. The optimal value of λ is obtained by a 10-fold cross-validation and computing the Deviance of the model fit to the response with different λ values, which is equivalent to maximizing the λ-penalized log likelihood.

In addition to MLR we also tested Random Forest (RF), a machine learning technique based on a bootstrap aggregation of classification and regression trees (Breiman, 2001, 1996; Breiman et al., 2017). It generates a bootstrap sample from the original data and trains a tree model using this sample. The procedure is repeated many times, and the bagging's prediction is the average of the predictions. RF are fast to compute with a moderate sample size, non-parametric, and robust to noise in the predictor variables, they are able to capture nonlinear dependencies between predictors and dependent variables, and can simultaneously incorporate continuous and categorical variables (Tyralis et al., 2019). Despite these advantages, they have been seldom used for regional flood frequency analysis (Desai and Ouarda, 2021). The main drawbacks are the complexity of interpreting the outputs and RF cannot extrapolate outside the training range. An out-of-bag predictor importance estimation by permutation (Hastie et al., 2009) has been applied to estimate the relative influence of each predictor.

For validation purposes, we compared two strategies, the first is a leave-one-out procedure (also called Jack-Knife), which consists of removing successively each basin and estimating flood quantiles with the remaining basin. The second approach is a k-fold cross-validation, where data is split randomly into 100 equal-size datasets, with 70 % of the data for model calibration and 30 % for validation. Different indicators are computed between the estimated and reference quantiles; the correlation I, the mean absolute error (MARE), and the relative bias between the observed (q_o) and estimated (q_e) flood quantiles:

$$r = \frac{Cov(q_0, q_e)}{\sigma_{qo}\sigma_{qe}} \quad (3)$$

$$MARE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{q_e - q_o}{q_o}\right| \quad (4)$$

$$Bias = \frac{1}{n}\sum_{t=1}^{n}\left(\frac{q_e - q_o}{q_o}\right) \quad (5)$$

4. Results and discussion

4.1. Flood event characteristics and trends

Flood events in North Africa tend to occur mostly during the extended winter season, from October to February, with a maximum occurrence in December and January for the majority of stations. The main driver for these floods is heavy rainfall events, even in the case of the few mountainous basins where the majority of severe floods do not occur during the snowmelt season (Zkhiri et al., 2017; Saidi et al., 2020). Regional envelope curves for maximum floods have been provided for Mediterranean catchments in southern Europe (Gaume et al., 2009; Tarolli et al., 2012; Amponsah et al., 2018), semi-arid to arid basins in USA and Israel (Metzger et al., 2020), or Australia (Zaman et al., 2012) but have never been provided for North Africa, or using a few stations and an extended area encompassing several African regions (Farquharson et al., 1992; Padi et al., 2011b). These curves can be elaborated with the maximum floods at different sites, in terms of specific discharge, that are related to the catchment area using a log-linear relationship, allowing comparison across different regions. The two parameters obtained for this relationship in North African basins (Fig. 2), the multiplier coefficient (131) and the exponent (-0.67), are more similar to those obtained in the Eastern Mediterranean (127 and −0.62) from Tarolli et al. (2012) than in the Western Mediterranean (120 and −0.4) from Amponsah et al. (2018). Consequently, the obtained envelope curve is quite consistent with other curves obtained for other Mediterranean regions.

The results of the trend analysis show significant, at the 0.05 significance level, upward trends in flood intensity at 6 stations, and

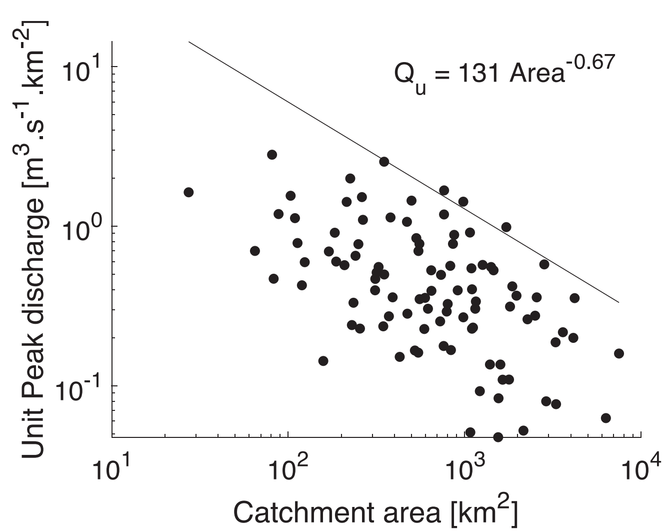

Fig. 2. Regional envelope curve for maximum specific discharge in North African basins.

downward trends at 5 stations (Fig. 3). Similarly, for the annual occurrence, an increased flood frequency is detected in 16 stations and a decrease in 5 stations. However, looking at these results individually station by station, the detected trends appear rather spurious, related either to the clustering of flood episodes during some years or individual events with a very large magnitude influencing the trend detection. This qualitative statement is supported by the fact that none of the detected trends are regionally significant, according to the False Discovery Rate procedure applied to the pvalues of the trend detection tests. These results are consistent with those obtained with a fewer number of stations (Khomsi et al., 2016; Tramblay et al., 2020), suggesting that the observed increase in the vulnerability to flood episodes in the region is likely not due to an increased flood hazard (Dahri and Abida, 2020). In this context of strong interannual and spatial variability among stations, trend detection is a difficult exercise, and results of individual tests could be misleading, thus regional approaches should be preferred. Overall, the present results suggest an absence of trends in flood severity or frequency at the regional level. Nevertheless, it should be pointed out that this result obtained from daily flow series does not imply that floods have not changed over time, particularly their instantaneous characteristic. For instance, several studies have reported changes in flood characteristics in various regions (Zhang et al., 2022), notably in Africa and in the Mediterranean (Tramblay et al., 2022, 2023), and this aspect should be further investigated.

4.2. Local flood frequency analysis

GP distributions have been adjusted to the flood time series extracted for each station. The quantiles obtained from GP distributions fitted by the two estimation methods of the GP model, GML and LMOM, are very similar, as shown in Fig. 4, top panel. Only slightly higher quantile values are observed for the 20-year return level for the LMOM method. For 100-year flood quantiles estimated by the original GML approach, there is a systematic negative bias compared to the L-Moments, leading to an underestimation of flood risk. When looking at the parameters of the fitted distributions, the alpha parameter is very similar between the two methods (Fig. 4). On the other hand, even if the values of k are also correlated, the values are very different. For the GML approach, the values of k vary between −0.2 and 0.3 while for LMOM between −0.6 and 0.8. There is a much larger spread in the shape parameter value using LMOM, since unlike the GML, the range of possible values for k is unbounded. Most values of k are superior to zero with the LMOM, for 81 stations, indicative of a Frechet heavy tail, while it is only the case for 41 stations with the GLM parameter estimation approach.

To investigate the validity of the prior distribution of the GLM approach in the study area, we compared the distribution of the shape parameters obtained with the L-Moment approach with the prior distribution from Martins and Stedinger (2000), using the 75 stations having at last 30 years of complete records, to ensure a robust model inference. The histogram of Fig. 5 reveals that the original prior of Martins and Stedinger (2000) is not adapted to the distribution of the shape values in North Africa, notably since it underestimates the frequency of heavy tails. Therefore, a new prior is proposed, best approximated with a Normal distribution fitted to the shape parameters values, with parameters mu = 0.19 and sigma = 0.21. As shown on Fig. 5, the new prior provides a much better fit for the estimated shape parameter values, notably for heavy tails. As shown on Fig. 6, the modified GML approach with the new prior provides more comparable shape parameters than with the L-Moment approach, and removes the systematic bias for the 20-year and 100-year floods observed between the two estimation methods on Fig. 4.

Regarding uncertainties in the quantiles estimates, a normalized uncertainty range has been computed from the confidence intervals of the quantiles to allow comparison between the LMOM and GML approaches. As shown in Fig. 7, the uncertainty range on flood quantiles is larger with the LMOM approach compared to both variants of the GML.

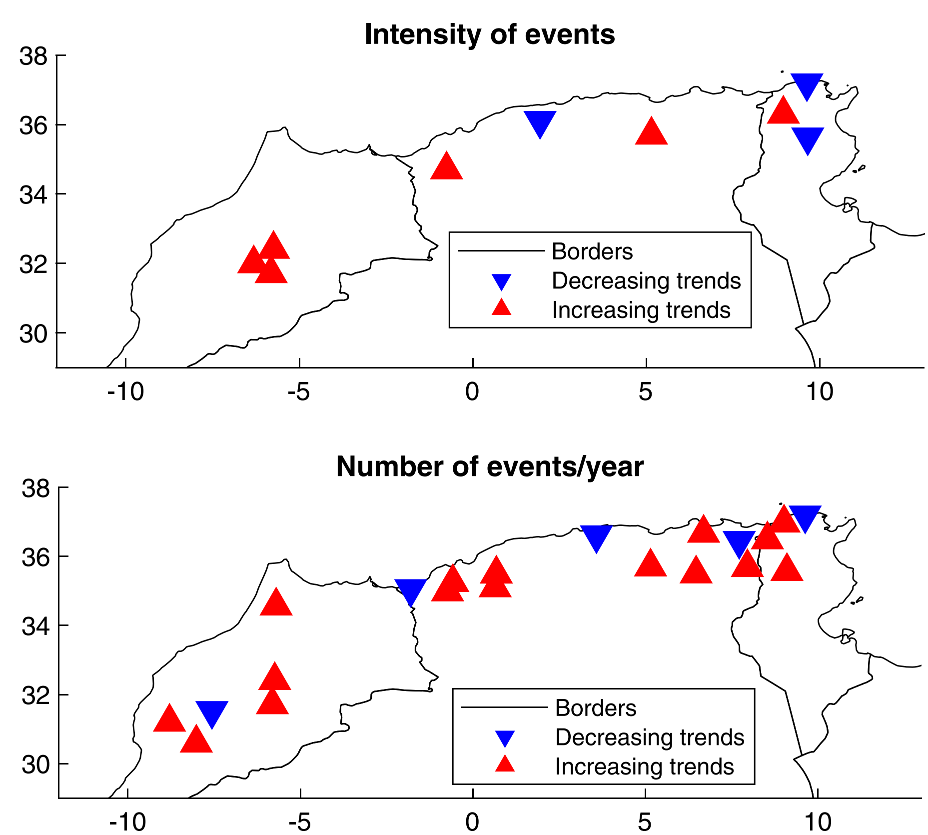

Fig. 3. Local significant trends in flood magnitude (top) and annual frequency (bottom).

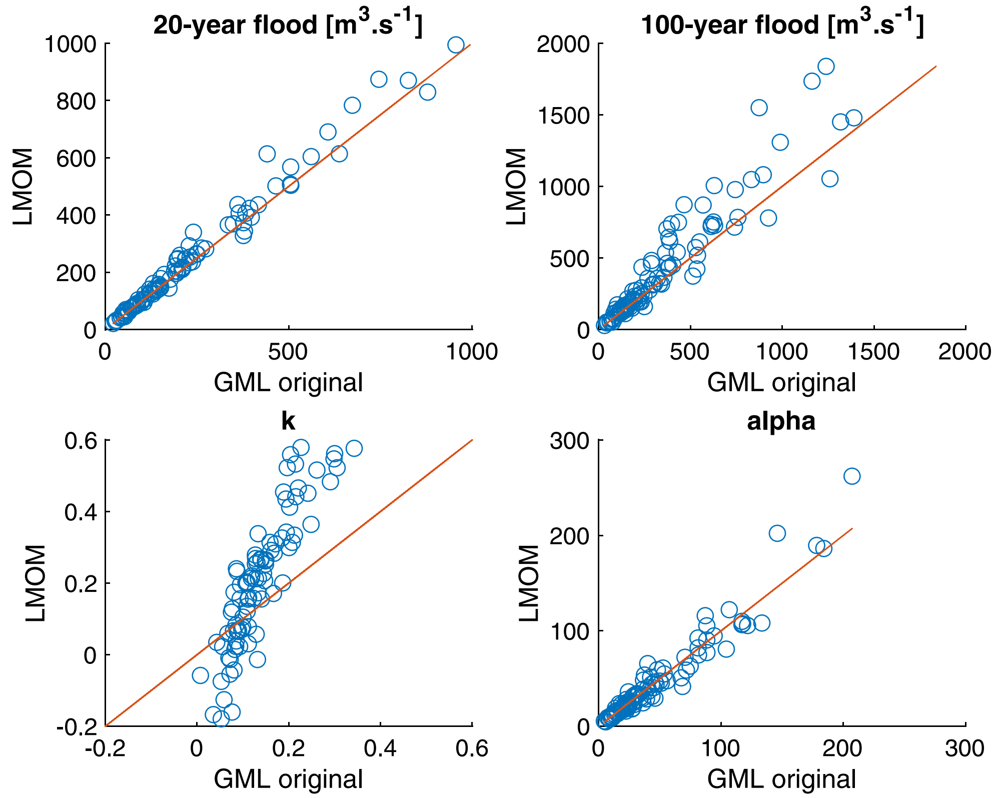

Fig. 4. Comparison of 20-year and 100-year quantiles computed with GPD distributions, adjusted with the L-Moment and the original GLM (using the prior of Martins and Stedinger, 2000) parameter estimation methods (top panels), together with the values of the shape (k) and scale (alpha) parameters of the GPD (bottom panels).

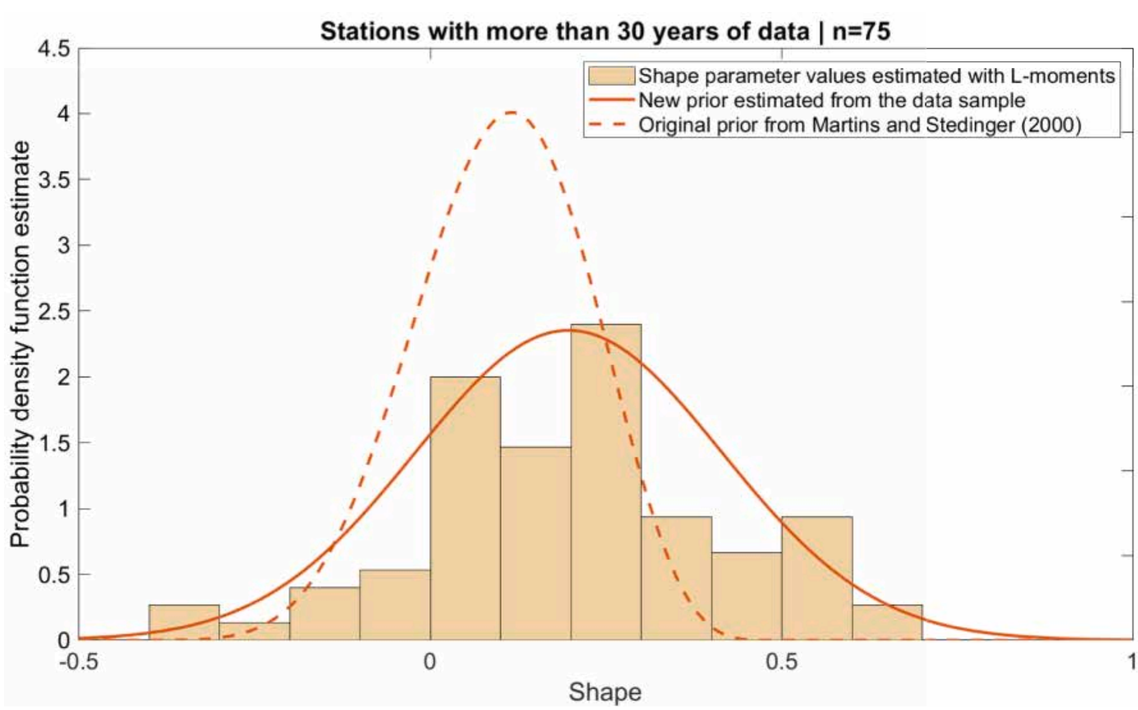

Fig. 5. Histogram of the values of the shape parameters of the GPD distributions fitted to floods at 75 stations having more than 30 years of data, together with the prior distribution of Martins and Stedinger (2000) and the new prior.

The median uncertainty obtained with the GML (LMOM) approach is 0.29 (0.34) for the 2-year flood and 0.48 (0.71) for the 20-year floods. The difference is much stronger for 100-year quantiles, with the median uncertainty range for the modified GML approach close to 0.9 while for L-Moments it exceeds 1.2. This indicates that even if the flood quantiles are very similar between the two approaches, there is more uncertainty

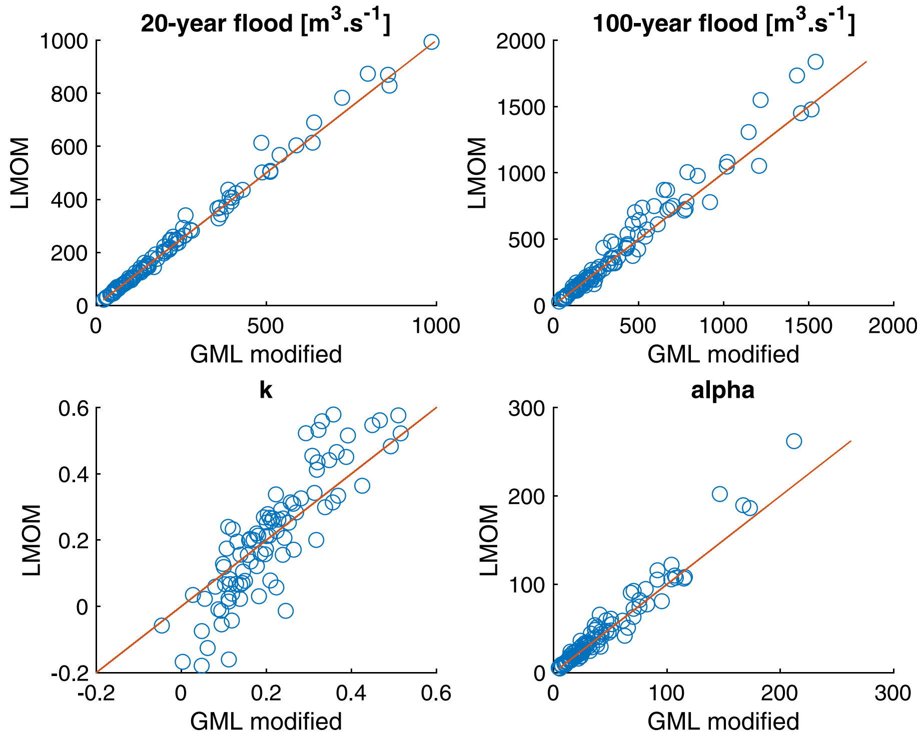

Fig. 6. Comparison of 20-year and 100-year quantiles computed with GPD distributions, adjusted with the L-Moment and the modified original GLM (using the new prior) parameter estimation methods (top panels), together with the values of the shape (k) and scale (alpha) parameters of the GPD (bottom panels).

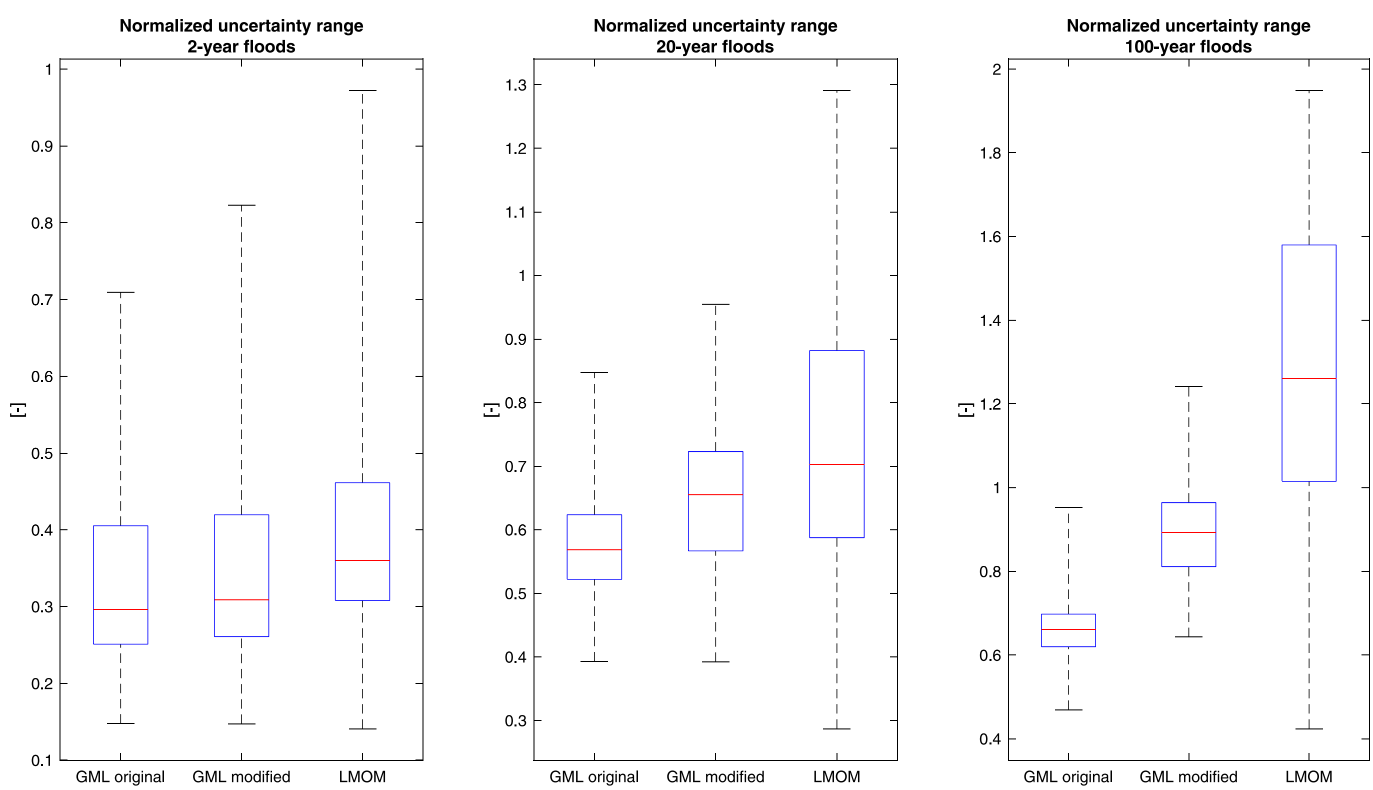

Fig. 7. Comparison of quantiles uncertainty for 2-year, 20-year and 100- year return levels, computed with L-Moments, the original and the modified GML estimation methods.

in flood quantiles estimates with the L-Moments approach than with the GML. As a consequence, the modified GML approach is kept for the estimation of flood quantiles, notably to avoid an underestimation of floods for long return periods and reduce the uncertainty on flood quantiles. The uncertainty of flood quantiles increases with aridity and the return level, there is indeed a significant correlation between the normalized uncertainty range and the aridity index (rho = -0.33, pvalue = $7.3.10^{-4}$ for 2-year floods and rho = -0.44, pvalue = $5.6.10^{-6}$ for 20-year floods). There is a significant correlation (rho = -0.43, pvalue = $7.7.10^{-6}$) between the tail ratio, defined herein as the ratio of the 100-year and 2-year quantiles, and the aridity index, indicating that the tail of flood distributions is getting heavier as the aridity increases, as previously shown in other semi-arid to arid regions (Zaman et al., 2012; Smith et al., 2018; Metzger et al., 2020). Similarly, there is a weak, yet significant link (rho = -0.27, pvalue = 0.0057) between the k parameter and aridity, with higher k in the aridest areas. For the scale parameter of the GP distributions, there is a significant correlation with catchment area (rho = 0.6, pvalue = $1.7.10^{-7}$. It should be noted that the relationship of GP parameters with basin attributes is highly scattered, preventing a robust estimation of the GP parameters for ungauged basins using catchment attributes.

About flood quantiles, Fig. 8 shows the correlations between the quantiles with a return period of 2, 20 and 100 years with all the basin properties considered. It can be seen that the strongest correlations (with rho > 0.4) are obtained with the size of the basins, TWI, and catchment maximum altitude. Geological properties (GWd, GWp, GWs) also have correlations with flood quantiles approaching 0.4. Overall, the correlations are stronger with physiographic attributes rather than climatic attributes, such as precipitation, temperature, and evapotranspiration. As shown on Supplementary Fig. S1, the different variables have a high degree of correlation between them. For instance, the different geological attributes are well correlated with area and TWI, and similarly, several soil properties and land use fractions (Bare, Sand, Sparse, CN) are correlated with altitude and PET.

4.3. *Regional flood frequency estimation with catchment attributes*

As shown in the previous section, the large number of predictors to be tested for the regional estimation of flood quantiles and the high degree of correlation between them requires methods able to account for collinearity of the predictors. This is precisely why the stepwise and the Lasso methods have been implemented for multiple regression, while the Random Forest approach is able to handle such variable dependencies in a non-linear fashion. In a first approach, the three regression methods have been applied to the whole data sample, to first check the most relevant predictors. For the Lasso regression, the variables with non-zero weights after regularization are the soil bulk density, topographic wetness index, forest, urban, irrigated crops, grassland, shrubland, and bare soils. For the stepwise regression, the selected variables were the soil bulk density, maximum altitude, topographic wetness index, forest, and mean annual precipitation. For the Random Forest model, all variables are considered, but a relative importance analysis (Supplementary Fig. S2) indicates that the most relevant ones are the topographic wetness index, altitude, curve number, soil bulk density, catchment area, mean annual precipitation and potential evapotranspiration. These results indicate the relevance of using the topographic wetness index, a variable selected in all three regression models, that has been seldom used in regional flood frequency analysis previously. In terms of model performance to estimate flood quantiles when using the full dataset (Supplementary Fig. S3), for the 2-year return level, lower values of the MARE and relative bias are obtained with the stepwise and Lasso regression compared to Random Forest, while for the 20-year and 100-year return levels, the difference between the methods are reduced, with correlations above 0.8, MARE close to 0.4 and relative bias between 0.12 and 0.29.

Since the main focus of the study is to test the feasibility of estimating flood quantiles in ungauged locations, a jack-knife resampling has been applied to consider in turn all stations ungauged. The results of this validation shown in Fig. 9 indicate an underestimation of the quantiles with the RF and Lasso approach for the highest values. In addition to the Jack-Knife resampling, a k-fold validation was also performed. The reason behind the comparison between the two validation approaches is that models compared with k-fold cross-validation have lower variance than with the Jack-Knife, since there is less overlap between training folds and thus it leads to smaller variability. The results of the cross-validation are presented in Fig. 10, overall showing a similar picture

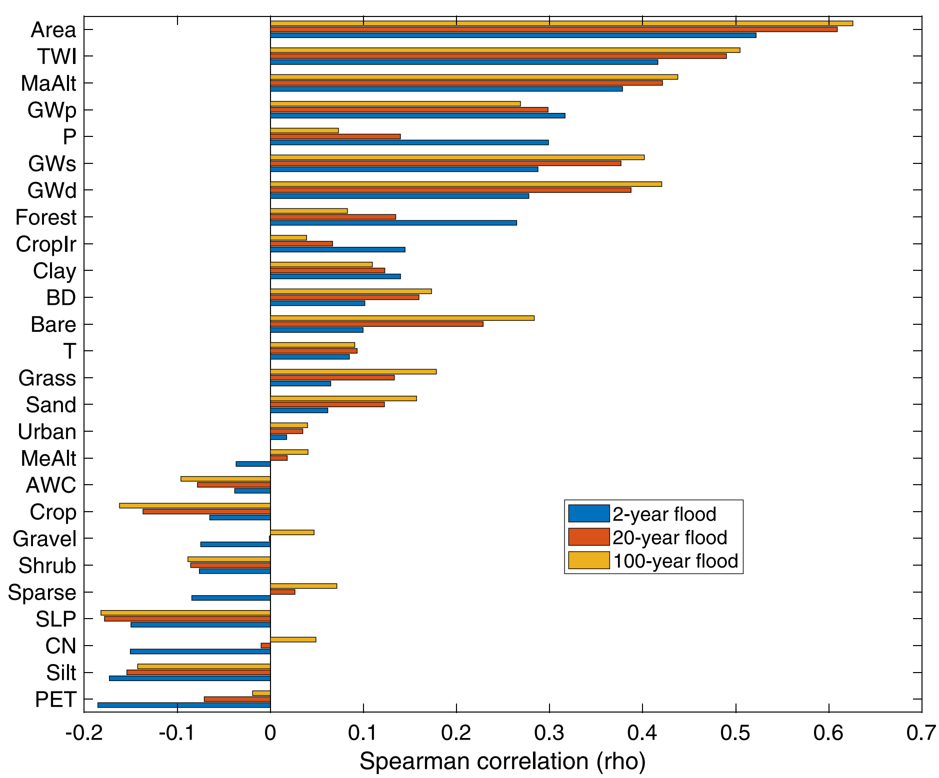

Fig. 8. Correlations between the different physiographic attributes and the 2-year and 20-year floods.

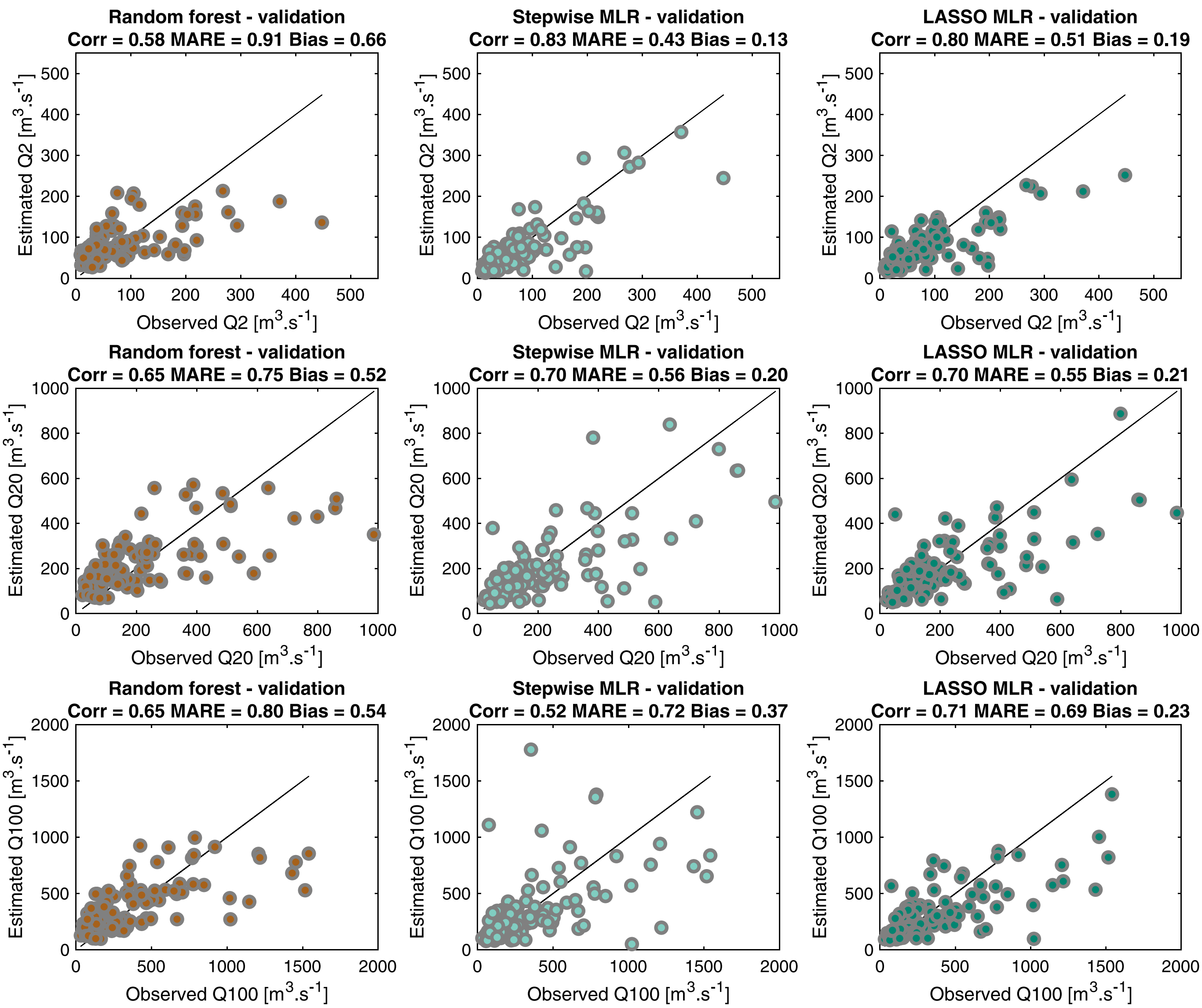

Fig. 9. Regional estimation of 2-year (Q2), 20-year (Q20) and 100-year (Q100) floods from different estimation methods with catchment characteristics; Random Forest, stepwise and Lasso multiple linear regressions. The results are presented in terms of correlation, mean absolute relative error (MARE), and relative bias using a jack-knife cross-validation.

as with the Jack-Knife. The best performances in terms of correlation, MARE, and relative bias are achieved with the two multiple linear regressions, stepwise and Lasso. In terms of variability across validation samples, the Lasso provided the less spread in the results, thus providing a more stable method to be used across different regions of North Africa. The mean absolute regional estimation errors are lowest for the LASSO regression for 20-year and 100-year quantiles, with MARE equal to 0.55 (0.57) and 0.69 (0.67), respectively, with the Jack-Knife (k-fold cross validation) validation approach. These results are slightly better than those obtained in other arid regions with a similar approach, for example, in Iran with a relative root mean square error of 0.63 (Allahbakhshian-Farsani et al., 2020), arid regions of Australia with a median absolute error of 0.69 (Zaman et al., 2012), and in the global studies of Salinas et al. (2013) or Smith et al. (2015), that are reporting estimation errors for 100-year flood quantiles for arid areas within the range of [0.61 1.31].

The estimation errors at the different stations only relate poorly to catchment attributes. The highest correlation is found with catchment area, with an average correlation (yet not significant) between the three regression methods of −0.14 for Q20 and −0.17 for Q2, indicating higher errors in smaller basins. Similarly, there is no relation between model residuals and aridity. This suggests that static catchment attributes are very poor predictors of the efficiency of the regional estimation for flood quantiles. There is also no apparent relationship between the bias of the different regional estimation methods and the geographical location of the basins (Supplementary Fig. S4). A regional characteristic that could explain the uncertainties in flood estimation solely based on catchment attributes is the importance of small-scale irrigation structures in these arid regions. Different types of traditional infrastructures are present in Algeria (Remini et al., 2010), Morocco (Ouassanouan et al., 2022), and Tunisia (Berndtsson et al., 2016): the *qanat* (also named *khettara, foggara, ngoula, kriga* depending on the country) that are underground tunnels carrying water by gravity from mountain areas or *seguia*, small earthen-made or concrete surface channels deriving water from a river. These systems could divert up to 80 % of the river flow as shown in south Morocco by Ouassanouan et al. (2022), and they are also affected by significant water losses by evaporation, infiltration, and leaks in the channels that could reach 50 % (Bakache, 2017). Except for a few local cases, these small-scale irrigation structures are largely unmonitored, so it is very challenging to estimate with precision the water

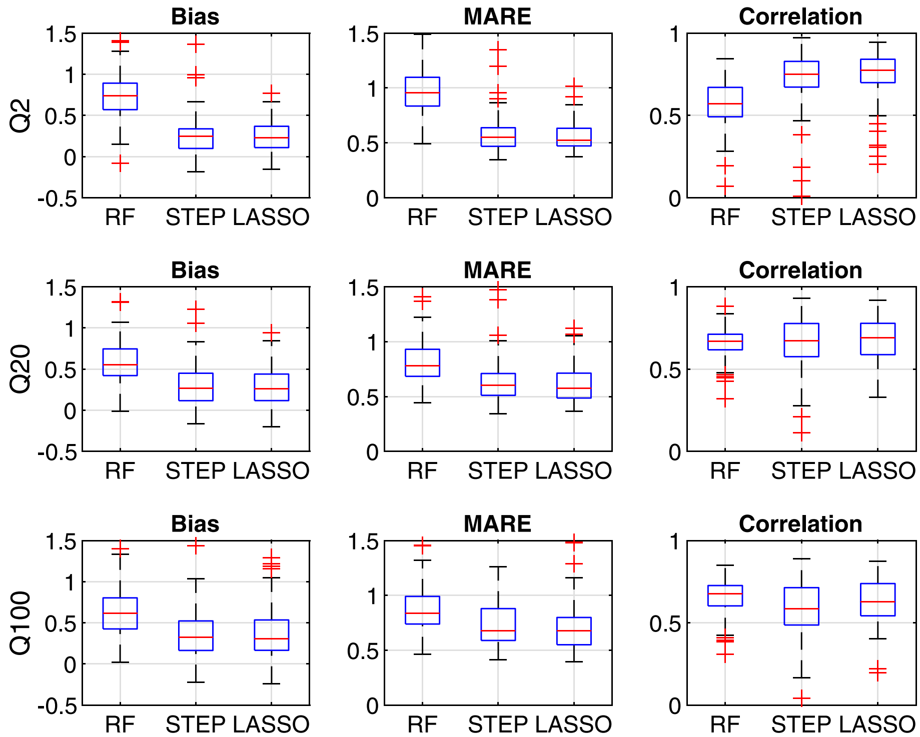

Fig. 10. Cross-validation of the regional estimation of 2-year (Q2), 20-year (Q20) and 100-year (Q100) floods from different estimation methods with catchment characteristics; Random Forest, stepwise and Lasso multiple linear regressions.

losses from the river discharge, which can vary from one river to another.

5. Conclusions

This study is the first to propose a regional analysis of flood trends in the Maghreb and an approach for estimating flood quantiles in ungauged basins. A database of 98 basins between Algeria, Morocco and Tunisia was compiled, including only basins with no large dams, which is larger and more exhaustive than any other study on the same domain. The results of the trend analysis do not reveal any clear upward or downward trend in flooding. Local trends are observed but are not significant at the regional scale. These trends seem to be linked above all to the high variability of floods in this region, with either very large isolated episodes, or very wet years with a succession of several episodes. An envelope curve has been proposed for estimating the maximum floods that can be observed in a range of different catchment areas, providing a robust tool for estimating maximum floods, particularly for sizing hydraulic structures. For the local flood frequency analysis, a modification of the Generalized Maximum Likelihood approach has been provided, with an updated prior distribution for the shape parameter of the Generalized Pareto Distribution to reduce the uncertainties on flood quantiles. An approach for regional estimation of flood quantiles has also been developed, by comparing different regression models with basin properties: Stepwise, Lasso multiple regressions, and Random forests. The results showed that flood quantiles for ungauged basins could be estimated regionally with an error close to 50 %, which is an order of magnitude comparable with the uncertainty obtained on local quantile estimation, already high in these semi-arid to arid basins.

Many uncertainties remain for regional flood analysis in this region. First and foremost, the measurement of floods in these dry environments is complex, not least due to the high mobility of river beds during floods, which necessitates regular updating of rating curves. The present study is based on daily discharge measurements, but it should be noted that for the smallest catchments but also the most arid ones, instantaneous discharge measurements should be considered, since in these basins the flood events could last only a few hours. Therefore, the flood peaks are likely underestimated in those basins at the daily time step. Furthermore, in addition to the large dams, there are a multitude of small irrigation works and most of them have not been inventoried and monitored. Thus, it is very difficult to take into account the quantities of water withdrawn in the absence of measurements. Similarly, little is known about regional interactions between groundwater and surface water, notably during floods, in a context of highly increasing groundwater abstraction for urban water supply and agriculture. However, this work opens several new perspectives given the large database of river runoff compiled. There is a need to better estimate the water uptake from irrigation, from the local scale to the regional scale, and recent satellite-based approaches could provide a preliminary answer given the ever-increased spatial resolution of satellite sensors (Dari et al., 2021). In addition, an analysis of the factors linked to the succession of episodes within the same season or hydrological year for a given area could improve operational forecasting systems by improving knowledge about flood-generating processes (Tramblay et al., 2022, 2023) and flood types in this region. In fact, this type of analysis has already been carried out in other regions, such as Europe (Lun et al., 2020) or North America (Villarini et al., 2013), showing a dependence between flood occurrence and climatic variability. This type of analysis could be carried out in the Maghreb with the database developed in the present study.

CRediT authorship contribution statement

Yves Tramblay: . **El Mahdi El Khalki:** . **Abderrahmane Khedimallah:** Writing – review & editing, Methodology, Data curation. **Mahrez Sadaoui:** Writing – review & editing, Methodology, Data curation. **Lahcen Benaabidate:** . **Tayeb Boulmaiz:** . **Hamouda Boutaghane:** Writing – review & editing, Data curation. **Hamouda Dakhlaoui:** Writing – review & editing, Data curation. **Lahoucine Hanich:** Writing – review & editing, Data curation. **Wolfgang Ludwig:** Writing – review & editing, Methodology. **Mohamed Meddi:** Writing – review & editing, Data curation. **Mohamed Elmehdi Saidi:** Writing – review &

editing, Data curation. **Gil Mahé:** .

Declaration of competing interest

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

Data availability

The flood event database and the catchment attributes are accessible in the online repository: https://zenodo.org/doi/https://doi.org/10.5281/zenodo.10277968.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jhydrol.2024.130678.

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