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ABSTRACT

Study region: This study is based on 22 gauged sites and 26 poorly gauged sites on the territory of Réunion Island, where quality hydrometric observations are available.
Study focus: Information on streamflow is crucial for good water resources management and for respect ecosystems. For gauged catchments, the hydrology can be investigate from observations. For ungauged catchments, the lack of streamflow observations do not allow it. In this context, regionalized models for rainfall runoff are valuable resources. They have been widely employed as a means of predicting the streamflow of ungauged catchments. However, the performances of regionalized hydrological models seems to depend on the spatial density of available flow gauging networks. Using observations available on poorly gauged catchments to help to regionalize hydrological models can be another way of solving the data scarcity problem. This paper presents a framework for evaluating the use of spot flow measurements in a regionalized hydrological model when performing low flow statistical estimations in ungauged catchments. Three approaches are used to evaluate how to include spots flow measurements in the hydrological model calibration process. We tested too the addition of the poorly gauged sites in the regionalization procedure of the hydrological model. The effectiveness of the methods was measured by cross-validation.
New hydrological insights for the region: It is found that an increased accuracy using the regionalized model with help from spot flow measurements to predict streamflow time series in ungauged catchments. The increase is more moderate in low flow statistical estimations (QMNA5) than in medium and high flows.

1. Introduction

Managing and predicting water resources is of paramount importance for water uses such as irrigation, water supply and water quality, navigation, hydroelectricity, and respect for ecosystems. Some river flows have been monitored at gauged catchments, but hydrological measurement networks do not allow observations to be used to investigate the hydrology of each ungauged catchment in Réunion Island's hydrographic network.

Accurate flow estimates in ungauged catchments have been a major focus of research throughout the PUB (Prediction in Ungauged Basin) decade, which was launched by the IAHS in 2003, and the FRIEND (Flow Regimes from International Experimental and

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Network Data) international research program. An exhaustive synthesis for this purpose (Blöschl et al., 2013, 2011; Castiglioni et al., 2011; He et al., 2011; Hrachowitz et al., 2013; Parajka et al., 2013a, 2013b; Razavi and Coulibaly, 2013) was published to understand and define methods that would predict different hydrological signatures, including low-flow indices, in ungauged contexts and over a wide range of climates, environments and hydrological processes.

Regionalized models for rainfall runoff are valuable resources, because they take into account the dynamics of the hydrograph and of low flow processes (Devia et al., 2015). These models have been widely employed as a means of predicting the streamflow of ungauged catchments, thanks to their simple, yet effective simulation strategies. Actually, using the conceptual rainfall-runoff model in climate change impact studies is one of the most pressing issues in hydrology (Broderick et al., 2016; Krysanova and Hattermann, 2017; Patil and Stieglitz, 2014; Yang et al., 2019). Rainfall-runoff models must use continuous streamflow data series to calibrate its parameters, which can then be regionalized for use on ungauged sites. Thus, the accuracy of regionalized models depends on calibration processes, as well as on the structure of the model, the quality of measurements and the performance of the regionalization method (Bastola et al., 2008).

Regionalization methods are tools that have been developed for any type of application involving the prediction of certain spatially variable values. The main regionalization methods are grouped into three categories including similarity-based methods, regression-based methods, and hydrological signature-based methods (Guo et al., 2021). The similarity-based regionalization implements the transfer of parameters using methods which take into account the spatial proximity and/or physical similarity (Karki et al., 2023; Neri et al., 2020; Oudin et al., 2008; Samuel et al., 2011; Yang et al., 2020). The regression-based regionalization relates the optimized model parameters to physiographic and climate characteristics (catchment descriptors) in gauged catchments through empirical equations, which can then be used to predict model parameters in ungauged catchments (He et al., 2011; Panthi et al., 2021; Parajka et al., 2013b; Samaniego et al., 2010; Xu, 2003). The signature-based regionalization method uses the regression method or machine learning to relate catchment attributes to hydrologic signatures in gauged basins. Some hydrologic signatures can be regionalized by spatial interpolation methods as krigeage or inverse distance weighted interpolation. Hydrological signatures are quantitative metrics that describe the dynamics (base flow index, flow duration curve, etc.) or statistical properties (such as example flow percentile, flood frequency) of data series (McMillan, 2021). The regionalization method, based on simple empirical relationships between streamflow statistics and the physical and climatic characteristics of basins, is the preferred approach in an operational hydrology context (Ouarda et al., 2008; Ries and Friesz, 2000; Riggs, 1972; Risley et al., 2008; Smakhtin, 2001; Tallaksen and Lanen, 2004; Yadav et al., 2007).

Since the decade on PUB, many comparative studies of regionalization methods have been analyzed worldwide (Arsenault et al., 2019; Beck et al., 2016; He et al., 2011; Karki et al., 2023; Kittel et al., 2020; Pool et al., 2021; Qi et al., 2021; Steinschneider et al., 2015; Yang et al., 2018; Zhang et al., 2023; Zhang and Chiew, 2009) and regionalization in hydrology has continually progressed, but determining optimal regionalization methods remains difficult. The most efficient methods depend on the study, due to the high diversity and heterogeneity of studied catchments, different hydrological models involving various concepts and structures, different densities of gauged catchments, and the use of poorly calibrated catchments (Sivapalan, 2003). All these reasons may affect the performance of a regionalization approach, and parameter estimations in ungauged catchments remains challenging. However, authors are discussing the performances of hydrological modeling in ungauged catchments, which seem to depend on the spatial density of available flow gauging networks and on hydro-climatic heterogeneity in the area of interest (Rojas-Serna et al., 2016; Merz and Blöschl, 2004; Neri et al., 2020; Oudin et al., 2008; Parajka et al., 2005; Qi et al., 2021; Samuel et al., 2011; Lebecherel et al., 2016). Recently, studies have also suggested that using a limited number of discharge observations for regionalized hydrological models can be another way of solving the data scarcity problem (Lerat et al., 2012; Perrin et al., 2007; Pool et al., 2019; Rojas-Serna et al., 2016).

Model calibration should ideally be based on long continuous streamflow data (Merz et al., 2009; Patil and Stieglitz, 2014; Singh and Bárdossy, 2012; Tada and Beven, 2012), or identified parameters may not be representative of a catchment's hydrological behavior and the model may lack robustness. However, some studies considered that a minimum of one year of continuous streamflow data can lead to robust model parameter estimates (Brath et al., 2004; Pool et al., 2017; Sun et al., 2017). Pool et al. (2017) showed that a limited number of observations can be informative if they represent the dominant hydrological process and cover a range of hydrological conditions. Further, non-continuous flow measurements are often available for the region of interest, as financial and technical constraints are less demanding than in continuous gauge stations. For example, in Réunion Island (https://donnees.eauRéunion.fr/) some intensive spot flow measurements were conducted by the Water Office over the last two decades. Thus, some measurement sites are the subject of annual or multi-annual gauging campaigns for monitoring low and medium water levels. For example, in France, systematic spot flow measurement campaigns have been coordinated by the Rhin-Meuse Water Agency for the three last decades to improve low-flow knowledge (Arts and Sary, 2000; Drogue and Plasse, 2014; François and Sary, 1994; Plasse et al., 2014). This alternative way of taking into account non-continuous streamflow data when parametrizing a model is often neglected due to insufficient knowledge of the flow evolution dynamics, which is necessary when calibrating a rainfall-runoff model by comparing observed and simulated catchment runoff responses. However, literature includes examples of studies that tested the impact of flow data limitation on efficiency and rainfall-runoff model parameters (Kim and Kaluarachchi, 2008; Perrin et al., 2007; Pool et al., 2019; Rojas-Serna et al., 2016; Sun et al., 2017; Tan et al., 2008; Vrugt et al., 2006; Yapo et al., 1996). Rojas-Serna et al., (2016) have concluded that the calibration of a parsimonious model carried out on 350 sporadic measurements that were taken at random from long streamflow data suffices to obtain robust parameter estimates. In addition, in most studies that involve the use of sporadic measurements to constrain a hydrological model, various sampling strategies were defined by extracting daily discharge observations from the observed time series. The selection based on a predefined acquisition strategy includes advanced sampling in peak flow events, in peak recession, or during low flow to improve the effectiveness of modeling (Pool et al., 2019, 2017; Seibert and McDonnell, 2015; Viviroli and Seibert, 2015). Assessing the efficiency of methods was therefore tested in controlled environments. However, this is not the scope of this article, which assesses the efficiency of methods in operational conditions with real spot flow measurements (rather than sampled from observed time series) and with very short observed periods depending on the catchment studied. Most often, field campaigns are restricted by practicalities, such as the accessibility of a catchment, time, or financial resources, which require a careful choice of observation times. Collecting at least some hydrological data during field campaigns could be a solution to overcoming challenges related to predictions in ungauged catchments. How can available spot flow measurements in poorly gauged catchments help improve the spatial robustness of the regionalized hydrological model based on spatial proximity? In this case, we first tested different ways to use sporadic measurement to calibrate a model by analyzing the model efficiency and the model parameter values. Secondly, we have evaluated whether their addition in the regionalization affects the regionalization efficiency.

This study therefore evaluates different ways of accounting for spot flow measurement campaigns to improve the spatial robustness of the regionalized hydrological model based on spatial proximity as a way of reducing uncertainty when assessing hydrological indicators at ungauged sites of island. The comparative assessment is motivated by the fact that regionalization model outcomes are subject to variations according to the density of a stream gauge network and by the fact that sparse streamflow information may improve regionalized model accuracy. The ultimate goal is to provide a decision-making support tool to quantify and manage water resources on the Réunion Island territory by simulating hydrological data in catchments with no daily information. This would allow the extraction of multiple hydrological indicators to characterize water resources (such as low flow, seasonality, mean annual streamflow).

This approach is based on Réunion Island data catchments, namely from 22 gauged catchments and 26 poorly ungauged catchments with sporadic flow observations. Three methods using spot flow measurements to calibrate a hydrological model at a poorly gauged catchment are evaluated. Then, we assessed whether the addition of the poorly gauged catchments to the regionalization procedure affects the efficiency of the regionalized model. The comparison of a statistical low flow (annual minimum monthly flow with a 5-year return period: QMNA5) obtained through classical regionalization methods in an ungauged context will make it possible to judge the performance of the hydrological model using spot flow measurements. The proposed approach was measured by a leave-one-out cross validation.

Section 2 presents studied catchments, the hydrological model, and its regionalization procedure. Section 3 details the proposed approach for integrating spot measurements, the evaluation methodology, and chosen criteria. Section 4 introduces and discusses results before suggesting conclusions.

2. Study areas, data and model

2.1. Study area

The study area is the territory of Réunion Island, which covers a total area of 2512 km^2. Due to its location, which is close to the Tropic of Capricorn (21° S, ~55° E), Réunion Island is subject to a southeasterly trade wind regime. Southeasterly trade winds carry large amounts of humidity and consequently, significant rainfall almost all year long on the windward (eastern) side of the island. By contrast, the leeward (western) side receives much lower rainfall with a high seasonal variability. In addition to the longitudinal contrast across the entire island, rainfall is highly variable in areas due to the complex topography of the island. Indeed, the island hosts deep canyons, ravines, steep ridges, calderas and two mountain peaks: the extinct volcano of Piton des Neiges (3070 m), the highest summit in the Indian Ocean, and the "Piton de la Fournaise" volcano (2632 m). La Réunion Island has a tropical maritime climate marked by two seasons: a rainy season, from November to April, and a dry season, from May to October. The rainfall field over the island shows a huge variability in both time and space, modulated locally by topography (Réchou et al., 2019). Spatially, average annual rainfall amounts feature a very marked west-east gradient, reaching values higher than 10–12 m in elevated sectors. As the island is subject to tropical cyclones, Réunion climate is one of the most abrupt and violent in the world, with world record rainfall amounts for all time scales (Morel et al., 2014).

The HydroDem software (Leblois and Sauquet, 2000) has been used to identify the drainage network using DEM for Réunion Island with a resolution of 50 × 50 m. This software was specially designed for hydrological purposes; its main advantage is that it allows building a hierarchically consistent drainage pattern. The drainage pattern is essential for calculating catchment variables (coordinates of the center of gravity, areal catchment rainfall and evapotranspiration).

2.2. Data

2.2.1. Hydrological data

The discharge daily time series were supplied by the water database of the Réunion water department (https://www.Réunion.eaufrance.fr/). Data selection was based on the quality of measurements, recording durations, and on the continuity of data

Table 1
Main characteristics of the 22 gauged catchments.

	Area (km^2)	PA (mm y^{-1})	QA (mm y^{-1})	PEA (mm y^{-1})	QA/PA	PA/PEA	Median elevation (m)
min	0.7	1933	561	545	0.2	2	313
max	109	6113	4858	1669	0.9	5.9	1714
median	17	4003	1883	1129	0.5	3.3	1136

availability over the study period, from 1981 to 2018. Catchments subject to a non-natural influence (significant changes of anthropogenic origin) according to station managers were excluded from the data set. A set of 22 hydrological stations was selected with at least 5 years' worth of data (not necessarily consecutive) over the 1981–2018 period. Catchments areas varied from 1.9 to 108.8 km^2, 50% of which have a basin area of less than 17 km^2. Table 1 summarizes hydrological characteristics calculated for these catchments. The mean annual precipitation (PA) calculated over the catchments varies between 1930 mm to 6110 mm, the mean annual flow (QA) from 561 mm to 4858 mm, and the mean annual evaporation (PEA) from 545 mm to 1667 mm. These values illustrate the hydro-climatic diversity of the catchments (Table 1).

Réunion's water department database provides spot streamflow measurements at other stream locations. 26 additional sites are measured without a perennial gauging station, proposing a valuable source of complementary information about flows. For this basin set, catchment sizes vary from about 1.3–72 km^2, with a median size of 22.5 km^2. Fig. 1A shows the locations of these 26 non-perennial gauging stations, named "poorly gauged" sites and noted "P_catchments." The 22 perennial gauging catchments, also called hydrological stations, are noted "J_catchments." Note that a gauged catchment necessarily includes spot flow measurements in addition to continuous flow data to control tare curve stability.

The table in Fig. 1B compares the number of spot flow measurements available between these two catchment sets. Overall, the number of unique flow observations on the poorly gauged site is lower; 16 sites have fewer than 50 observation points.

2.2.2. Climatic data

Daily meteorological data was provided by the French Weather Service (Météo-France). The French Weather Service maintains a dense network of rainfall observations covering most parts of the island. In total, 105 daily rainfall stations were retained for the 1971–2018 period. The KED method (Kriging with External Drift [Hengl et al., 2007]) was used to interpolate observed rainfalls over the island because of the island's specific meteorological conditions and of high-altitude variability. Auxiliary predictors (derived from topography) are used directly to solve multiple linear regressions; the interpolated residual is estimated using ordinary kriging. This method generally performs well in areas of complex topography, which tends to enhance rainfalls due to synoptic disturbance by orographic effects (Cantet, 2007; Prudhomme and Reed, 1999; Smith et al., 2012). Aubert et al. (2018) have already implemented the method in Réunion Island. Daily simulated spatial rainfalls are notably good when compared to results reported by other methods, such as ANTILOPE radar rainfalls (J+1) (Champeaux et al., 2009; Pauthier et al., 2016) at different times in recent years (from 2014 only), and against the isohyet method map calculated by Météo-France.

Only 16 climatological stations provide daily evapotranspiration (PET) calculated with the Penman-Montheith method. One station (Gillot airport) provided a full data series. The other stations had gaps in the time series, with an average gap rate between 30% and 50%. For this reason, a temporal reconstruction of the time series was carried out before the spatial interpolation of evapotranspiration. Two methods for filling gaps in the series were compared, based on the pseudo-proportionality of climatic data from neighboring stations, which assumes that they all undergo variations in the same direction and in similar proportions. The first method consisted in applying multiple regressions between the PET gap series and the complete series. This method is frequently used to fill in daily climate series (Arléry, 1971; Boyard-Micheau and Camberlin, 2015; Eischeid et al., 2000). The second method is based on the quantile-quantile method (Déqué, 2007) applied to climatic data. It considers two neighboring stations, one of which represents the complete series as the reference series to fill in missing values. The quantile-quantile correction function involves determining a corrective factor for each value class of the variable (PET) that needs to be reconstructed. The correction function is defined on the

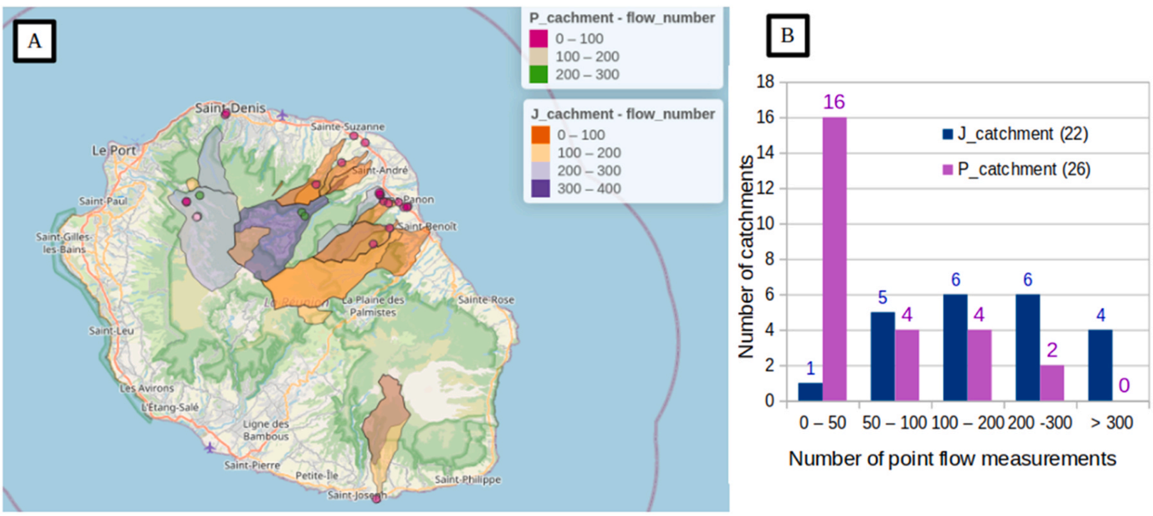

Fig. 1. A: Location of gauged catchments, represented by a shape (J_catchment) and spot flow measurements represented by a symbol (P_catchment) on Réunion Island; B: Number of catchments vs. number of spot flow measurements on J_catchments and P_catchments.

basis of the data period available at the Gillot airport station (complete series) and at each station to be completed. The function is then applied to the period where data is missing to generate complete PET data for each station. This method respect high or low PET values and does not create a systematic bias, retaining mean and standard deviations of observed data. Finally, as previously described, the KED method was used to interpolate PET data across the island.

2.3. Hydrological model

We used a parsimonious lumped hydrological model derived from daily GR-models (Perrin et al., 2003), called GRLoiEau3J, which features only three parameters. The structure has been developed to provide low flow statistical indices in ungauged catchments without reducing simulation qualities of other indices such as seasonality or annual flows on the French territory (Flinck et al., 2021; Folton and Arnaud, 2020; Garcia, 2016). As we are in a tropical climate, the snow routine is not used. The production function is represented by a reservoir parameter by X1 [mm], which is the reservoir's maximum capacity. The routing function does not include a unit hydrograph. The non-linear transfer reservoir, which has a maximum capacity X3 [mm], makes it possible to reproduce the temporal variability of daily flows. It has a small impact on the basin's water balance, with an important role on base flows. The catchment's water balance is ensured by the positive parameter X2[-]. It involves a multiplication factor applied to daily simulated discharges (Fig. 2).

To calibrate the model, we used the criterion KGE, suggested by Gupta et al. (2009), which has been increasingly used to calibrate rainfall–runoff models. Its optimal value is 1. Selecting an objective function is of great importance since it will have a great influence on the values of calibrated parameters and thus on simulation results in the rainfall-runoff model. As the main objective of this is simulating low-flow indices, we used the combined objective functions (Garcia et al., 2017; Pushpalatha et al., 2012) to emphasize recession and low-flow periods: KGE mean applied to the discharge (KGE [Q]) and KGE applied to the reverse discharge (KGE [1/Q]). This combination is noted: FO = 0.5× KGE [Q] + 0.5×KGE [1/Q].

2.3.1. Reference regionalization method

By using the regionalization methods, the parameter sets of hydrological models on gauged catchments can be transferred to a target ungauged catchment following different procedures. Regionalization is widely considered a difficult task in hydrology (He et al., 2011; Parajka et al., 2013b; Samuel et al., 2012; Sivapalan, 2003; Stoll and Weiler, 2010), primarily due to the lack of observed flow data. Additionally, regionalization method studies produce different results depending on the hydrological context and on chosen sites. Therefore, a universal regionalization method does not exist. We chose the post-regionalization technique, which consists in transferring parameters from one site to another after calibrating the model, using similarities defined between the basins. This technique is one of the most widely used regionalization approaches, as indicated in the literature (Arsenault and Brissette, 2014; Farfán and Cea, 2023; Merz and Blöschl, 2004; Oudin et al., 2008; Parajka et al., 2005; Poissant et al., 2017; Razavi and Coulibaly, 2013). It is used to regionalize calibrated model parameters between gauged and ungauged basins using methods such as regression relationships, spatial proximity and physical similarity. The other technique, called simultaneous

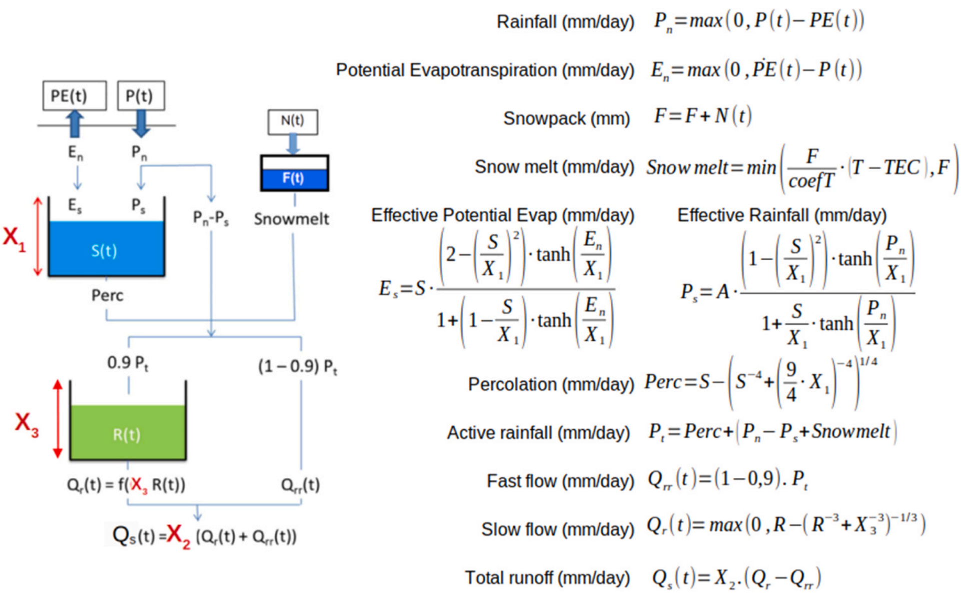

Fig. 2. Model structure and equation of GRLoiEau3J.

regionalization, is achieved by calibrating the parameters of a transfer function, assuming prior relationships between the catchment predictors (e.g. altitude, slope, soil texture or vegetation characteristics) and the model parameters (Beck et al., 2020; Samaniego et al., 2010). This second approach is more complex in terms of the algorithm used to calibrate the transfer function parameters coupled with the hydrological model and is therefore not preferred. With post-regionalization technique, physiographic and geographic similarities were tested. The geographic similarity, which assumes that two basins will be more similar in terms of their hydrological behavior when they are closer, proved to be the most relevant. The effectiveness of the regionalization method reaches its optimum performance level for our study, with four donor basins based on geographic distances computed using the Euclidean distance between catchment centroids. To combine information from donor catchments, we considered the "output average" option that averages runoff simulations calculated using individual parameter sets from donor catchments to ungauged catchment inputs, which outperformed the parameter averaging option. Many authors have shown that it is better to transfer the set of parameters from each donor, thus maintaining the correlation between parameter values (Arsenault et al., 2019; Neri et al., 2020; Oudin et al., 2008; Qi et al., 2021; Samuel et al., 2011; Yang et al., 2020, 2018) particularly with the use of parsimonious hydrological model (Yang et al., 2023).The method is noted "SP."

3. Methodology

3.1. Proposal approach

This section describes how spot measurements could be used to simulate daily streamflow data and identify hydrological model parameters. This would increase the number of donor basins and improve the robustness of the regionalization approach (SP), which depends on the availability of observed data.

Different approaches were applied to use spot measurements for modeling purposes. However, these methods are based on the hypothesis that daily flow data is considered representative of an instantaneous flow, which would have been measured on the same day at "t" time. The assumption is acceptable during low and medium flows, given that intraday flow variations are low during this period. Moreover, depending on flow dynamics at the time of measurements and on the slowness or quickness of the catchment's hydrological response, the instantaneous flow may be representative or very different from daily flows. This is therefore especially true for very small basins and very highly reactive basins. In our context, instantaneous flow refers to a point measurement of flow in the river obtained through a gauging method. Depending on the gauging method used, errors may occur in this measurement (Le Coz et al., 2014). We compared, in Fig. 3, the daily flows (from observed time series) to unique flow measured (obtained by gauging) on the same day over the 22 gauged catchments.

Biases (Qi/Qj) were calculated for each couple comprising the spot measurement named "Qi" and streamflow values at the daily time named "Qj". Fig. 3A shows this bias ordered according to non-exceedance probabilities calculated on daily flow time series. For low flows (Qj< Q0.2; Q0.2 being the discharge no-exceeded on 20% of all the time), significant differences occur, particularly in underestimations. It is important to note that spot measurements are carried out on natural sections of the river (without structures such as weirs). These measurements are generally highly uncertain at low flows, due to morphological changes in the stream bed and uncertainties in velocity measurement in slow flow (Le Coz et al., 2014, 2013). The most notable biases are observed in catchments with a larger number of point measurements (Fig. 3B). For medium and high flows, differences are more important. Fig. 3B shows the bias ordered according to the catchment sizes. The bias does not depend on the catchment sizes. It is therefore worth remembering that tested methods sometimes use spot measurements which differ from daily flow values.

Three calibration methods based on sparse data were tested. They are based on existing approaches adapted to the context of Réunion Island:

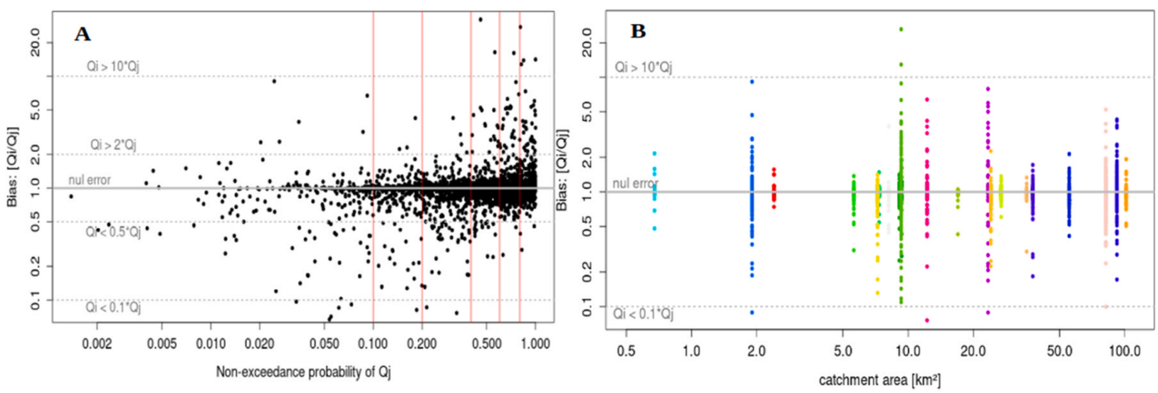

Fig. 3. A: Bias between spot measurements and daily streamflow values ordered according to non-exceedance probabilities calculated on daily flow time series. B: Bias between spot measurements and daily streamflow values ordered according to the size of catchments on the 22 gauged catchments.

3.1.1. QP method

The first method (noted QP) used data directly to constrain the estimation of set parameters. Therefore, when calibration data is lacking, the search algorithm can be less effective and limit effectiveness. One solution is to limit the exploration of the parameter space when calibrating within a collection of parameter sets previously obtained in other gauged catchments (Perrin et al., 2007). The model has been calibrated with only spot measurements, and we obtained set method parameters, called (θ_{QP}).

3.1.2. QR method

The second method (noted QR) suggests reconstructing daily flow time series by identifying a relationship between spot measurements, collected over several years of observation, and concurrent daily flow data for a gauged reference station nearby (Catalogne et al., 2012; Flynn, 2003; Risley et al., 2008; Sauquet et al., 2016). The correlation can be linear, a transformation of flows can also be used as a logarithmic transformation (the log-linear model allows for curvatures), or a square root curvature (model also allowing curvature). The relationship is defined by flows expressed in l/s, allowing comparisons between basins of different sizes. The accuracy of flow correlations between sites depends on the proximity between the two sites (gauged and poorly gauged), and on similarities in physical, topographic and climatic characteristics between catchments. This method involves numerous rules (Chopart and Sauquet, 2008):

- To ensure a robust empirical relation with concurrent flows of both catchments, the amount of flow pairs should be greater than 15. According to (Flynn, 2003), 8–10 measurements located preferably on recession curve defines an adequate relation.
- The two catchments should be close in size and topography. The surface ratio (R_A) between the poorly gauged (S_P) site and the reference gauged station (S_G) is considered so as to respect a co-fluctuation of flows related to the same climatic response. This ratio is calculated according to the following principle: $R_A = \max(S_P / S_G; S_G / S_P)$. A maximal R_A value of 5 was imposed in our context.
- Gauged reference sites must identify catchments with the strongest behavioral similarities to those of poorly gauged basins, in the same climatic context (Sauquet et al., 2016). Adjacent neighbors may be preferentially selected depending on the degree of hydraulic connectivity between the upstream/downstream stream in the gauged station and the target site. A maximum admissible Euclidean distance (15 km) between two catchment outlets is imposed given that hydrological variations must correspond to the same climatic response.
- To provide adequate data and minimize errors, the determination coefficient (*R*-squared or R^2) should be of at least 0.70. A thorough analysis of residuals (with a mean that is close to zero, and normal distribution) is performed to exclude unrepresentative correlations. The root-mean-square error normalized by the observation mean is calculated: NRMSE (Otto, 2019). To make it more meaningful, this indicator is expressed as a percentage of the observation values. It is associated with the Mean Absolute Percentage Error: MAPE (de Myttenaere et al., 2016). The smaller their value, the better the regression model performance.

$$\mathrm{NRMSE} = \frac{\mathrm{RMSE}}{\overline{X_i}} = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_i - X_i)^2}}{\overline{X_i}}$$

Formula 1: The root-mean-square error normalized by the observation mean

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\frac{Y_i - X_i}{X_i}\vee$$

Formula 2: The mean absolute percentage error

where *n* is the total number of spot measurements, X_i and Y_i are the observed and predicted spot measurements at each *i* value.

The “QR” method reconstitutes continuous daily flows from regressions obtained using spot measurements. This reconstituted series helps determine $\theta_{QR,}$ hydrological parameter sets.

3.1.3. DISP method

The third method involves the discrete parametrization method, noted “DISP,” introduced by Perrin et al. (2007). We used the modified DISP method, proposed and detailed by Rojas-Serna et al. (2016). It is similar to the chosen regionalization method (SP) and uses donor catchments. Flow reconstitution at the target site is calculated by spatial transposition of parameter sets from the hydrological model, based on a distance that combines spatial proximity (as SP method) and hydrological similarity. To calculate the combined distance, a combined rank is computed as:

$$r_j^c = a r_j^{geo} + (1-a) r_j^{hydro}$$

Formula 3: The combined rank

where r_j^c is the combined rank of *j* donor catchments, r_j^{geo} is the *j* donor catchment rank according to spatial proximity (Euclidean distance), and r_j^{hydro} is the *j* donor catchment rank according to hydrological distances. The hydrological distance between the target site and donor catchments was calculated according to streamflow simulations and spot measurements at the target site. The library of parameter sets calibrated on gauged catchments (without target sites) is used to run the model on the target site. An error metric computed with spot measurements from the target site (RMSE on a square root transformed streamflow) provides the donor rank (r^{hydro}) with the lowest model error. As coefficient *a* varies between 0 and 1, it must be determined empirically. For $a = 1$, the method is similar to the SP approach and for $a = 0$, the method uses only spot measurements. This method was most effective with four donors and $a = 0.2$. It allows the reconstitution of continuous daily flows obtained using spot measurements. This reconstituted series allows the determination of the hydrological parameter set $\theta_{DISP.}$

3.2. Assessment methodology

First, the performance assessment and the potential for generalizing these three methods were tested using 22 gauged stations in a "poorly gauged" context. Only spot measurements at each target site were used in order to generate a reconstituted daily streamflow and calibrate the lumped continuous rainfall-runoff model. Thus, on the time series reconstituted with the QR and DISP methods, the model was calibrated and the set of parameters were respectively named θ_{QR} and θ_{DISP}. The set of parameters obtained by model calibration on spot measurements was named θ_{QP}. To have a reference in the comparative assessment, the hydrological model was calibrated using the time-series of observed flows and the set of parameters was named (θ_{QJ}). These last parameter sets constituted the library of parameters used for the QP and DISP methods. The hydrological model was applied for each parameter set and for each method to simulate flows for the entire period [1981–2018], with the first year used as a model warm-up. Simulated statistical indices were compared and the observed period was studied.

Next, the three methods described in 3.1 were applied to the 26 poorly gauged catchments. A set of parameters was obtained for 26 complementary basins, for each method. The regionalized model performance was evaluated by comparing the following regionalization methods:

- Regionalized model with 22 gauged catchments (θ_{QJ} calibration),
- Regionalized model with 22 gauged catchments (θ_{QJ} calibration) and 26 poorly gauged catchments calibrated successively with the QR, QP, and DISP methods.

To ensure robust validation, we used the leave-one-out cross-validation procedure (LOOCV). It involves using only one catchment as the validation set, with the other remaining catchments as the training set. The best model is the one which minimizes the error between predicted and observed values. To evaluate these modeling performances, several criteria were used and are defined in the next section.

3.3. Evaluation criteria

The method was evaluated based on model performances obtained in the calibration mode as measured by the Nash-Sutcliffe efficiency, noted NSE (Nash and Sutcliffe, 1970). NSE varies within the interval (- ∞,1). The NSE criterion was calculated using three discharge transformations: NSE_Q, which puts more weight on high flow, NSE_rQ (square root of discharges) which does not favor high or low flow and NSE_1/Q (inverse of discharges), which puts more weight on low flow. To assess the seasonality fit, a NSE was calculated over the 12 observed and simulated mean monthly discharges (NSE_QMM). Two additional hydrological indices were selected for their relevance in water management. These hydrological indices were estimated based on hydrological years between 1981 and 2018, with the hydrological year calculated from March of *(n)* year to February of *(n+1)* year: MAR is the mean annual runoff and QMNA5 represents the annual minimum monthly discharge of a 5-year return period, widely used in France for low-flow management and drought management plans. The distribution of this index was fitted to a log-normal distribution and the parameters of the log-normal distribution were estimated by the maximum likelihood method as in Catalogne (2012).

To evaluate the models, we calculated the bias (error) between the simulated MAR and the observed MAR (Er_MAR), and the bias between the QMNA5 estimated from simulated and observed flows (Er_QMNA5), an indicator of over/under prediction of simulated flows for average flow conditions and low-flow conditions. A value close to 1 means perfect simulations for all criteria. The results are presented in boxplots which show the 0.1, 0.25, 0.5, 0.75 and 0.9 percentiles.

4. Findings and discussion

This section first presents results for each method using spot measurements (QP, QR and DISP), to calibrate the hydrological model and simulate daily flow time series for the 22 gauged catchments in the context of poorly gauged catchments. The reliability of these different methods was judged by criteria introduced in Section 3.3. Next, the regionalized model performance was evaluated by applying the regionalization method with 26 more poorly gauged catchments which were compared to other regional methods.

4.1. Poorly gauged catchment contexts: findings of methods using spot measurements

4.1.1. Reconstitution of daily streamflow time series on hydrological stations considered as poorly gauged

As previously written, the evaluation of the assessment and generalization potential of the three previously methods was tested on a sample of 22 gauged catchments, which both have spot measurements and daily streamflows series. In this sample, only 15 stations allowed for the application of the QR method, which is more restrictive than the QP and DISP methods, because it requires finding an adequate regression with a neighboring station. These 15 catchments then constitute a comparison set for the three methods in poorly gauged context and in ungauged context.

In the QR method, the R^2 median of regression relation is 0.828 and the minimum and maximum R^2 values are respectively 0.721 and 0.947. NRMSE values varied between 0.26 and 5, while MAPE values were between 0.09 and 3.9. The regression equation was quite satisfactory. The median number of common flow points for calibrating regression is 60, and the minimum and maximum values were respectively 34 and 101.

Fig. 4 shows evaluation criteria calculated for simulated streamflows throughout the observed period, based on the set of 15 catchments. The calibration processes named “CQJ” and “CQP” were respectively associated with a calibration of the hydrological model from all observed daily flows “t” and respectively from only the spot measurements of the time series. The calibration process named “CQR” and “CDISP” were respectively associated to calibrations of the hydrological model from reconstructed daily streamflows obtained by respectively the “QR” and “DISP” methods. As expected, CQJ calibration presents the best results for all the hydrological variables tested. The model better identifies a catchment’s hydrological behavior when calibration information was maximal. But it is the only calibration using streamflow time series of gauged catchments, as the other methods employ reconstituted streamflow time series with different approaches that use spot measurements.

CQR calibration is more effective than CQP and CDISP calibration methods and shows the same trend as CQJ. Information brought by spot flow measurements does not easily yield reach robust calibrations when calibrated from these spot flow measurements (CQP method). It presents the worst results with the highest variability. When information about calibration was scarce, parsimonious calibration model does not seem robust to simulate high and low flows; only medium flows were quite good. The CQP process uses spot flow measurements whereas the others calibrations use daily streamflows. In Fig. 3, higher bias were observed between spot measurements and daily streamflow values. We verified the evolution of these differences with the efficiency criteria (NSEQ) for the CQP calibration processes. Lower differences between observed flow don’t show better efficiency criteria than higher differences on this calibration.

The DISP method was less robust for low flows, as seen in the error distributions of QMNA5 and NSE_1/Q, which were the largest. It should be remembered that this method is regional and based on a selection of four donor catchments. Methods such as QR and DISP seem to be an advantage when streamflow information is low to reconstitute a flow time series. Its properly simulate the dynamics of flow evolution, with improved effectiveness in the QR method for all the hydrological variables studied

4.1.2. Influence of the availability of spot measurements

To assess the impact of the availability of spot measurements on the effectiveness of the QR and QP methods, several levels of flow availability were assessed for the methods over the 15 gauged catchments. The DISP method was not tested, because it has already been shown that the effectiveness of this method increases with denser information at a target site (Drogue and Plasse, 2014; Plasse et al., 2014).

Spot measurements were sampled without following a predefined acquisition strategy. They were randomly drawn from available spot measurements in each catchment. To represent what happens in operational conditions, spot data was drawn incrementally: a new flow measurement drawn from the flow measurement series was added to the set of preselected flows (i.e. a sample of k +1 measurements includes existing k measurement samples). An increasing amount of flow measurements was successively used (n= 5, 10, 15, 20, 40, 60, 80, 100, 150, 200, 260). To obtain more general results, the random selection was repeated ten times per catchment. For example, for a catchment with 72 available spot measurements, measurements were distributed randomly into six sets of size n (from n= 5 to n=60). The first set (n=5) was included in the second set (n=10) and so on. This sampling was repeated 10 times per catchment.

For the QP method, the calibration model was made based on each set of flow measurements drawn (n) (only random data was used to compute the objective function) and the simulation was performed for the entire 37-year record to calculate the three Nash criteria between daily observed and simulated flows. For the QR method, the regression was calculated based on each sample of n measurements, the calibration model was performed from daily reconstituted flows, and effectiveness criteria were obtained between daily

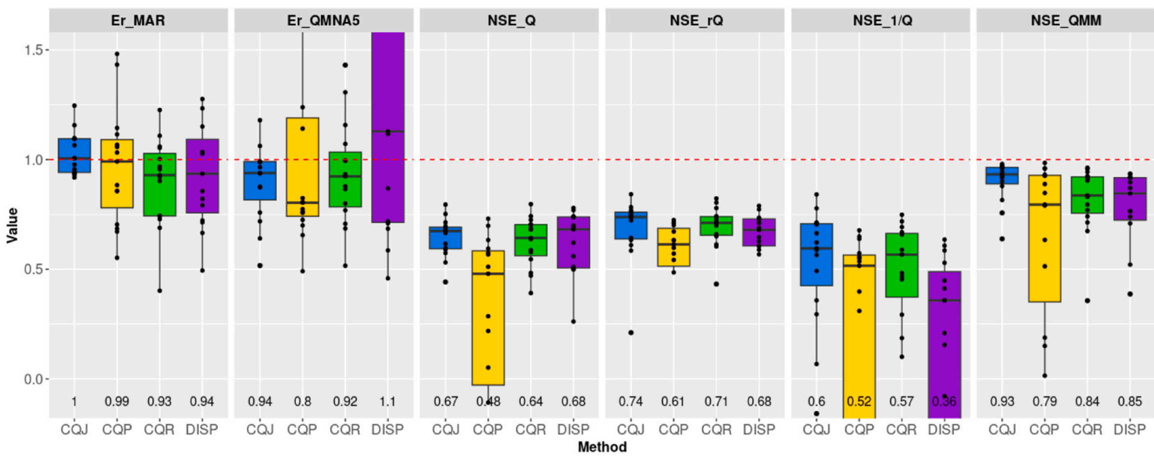

Fig. 4. Evaluation criteria according to 4 calibration processes over 15 gauged catchments considered as poorly gauged catchments: “CQJ” model calibrated on observed daily flows, “CQP” model calibrated on observed spot measurements “CQR” model calibrated on daily flows reconstructed by regression and “DISP” method.

observed and simulated flows.

Table 2 provides mean and standard effectiveness deviations from ten samples in each catchment for three criteria respectively, NSE_Q, NSE_rQ, NSE_1/Q.

For the QR method, two classes of *n* only yielded 7 and 5 available catchments *(n = 80 and 100),* and for the QP method, another two classes of *n* only yielded 8 and 7 available catchments (*n = 150 and 260*). Results for both calibration models show the same trend, with different results. Effectiveness tends to improve when the number of selected spot measurements increases, and is confirmed when considering the NSE_1/Q criterion, which puts an emphasis on low flows.

With the QP method, the model better identifies the hydrological behaviors of catchments when there is more information for the calibration set. The model's effectiveness starts to reach correct NSE values (~ 60 when NSE_rQ is considered and ~ 50 when NSE_Q is considered) with *n* values above 60. When *n* is low, the method's effectiveness decreases and struggles to reach a robust calibration. For this QP method, it is more difficult for the model to reach robust parameter sets when information levels are low.

The use of the QR method shows greater effectiveness, as evidenced by higher median NSE values and lower standard deviation of NSE values. With *n* values above 10, the model's effectiveness stabilizes with correct median NSE values (NSE~ 0.6) when NSE_Q and NSEr_Q are considered. The regression coefficient median for the 15 gauged catchments and for the 10 samples, indicated in Table 2, shows high effectiveness ($R^2 > 0.8$) regardless of the *n* class. It seems to decrease slightly when *n* increases, and when effectiveness increases. This suggests that the additional measurements provided significant added values for reaching more robust regressions and then more robust calibrations. In these tests, the QR method seems to be superior when information is sparse.

4.1.3. *Impact on parameter estimates*

A, B, and C plots in Fig. 5 compare parameter distributions from the 15 gauged catchments according to the three different model calibrations: the CQJ calibration, the CQP and CQR calibrations. For ease of comparison, logarithmic transformations on X1 and X3 parameters were performed, which varied within the (-10, 10) interval. The calibrated model on spot measurements (CQP method) presented the highest magnitude for the X3 parameter and the lowest magnitude for the X2 parameter. It is worth remembering that the X3 parameter has an essential role when reproducing temporal flow variability for the daily time series.

D, E, and F plots in Fig. 5 show the evolution of parameter values obtained from 10 samples when the amount of flow measurements (*n*), used for calibration, increases with the QP and QR methods over the 15 gauged catchments. With both methods, the variability of X1 and X2 parameters seem stable when *n* increases. Median parameter values obtained with a CQP calibration are lower than those obtained with the QR method. Different behaviors were observed for X3 parameter values: the QR method stabilized more quickly than the CQP calibration when *n* increases. The variability of this parameter is important for the CQP calibration even if the uncertainties in the estimation of this parameter decreases as *n* increases. And the estimation of this parameter seems to remain poorly defined even for high *n* values. Overall, however, the QR method determined X3 more effectively using fewer uncertainties, regardless of *n*. The QP method appears demanding in terms of the quantity of information required for calibration and systematically underestimates the value of the parameter X3 when *n* is low.

4.2. *Ungauged context: impact on the robustness of the hydrological regional model*

4.2.1. *Reconstitution of flow time series*

The impact on the robustness of the regional model in ungauged context was analyzed as described in 3.2. As a reminder, the regionalization approach of spatial proximity is named SP. With the output averaging applied to the 22 gauged catchments, the regionalization approach was named SP22. With the output averaging applied to the set of 48 catchments (22 gauged catchments and 26 reconstituted daily streamflows for the QR, QP and DISP methods), the regionalization approaches were respectively named SP48_QR, SP48_QP, and SP48_DISP. To get a parameter set over 26 poorly gauged catchments using the DISP method, the hydrological

Table 2
Median and standard effectiveness deviations obtained using the calibration model with the CQR and CQP methods in validations over a sample of 15 catchments. *Indicates that there were fewer than 15 catchments.

Statistics		Method	Number of *n* spot measurements used									
			5	10	15	20	40	60	80	100	150	260
NSE_Q	Median	CQR	0.52	0.58	0.60	0.60	0.64	0.58	0.62*	0.55*	-	-
		CQP	0.25	0.34	0.41	0.30	0.45	0.50	0.33	0.33	0.40*	0.47*
	Standard deviation	CQR	0.22	0.14	0.12	0.12	0.12	0.15	0.13*	0.12*	-	-
		CQP	1.47	0.30	0.22	0.25	0.30	0.63	0.34	0.50	0.13*	0.42*
NSE_rQ	Median	CQR	0.62	0.66	0.64	0.67	0.67	0.67	0.66*	0.62*	-	-
		CQP	0.42	0.49	0.53	0.49	0.56	0.60	0.57	0.54	0.53*	0.57*
	Standard deviation	CQR	0.11	0.08	0.17	0.45	0.08	0.08	0.08*	0.09*	-	-
		CQP	0.39	0.16	0.12	0.11	0.12	0.13	0.12	0.12	0.10*	0.14*
NSE_1/Q	Median	CQR	0.35	0.37	0.35	0.37	0.40	0.43	0.15*	0.16*	-	-
		CQP	0.22	0.24	0.42	0.36	0.39	0.42	0.43	0.47	0.49*	0.49*
	Standard deviation	CQR	0.51	1.10	1.79	1.51	1.82	2.60	2.86*	3.44*	-	-
		CQP	0.13	0.16	0.20	0.69	0.18	0.20	0.26	0.26	0.11*	0.17*
R^2	Median	CQR	0.89	0.91	0.88	0.88	0.84	0.83	0.83*	0.87*	-	-
	Standard deviation	CQR	0.10	0.07	0.08	0.09	0.088	0.11	0.12*	0.06*	-	-

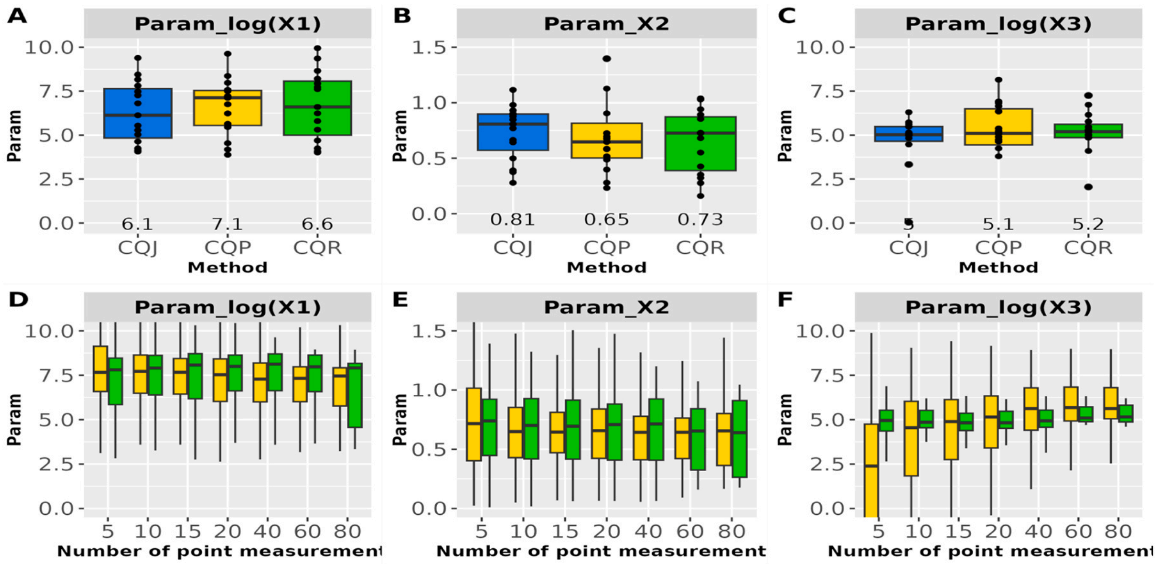

Fig. 5. [A, B, C]: Parameter distribution from three calibrations over the 15 gauged catchments, with the CQJ hydrological model calibrated from observed daily flows, the CQP model calibrated from spot measurements and the CQR model calibrated from daily flows reconstructed by regression. The value indicated is the median of each distribution. [D, E, F]: Evolution of model parameter values using the number of spot measurements (n) using samples from the CQP and CQR methods.

model was calibrated from streamflow time series obtained with this method.

The neighborhood approach was applied in a leave-one-out-cross-validation over the 22 gauged catchments in order to test the approach in an ungauged context. Fig. 6 shows distributions of effectiveness criteria based on the reconstitution of flow time series on the 15 gauged catchments, previously presented. Overall, improved effectiveness was observed using the largest set of catchments (SP48), especially with the QP and DISP methods. Improved effectiveness was also noted on low flows (NSE_1/Q) obtained with SP_48 approaches. This is consistent with results found by Andréassian et al. (2012); and Lebecherel et al. (2016), at the French level, by Samuel et al. (2012) in Ontario, and more recently, by Neri et al. (2020), in Austria. The effectiveness of the neighbor catchment model decreases with a sparser stream gauge density. The QR and DISP methods slightly outperformed the QP method, showing the highest

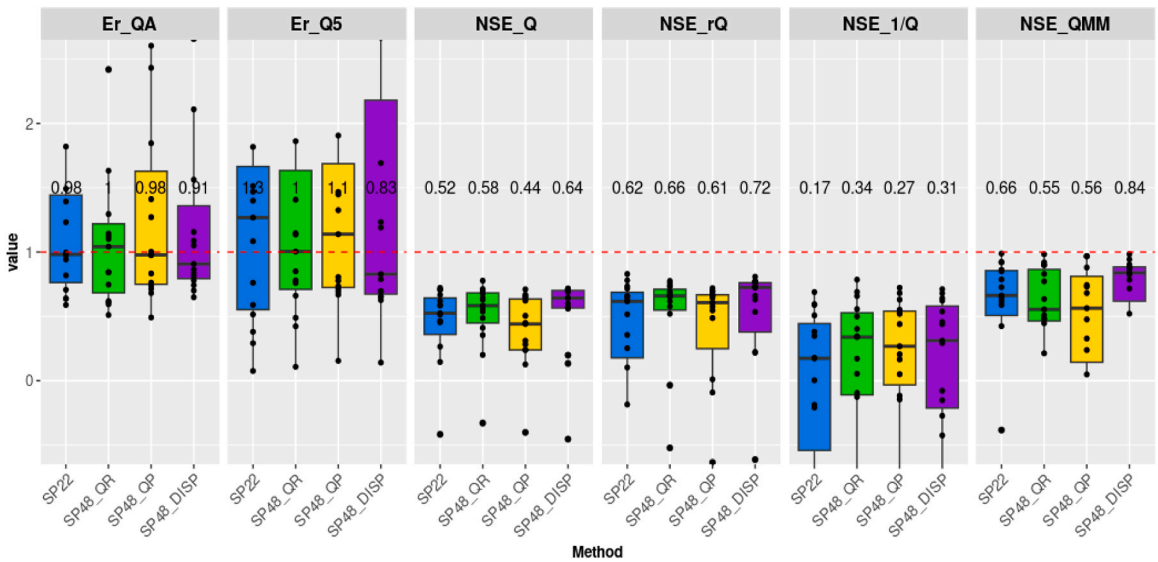

Fig. 6. Comparison of effectiveness for the four regionalization methods tested over the 15 gauged catchments in ungauged conditions: SP_22: SP method over 22 catchments, SP48_QR: SP method over 48 catchments with parameters for 26 poorly catchments using the QR method, SP48_QP: SP method over 48 catchments with parameters for 26 poorly gauged catchments using the QP method, SP48_DISP: SP method over 48 catchments with parameters for 26 poorly gauged catchments using the DISP method (SP method: four neighbors with average outputs). The value indicated is the median of each distribution.

distribution of effectiveness criteria (NSE_Q, NSE_rQ).

Low flows, as QMNA5 statistics, are the most difficult to simulate as shown in Fig. 7B where the bias of QMNA5 was plotted. The four smallest catchments with a QMNA5 value lower than 0.50 mm/day revealed significant errors in regionalization. It's mainly on very low flows that the predictive regional model failed with a systematic overestimation whereas the predictive calibrated model fit well. The Fig. 7A shows the bias of MAR. Errors due to the regional model generally tend to significantly decrease as the flows increase.

4.2.2. Comparative analysis of estimation methods using QMNA5 statistics

To better characterize low flows in ungauged catchments, studies focused more specifically on certain statistical flows and proposed the use of sporadic measurement data to estimate low flow characteristics. On the French territory, and consequently on Réunion Island, water legislation has imposed QMNA5 as the reference flow for drought management plans and it has become an operational necessity for quantitative resource management. Alternative approaches cited in the introduction have been proposed to determine this hydrological variable. These approaches can involve different contexts, such as poorly gauged or ungauged catchments. Several of them were chosen for the operational mode to be applied in the hydrological context of Réunion Island. Only Er_{QMNA5} was analyzed. The comparative study was carried out on the 15 gauged catchments seen as three relevant catchment contexts: gauged, poorly gauged, and ungauged catchments. Each method was tested using the leave-one-out cross-validation procedure (LOOCV). When catchments were considered to be "gauged," QMNA5 was deducted from daily streamflows simulated with the hydrological model calibrated using the CQJ process. When catchments were considered to be "poorly gauged," one additional direct method using spot measurements and based on one neighboring gauged catchment were frequently used in an operational hydrological context to estimate statistical low-flow references. This approach named Q5_Reg, is described here:

- The Q5_Reg approach, inspired by Sauquet et al. (2016), proposes a log-linear relation between the QMNA5 at the target station and the QMNA5 at the neighboring station. Obviously, choosing a nearby catchment is conditional on a high degree of hydrological similarity. Neighboring catchments and relationship found when applying the QR method were used and applied on QMNA5 value. The relationship used to reconstitute the QMNA5 value was therefore:

$$QMNA5_{cib} = a.\left(QMNA5_{ref}\right)^{b}$$

Formula 4: The Q5_Reg approach

This approach is compared to the previous QR, QP, and DISP methods used in a poorly gauged context.

When catchments were considered to be "ungauged," one regional method commonly used in hydrology was added to the comparison: the kriging with external drift (EDK). The QMNA5 was estimated using this method with two alternative sets of catchments (22 and 48 catchments) in LOOCV process.

The method used the external drift kriging technique (EDK). It assumes that one factor is able to explain spatial variability of the data studied, in our case, the variable QMNA5. The method consists in isolating the deterministic component of variable QMNA5 by adjusting a multiple linear combination with predictors or external drifts and the residual ε is the stochastic component which is interpolated by kriging. The choice of predictors was based on the ease of variable calculations and their influence on dominant processes (Engeland and Hisdal, 2009; Haslinger et al., 2014; Laaha et al., 2014; Ries and Friesz, 2000). Relationships were established through multiple regressions on raw or transformed data. Terrain features were calculated from the DEM for Réunion Island using the raster R package (Hijmans et al., 2015), with the addition of distance to coastlines (West and East) and climatic variables (annual rainfall and PET). The residual ε determined from the above relationship constitutes the stochastic component; it is interpolated via kriging using the Sten variogram (Cantet, 2017). Interpolated residuals are then added to estimates obtained by selected predictors to deduct the value of the regionalized QMNA5. This method has been commonly used specially in low flow context (Chopart and

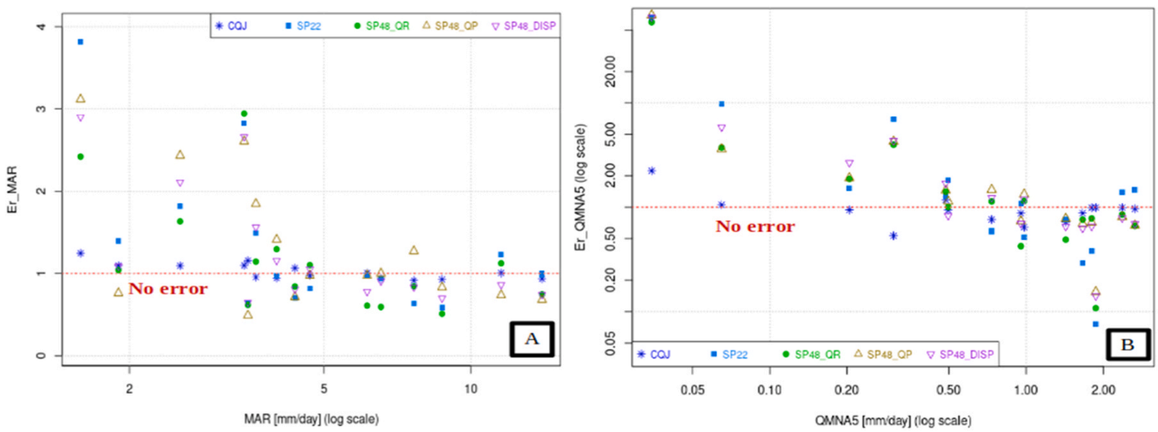

Fig. 7. A: MAR errors ordered by observed MAR;B: QMNA5 errors ordered by observed QMNA5, for four regionalization methods and calibration model CQJ on the 15 gauged catchments, error is the bias between the simulated and observed value, the bias is close to 1 for zero errors.

Sauquet, 2008; Laaha et al., 2014, 2013; Skøien et al., 2005).

The most significant variables are the characteristics of the terrain and the distance to the coastline. The regression model that performs the best for the 22-catchments set includes four variables: aspect, slope, distance to the west coastline, and roughness. The coefficient of determination (r^2) is 0.7. The regression model for the 48-catchments set also includes three terrain characteristics: aspect, distance to the west coastline, and flow direction. However, the coefficient of determination is low (r^2= 0.2). The preponderance of terrain characteristics in the relationships founded could be due to the island's strongly accentuated relief. The variances of the QMNA5 values observed within each set of catchments are similar. The multiple linear regression procedure is based on the normality distributed data. The Shapiro-Wilk test is used to verify this assumption (H0 hypothesis: normality distributed data, with α= 0,05). With the 22-catchments set, the QMNA5 values observed are normally distributed; the p-value of the Shapiro-Wilk test is equal to 0.1 (p-value > 0.05). And with the 48-catchments set, the p-value of the Shapiro-Wilk test is < 0.05; the normal distribution is not assumed, even if the data were transformed. This fact can explain the lower efficiency of the relationship obtained on the 48-catchments set.

For the comparison of regionalization method of QMNA5 statistic, the SP48_QR regionalization method which proposes a median QMNA5 errors closest to 1 (Fig. 6) is considered as the upper benchmark. As a reminder, the performance of the calibrated hydrological model on daily streamflows (CQJ, in gauged catchment context) on the QMNA5 values is shown on Fig. 8A. Fig. 8B shows errors in poorly gauged catchment context. Operational method (Q5_Reg) presented good overall results as the CQR calibration process with a tendency to overestimate for Q5_Reg method (median = 1,1) and a tendency to underestimate for CQR calibration process (median = 0,92). The operational method (Q5_Reg) implicitly relies on a important temporal correlation of flows at two sites. It exploits the lower part of this relationship obtained between spot measurements at the target site and daily flows at the reference site. This part of the curve represents the "base flow" component which mainly determines the spatial variability of the QMNA5.

As previously stated, regionalized methods such as DISP involve more difficulties. The CQP calibration process is not as effective as the CQR calibration process. However, the DISP, CQP, and CQR methods resulted in other statistics than Q5_Reg method.

Fig. 8C shows the ungauged context. In this context, the EDK method with the 22-catchments set is the most effective. And the EDK method, with the 48-catchment set, is less robust as described above. A significant decrease in effectiveness using this largest set of catchments was noted, which is due to the low explanatory power of the relationship linking the QMNA5 and the selected descriptors in this set of catchments. For the SP method, the use of spot measurements made it possible to increase data sets on which they are applied and to increase their effectiveness. The SP48_QR method performs better than SP22 method, the dispersion of QMNA5 errors is smaller and the median of the QMNA5 errors is close to 1.The median of the QMNA5 errors for EDK method with the 22-catchments set is 0,85 showing a tendency to underestimate.

The method directly estimating the QMNA5 variable (EDK method for the 22-catchments set) is more efficient than a regionalized hydrological model, which is generally designed to reproduce all the flow generation processes. However, the hydrological modeling

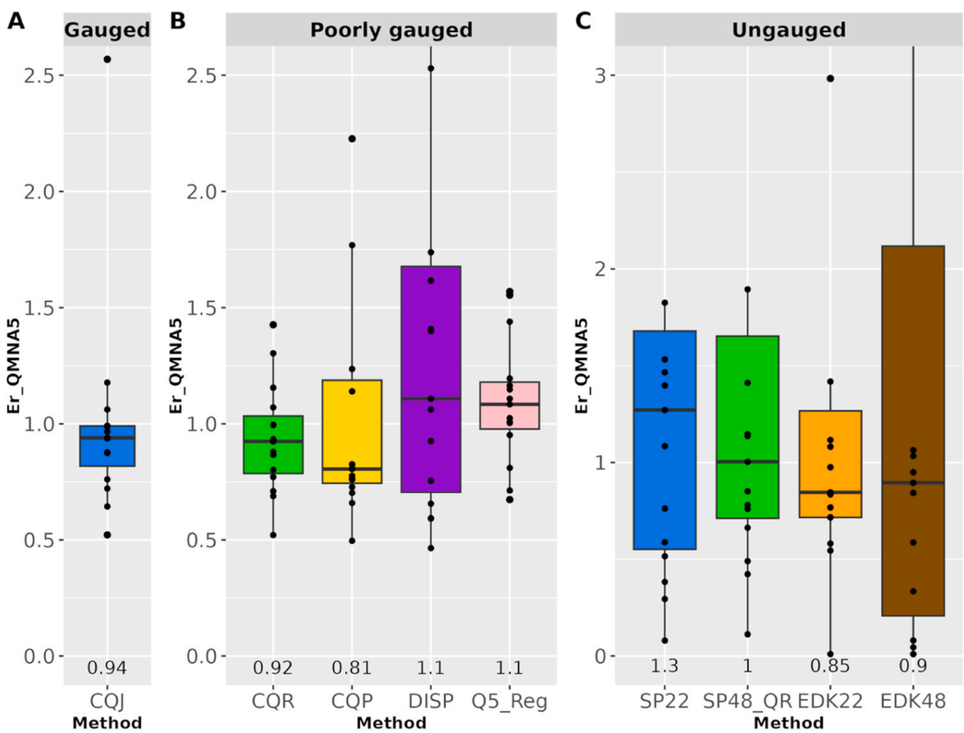

Fig. 8. Distribution of QMNA5 errors for the methods: A: gauged catchment context, B: poorly gauged catchments context, C: ungauged catchments context over 15 gauged catchments. The values indicated is the median of each distribution.

approach makes it possible to ensure a degree of consistency between the different estimated variables (for example, several quantiles of return periods), which would not be guaranteed by the use of independent estimation procedures.

5. Conclusion

This study aims to evaluate different methods of integrating spot measurements of poorly gauged catchments using a regionalization method when reconstructing daily time series in ungauged catchments. The study was based on a network of 22 gauged catchments and 26 sites with spot measurements, available in Réunion Island. The study shows the potential for calibrating hydrological models using spot measurements. Three approaches were tested in a gauged catchment context in order to study its generalization potential. The QR method allows for the reconstitution of the daily flow series for a target station from a relationship established between measured flows at a target site and daily flows observed at the same time at a neighboring reference station. The QP method directly uses flow measurements at a target station to calibrate the hydrological model and provide a daily flow time series. The DISP method is a regionalized proximity approach using four neighbors selected according to a distance calculated in the target site's hydrological space. The hydrological distance is calculated between flow simulations and spot measurements at the target site. The following conclusions can be drawn:

- A larger performance in the regionalization process has been observed with an increased number of total catchments. Including poorly gauged catchments in the regionalized hydrological model improve its performances, especially in high to medium flows. This finding is more moderate for low flows. However, the regionalization performance depends on the method used to incorporate spots flow measurements in the hydrological model.
- Using model parameters calibrated directly on spots flow measurements in the regionalization process does not guarantee a good performance of streamflow prediction in ungauged catchments. Better results are found with QR and DISP methods which use model parameters calibrated on reconstituted streamflow time series, highlighting the importance of using appropriate parameters in the regionalization process.
- When the focus was on a statistical low flow (QMNA5), estimates simulated by the hydrological model were compared to different direct estimation methods used operationally at the poorly gauged catchments. The CQR method yielded low errors, with a magnitude of errors that was comparable to those obtained with the direct method (Q5_Reg). These two methods are based on selecting a donor, a major constraint based on rules for complying with physical, topographical, and climatic similarities. The advantage of the hydrological model is that it can provide other hydrological variables relating to a duration or a return period, while the two local methods must be re-evaluated for each additional hydrological indicator. In ungauged context, estimates simulated by the regionalized hydrological model were also compared to those provided by one other regionalization method (kriging with external drift) with additional sites by cross-validation. These purely regional approaches were less effective than previous local methods, but the latter cannot be used in an ungauged context. In this context, the KED method on the 22-catchments performed better, however it was less robust when the number of catchments increased than the regionalized hydrological model.
- When we consider only poorly gauged catchments, the QR methods perform best to simulate daily streamflow time series.

From an operational point of view, there is an obvious gain in taking several flow measurements to supplement information extracted from a network of hydrometric stations on sites where precise knowledge of low flow characteristics is desired.

The conclusions set out in this article are specific to the climatic context of Réunion Island. They may be called into question in other hydrological contexts.

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CRediT authorship contribution statement

Nathalie Folton: Writing – original draft, Visualization, Validation, Resources, Methodology, Investigation, Formal analysis, Conceptualization.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Nathalie Folton reports financial support was provided by French National Institute for Agricultural Research INRAE. If there are other authors, they 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 authors do not have permission to share data.

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