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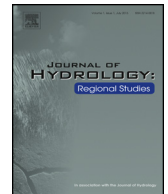
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Catchment model regionalization approach based on spatial proximity: Does a neighbor catchment-based rainfall input strengthen the method?

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ABSTRACT

Study region: The Upper Rhine-Meuse catchment (French part).

Study focus: A rainfall input-related sensitivity analysis was conducted to assess if, with a neighbor catchment-based knowledge of optimal rainfall input, rainfall-runoff modeling becomes more competitive for estimating streamflow at ungauged catchments.

New hydrological insights for the region: Results show that when streamflow is known at the outlet of a catchment, optimal rainfall input for a lumped catchment model is mostly computed with a subset of raingages. When streamflow is unknown at the outlet of a catchment, a regionalisation approach of model parameter values based on spatial proximity is not able to take advantage of a neighbor-catchment based knowledge of optimal rainfall input. This report encourages to search for a catchment model regionalization approach based on spatial proximity which makes no explicit use of measured rainfall to estimate streamflow at an ungauged location.

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1. Introduction

Precipitation is the main atmospheric forcing of the hydrological catchment response. As stated by Larson and Peck (1974), “without accurate measurements or estimates of precipitation, water balance studies and modelling become meaningless”. Hence, quantifying accurately precipitation still remains a challenge for many hydrological applications especially in regions with complex topography due to orographic effects and small-scale slope effect (Sevruk, 2004). A 10% error on precipitation estimates may lead to a higher error on streamflow estimates according to the non-linearity of the precipitation-streamflow transformation.

While space correction and integration of the point meteorological precipitation records have clear benefits providing the model with consistent rainfall data (see, for example, Stisen et al., 2012), producing consistent catchment-scale estimates for rainfall-runoff modelling operational purposes implies to go one step further. In order to assess “how areal rainfall, calculated from a consistently estimated field, is transformed into runoff” (Andreassian et al., 2001), the catchment precipitation estimate issue should not be considered independently to the catchment system which acts as a filter attenuating the rainfall

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variability. A rainfall-runoff model being a simplification of the real catchment behaviour, the characteristics of the raingage network, the quality and the quantity of rainfall data should be adjusted to the specific needs of catchment modelling.

Scientific works conducted on this topic demonstrated the usefulness of the rainfall information provided by optimal raingages (Ancil et al., 2006; Bardossy and Das, 2008; Dong et al., 2005; Tsintikidis et al., 2002; Xu et al., 2013). A common feature of these publications is that specific subsets of raingages may lead to a better hydrograph estimation than when all available raingages are used to calculate the catchment precipitation input.

While contributing to a significant breakthrough in the diagnosis of model behaviour when streamflow is known at the outlet of a catchment, all these sensitivity studies do not focus on how the regionalization problem in rainfall-runoff modelling is impacted by rainfall knowledge at the catchment-scale. Hence, we believe that additional researches should be carried out to improve our expertise on the sensitivity of hydrograph estimation to raingage network distribution at river points where streamflow is unknown. In order to identify potential optimal raingage networks, our research firstly focused on how sensitive a lumped catchment model is to a change in the selected raingages and related rainfall input at gauged catchments. Secondly, we tested the impact of using the optimal raingage networks for rainfall estimation as input in a catchment model, regionalised through the transfer of parameter sets from a combination of a few neighbor catchments to the target catchment.

2. Case study and data

2.1. General characteristics of the study area

Bordered to the west by the Meuse river and to the east by the Rhine river, the investigated territory mainly corresponds to the French part of the Rhine-Meuse district (Fig. 1). It comprises a large panel of relief units like the Lorraine cuestas, the low Vosges Mountains, the Ardennes and part of the Rhine graben. The Vosges Mountains, because of their north to south axis, induce climatic gradients among the highest in France. Therefore the semi-oceanic climate of the Lorraine plateau is relayed east of the Vosges by a climate where the continentality is expressed with more strength. The nivometric coefficient (ratio of solid precipitation to liquid precipitation) is estimated at 4% in the Rhine graben, 20% around 700 m a s l, 30% around 1000 m a s l and 60% around 1350 m a s l close to the top of the Vosges. However, the areas affected by an important snowing up are reduced. Considering the weak influence of snow on the hydrological regime of the upstream mountain rivers, the snow component was not taken into account in this paper.

2.2. Period of investigation

To conduct a robust dynamic sensitivity analysis of a catchment model to rainfall data, it is preferable to have several years of measurements. The period appointed for our analysis extends from 1990 to 2002 because it makes it possible to carry out the sensitivity analysis with the same set of raingages over a relatively long period. The average, minimum and maximum annual catchment rainfall values are respectively 1180 mm/year, 760 mm/year and 2430 mm/year.

2.3. Meteorological dataset

Based on the data collected by the various national weather services of the study area, the climate data set mobilized for our study consists of 90 daily rainfall series and 69 monthly air temperature series (Fig. 1). For a specific catchment, the set of meteorological stations consists of stations whose perimeter of influence intersects the catchment contours (Fig. 1). The measurement network density is quite high, with an average area of about 400 km² per raingage and 550 km² per air temperature monitoring station. However, beyond a certain altitude (approximately 600 m a s l), like in many other mountainous areas in France, the area becomes data-scarce. For example, in the meteorological database that we set up for this study, only 1 raingage providing a continuous series of daily precipitation depths over the period 1990–2002 is located at an altitude higher than 800 m a s l. This corresponds to a density of approximately 1 raingage per 2400 km², which is much coarser than a density of 1 raingage per 250 km² as recommended by the WMO for the mountainous areas (WMO, 2008). The same is valid for the air temperature monitoring network. This low density of monitoring stations may have an impact on the sensitivity of the catchment model to rainfall data.

2.4. Hydrological dataset

The sensitivity analysis reported in this paper relies on a dense hydrometric network (approximately 1 station per 260 km²) made up by 148 reliable hydrometric stations offering daily streamflow values validated on the target period 1990–2002 (Fig. 1). The streamflow regime of the rivers selected for the study is considered to be “natural”, i.e. being not significantly influenced by anthropogenic activities (regulation, water pumping, etc). The sample of catchments includes 106 stations located along the hydrographic borders of the French part of the Rhine-Meuse catchment whereas 42 stations are located on their circumference, in a corridor of 20 km, in France (29), Germany (9) and Belgium (4) (Fig. 1). These peripheral stations are included in our analysis to increase the number of potential donor catchments (see Section 3.3). The drainage areas are distributed as follows: 68 lie between 5 and 250 km², 41 between 250 and 800 km² and 39

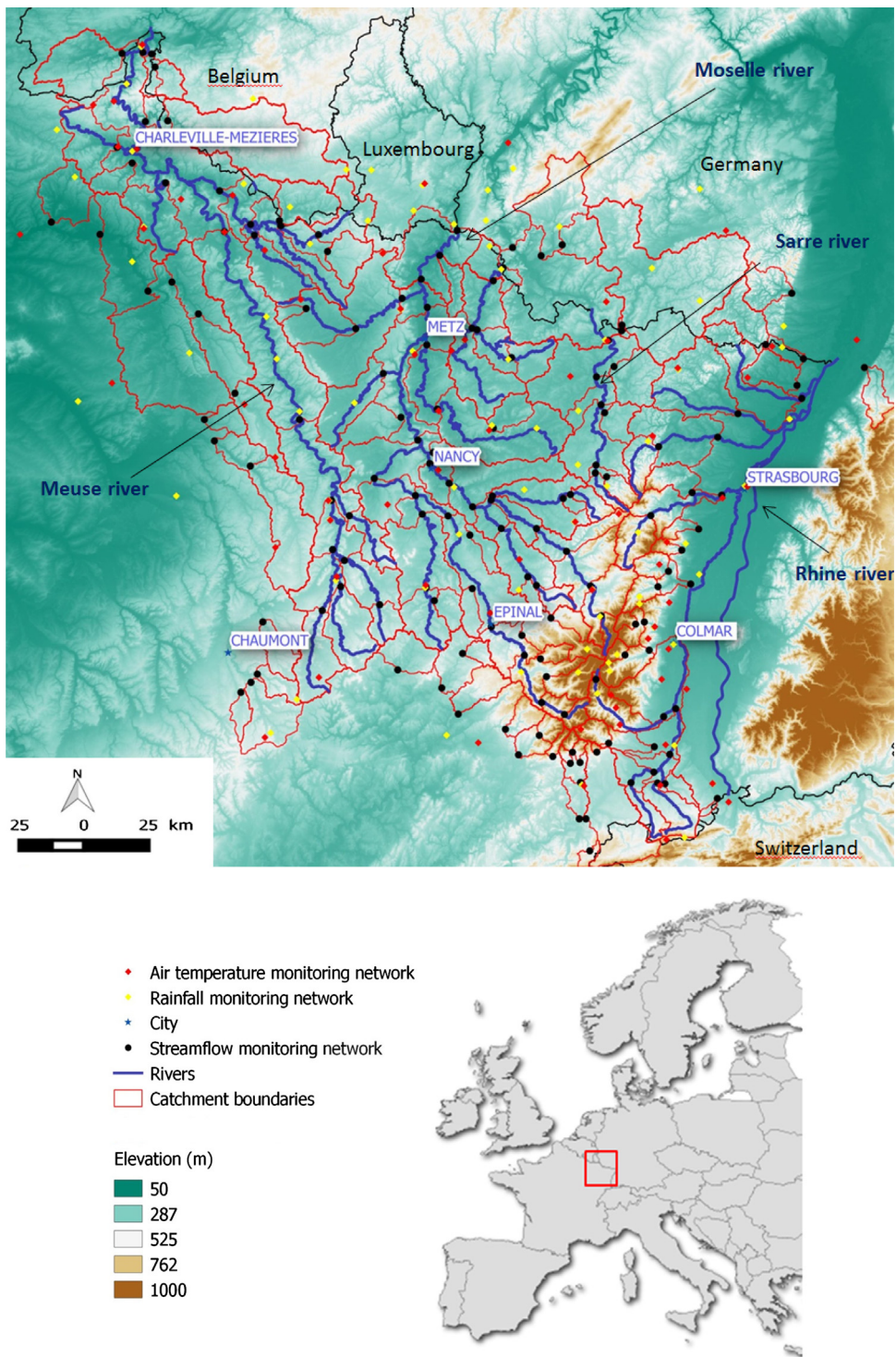


Fig. 1. Study area and hydro-meteorological monitoring networks.

between 800 km² and 11,500 km². The average, minimum and maximum annual runoff values are respectively 550 mm/year, 130 mm/year and 1660 mm/year. The catchment median elevations lie between 180 m and 961 m a.s.l. The territory covered by our selected catchments is approximately 38,000 km². This accounts for 17% of the total drainage area of the Rhine-Meuse basin (≈220,000 km² at the mouth).

3. Setting the experiment

An assessment of spatial transferability of catchment model parameters was already carried out at the level of the French part of the Rhine-Meuse river basin (see Drogue and Plasse, 2014; Plasse et al., 2014). In the simulation experiment reported in this paper we tested whether the rainfall-runoff estimation method based on nearest neighbor catchments is sensitive to the set of raingages used to compute rainfall input at gauged and ungauged catchments. The objective is to find the best strategy to estimate streamflow time series at ungauged pollution-sites monitored by the French Water Agency with hydro-meteorological information provided by neighbor catchments at short lead times.

3.1. Rainfall-runoff model description

This study makes use of the GR4J model, of which the structure and mathematical description are presented in details in Perrin et al. (2003). This lumped and parsimonious daily rainfall-runoff model has been tested on a large sample of French catchments and proves to have a well-performing fixed model structure (see, for example, Oudin et al., 2008; Van Esse et al., 2013). The GR4J model represents the transformation of the precipitation into streamflow over a catchment using a structure having two stores, a production store and a routing store, respectively acting as a filter that transforms part of the rainfall input into a fast catchment streamflow response and a slow catchment streamflow response (Fig. 2). The GR4J model is well-suited to the catchment whose production of streamflow is conditioned by the catchment humidity level what is generally the case in our non Mediterranean temperate region. Four free parameters ($X1$, $X2$, $X3$, $X4$, see Fig. 2) should be determined to solve the mathematical equations of the model. Regression analysis between the four free GR4J parameters and catchment physical attributes have shown that their physical interpretation is not straightforward (Oudin et al., 2008).

3.2. GR4J model calibration and validation

The performance and the parameters of the GR4J model have been determined for each catchment using a differential split-sample test procedure: the 8-year period extending from 1990 to 1997 has been used for calibration and the 8-year period extending from 1995 to 2002 for validation and vice-versa. As shown by Fig. 3, the 1990–2002 period is characterized by a relatively stable annual average temperature of about 10, 8 °C, and by a rather « dry » segment at the beginning of the period followed by a wetter segment with a 10% increase at the end of the decade. Through this differential split-sample test we check if our modelling experiment results are climate sensitive or not. The three first years of both 8-year periods were used for model warm-up. The validation period allows to estimate the spatial and/or temporal extrapolation capacity of the model at gauged and pseudo-ungauged catchments. The optimal parameter set over the training period was determined using a hill climbing optimization technique based on the Broyden–Fletcher–Goldfarb–Shanno algorithm (Byrd et al., 1995). The coefficient of Nash-Sutcliffe (NS) applied to the square root of the daily streamflows ($NS_{\text{sqrt}Q}$) is used as the objective function. The square root transformation applied to the streamflow values makes it possible to define a parameter set representative of the catchment behavior for the full streamflow range. The $NS_{\text{sqrt}Q}$ objective function was indeed shown to be a good compromise between several alternative criteria (Oudin et al., 2006a). By repeating the model calibration and validation for all the catchments, a regional library of parameters was obtained, containing 148 vectors for the four optimal parameters.

3.3. Regionalization method

In this paper, the strategy to estimate daily hydrographs at pseudo-ungauged catchments relies on a simple and old idea: we consider the hydrological functioning of a catchment more similar to that of a neighbor catchment than to that of a distant catchment. The basic assumption of our regionalization method is that the unknown streamflow at the outlet of a catchment is better estimated with hydrological information transferred according to spatial proximity. This hydrological information takes the form of model parameters sets. The geographical distance-based approach has proven to be valuable for hydrological regionalization purposes, especially for well-modelled catchments and areas with dense hydro-meteorological network – typically 500 km² per hydrometric station – in temperate climates (see, for example, Parajka et al., 2005; Oudin et al., 2008; Drogue and Plasse, 2014). In our case, the criterion of spatial proximity between the donor catchments and the receiver catchment is defined as a horizontal euclidean distance between catchment centroids. A protocol of leave-one-out cross validation has been implemented over the validation period. Each gauged catchment is then alternatively considered as ungauged and the simulated hydrograph is compared to the observed one through the computation of the $C2M_{\text{sqrt}Q}$ coefficient (see the next section).

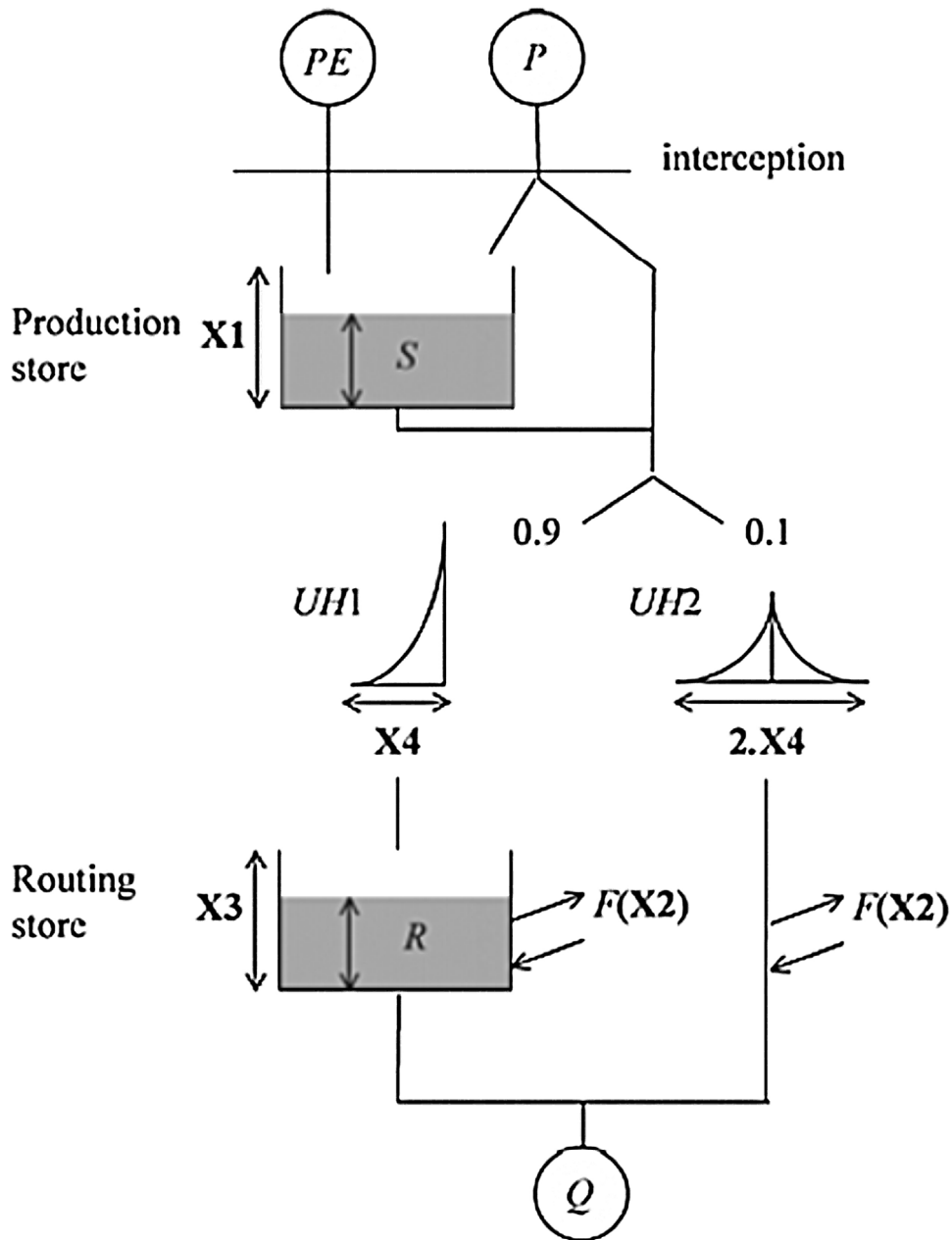


Fig. 2. Structure of the daily GR4 rainfall-runoff model. *PE*: potential evapotranspiration (mm); *P*: rainfall totals (mm); *S*: level of the production reservoir (mm); *UH*: Unit Hydrograph; *F(X2)*: non atmospheric exchange function; *R*: level of the routing reservoir (mm); *Q*: total streamflow (mm); *X1*: maximal capacity of the production reservoir (mm); *X2*: water exchange coefficient (mm); *X3*: capacity of the non linear routing reservoir (mm); *X4*: unit hydrograph time base (day).

3.4. Quantifying error of hydrograph estimation

For model assessment, we used a bounded version of the NS coefficient, which is written as (Mathevet et al., 2006):

$$C2M_{\text{sqrt}Q} = \frac{NS_{\sqrt{Q}}}{2 - NS_{\sqrt{Q}}} \quad (1)$$

Where $NS_{\sqrt{Q}}$ is the Nash-Sutcliffe coefficient applied to the square root of the daily streamflow time series. The use of the C2M coefficient bounded in $[-1; 1]$ makes it possible to reduce the weight of the strongly negative values of the NS coefficient, which tends to skew the total performance assessment of a hydrological model when one works with numerous catchments.

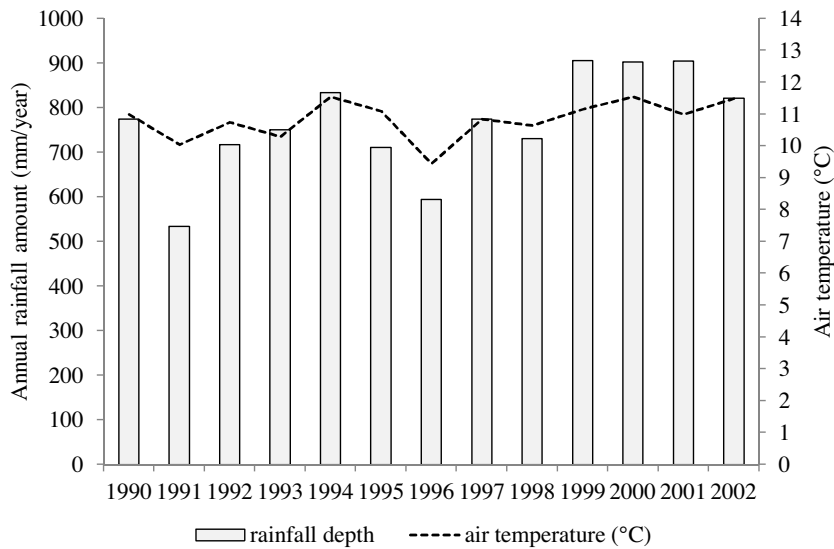


Fig. 3. Annual rainfall amounts and mean annual air temperatures recorded at the synoptical station of Metz-Frescaty (49.069N, 6.125E, 192 m a s l)—Moselle (France), on the 1990–2002 period.

3.5. Approach to the input-related sensitivity analysis of the model

In hydrological modelling, the input-related sensitivity analysis of a model usually aims at quantifying the change of parameters and catchment model responses induced by a change in the meteorological inputs of the model. Following the typology of Andreassian et al. (2004), we performed a dynamic sensitivity analysis of our model instead of a static one. In that way, we account for the dependence between model errors and input data since we acknowledge explicitly that the calibrated catchment parameters depend on the input data. This is a reasonable assumption for the type of model we run. As stated by Andreassian et al. (2004), a dynamic sensitivity analysis approach involves a reference calibration (and a corresponding reference streamflow simulation), using a reference rainfall estimate. Model recalibration is done after change in the rainfall estimate, and the reference simulation is then compared to the streamflow simulated with the recalibrated catchment model (Fig. 4). Regarding potential evapotranspiration (PE), we used the formulation of Oudin et al. (2005) as it is a simple (i.e. air temperature-based) and efficient potential evapotranspiration model for rainfall–runoff modelling in French catchments. For each catchment, the catchment-scale Oudin PE has been computed with the assumption that the mean areal PE estimate is equal to the PE at the mean elevation of the catchment. Available monthly air temperature records were then corrected according to a monthly mean vertical air temperature gradient fitted at the regional scale using all available air temperature stations. Given that lumped rainfall–runoff models are almost insensitive to detailed PE estimation, we decided to compute daily PE values by simply dividing monthly PE values by the number of days in each month.

3.6. Random generation of rainfall input estimates

Two procedures exist for investigating the relationship between the catchment model predictive capacity and rainfall input estimates: (i) a data-cleansing procedure where raingages in the full region are progressively excluded from the total raingage network available, (ii) a sub-sampling procedure where subsets of all raingages per catchment are generated. As we want to get a diagnosis from the sensitivity test at the catchment scale, we decided to treat each catchment separately and we decided to implement the sub-sampling procedure (Fig. 4). To establish the total raingage network of a catchment, all raingages are considered that have an area of influence that intersects with the catchment contour.

The binomial coefficient allowing to generate p combinations of k raingages among a total of m raingages is given by:

$$C_n^k = \frac{m!}{k!(m-k)!} \quad (2)$$

where ! is the factorial operator. The maximum number of k subssets is set to 100. For example, for a raingage network of 38 gages that gives 3577 subssets on the whole. We generate a total of 38,709 subssets of k raingages. Given that producing grids for a very high number of subssets of raingages is really time-consuming we simply used the mean average of rainfall records for computing the rainfall estimate. As we retained only the best model parameter set for each k value (see Fig. 4), that is the parameter set leading to the best model efficiency in validation, the total amount of subssets is 869. Fig. 5 shows the change of the total number of raingages per catchment according to a change in drainage area. The fifteen catchments having only 1 available raingage were only used as donor catchments. Few optimal rainfall inputs obtained for the Moselle catchment at Hauconcourt (9384 km²) along with the model efficiency in validation mode (period 1998–2002) are given in Fig. 6. It

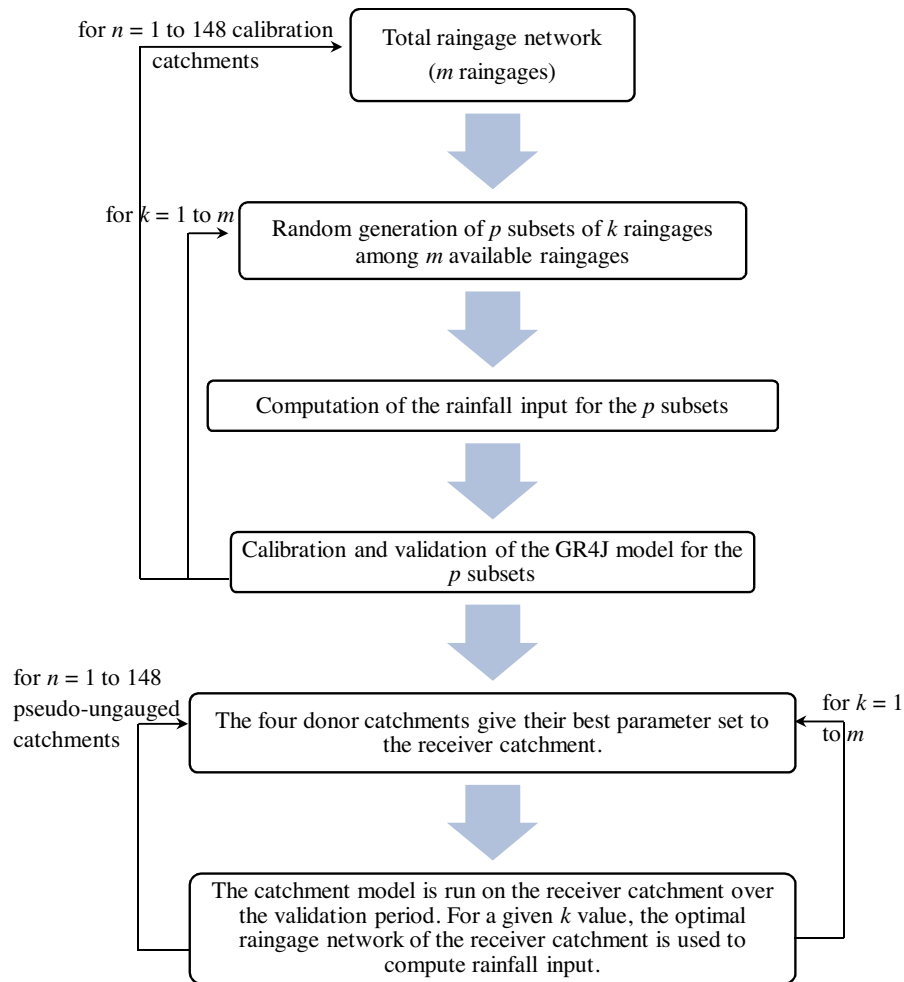


Fig. 4. Iterative procedure of sub-sampling and model simulation designed for testing the dynamic sensitivity of the GR4J model to raingage input at gauged and pseudo-ungauged locations.

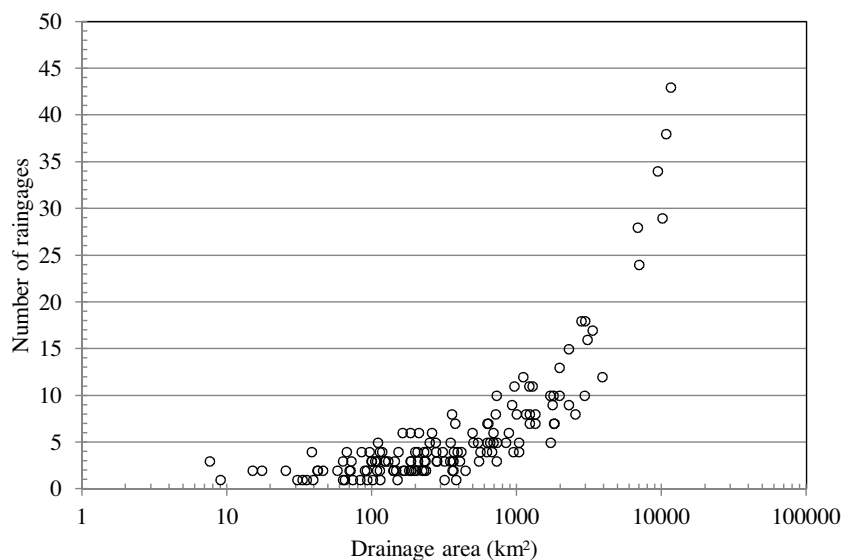


Fig. 5. Relationship between the catchment drainage areas and the number of raingages per catchment. Results are given for the 148 catchments used for this study.

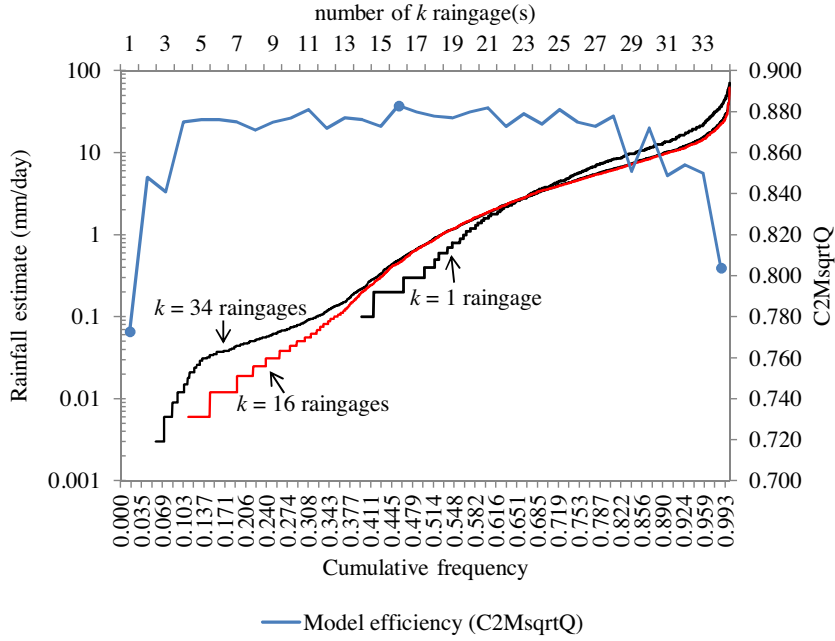


Fig. 6. Rainfall inputs leading to the best catchment model simulation in validation mode (1998–2002 in this case) for $k=1$, 16 and 34 raingages (total raingage network). The corresponding $C2MsqrtQ$ coefficient values are also provided. Results are given for the French Moselle catchment at Hauconcourt (9384 km²).

shows that a growing number of raingages impacts the rainfall input by attenuating its variability. This is a common feature for rainfall inputs used in this study. The model efficiency is optimal for 16 raingages and it drops quickly when the 34th raingage is included because of a higher contribution of low rainfall intensities (≤ 0.3 mm/day) in the rainfall input estimate. Similarly to what [Dong et al. \(2005\)](#) found, one can also notice that beyond a critical number of well-located raingages (three in this case), the spatial sampling density of rainfall is already « good enough » for flow simulation. This critical number of well-located raingages varies between 1 and 3 for the 81 catchments in our catchment set having more than three raingages in their total raingage network.

To assess the characteristics of rainfall input to the model, two simple indices introduced by [Andreassian et al. \(2001\)](#) have been computed: the GORE and BALANCE indices. The GORE index (Goodness Of Rainfall Estimation) is similar to the Nash-Sutcliffe coefficient and compares the reference rainfall estimate computed with the total raingage network and the rainfall estimate computed with a subset of raingages. The GORE index is defined as:

$$GORE = 1 - \frac{\sum_{i=1}^n \left(\sqrt{P_i} - \sqrt{\hat{P}_i} \right)^2}{\sum_{i=1}^n \left(\sqrt{P_i} - \overline{\sqrt{P_i}} \right)^2} \quad (3)$$

where P_i is the reference arithmetic daily mean areal rainfall using all raingages at time step i , \hat{P}_i is calculated from a subset of raingages. Square roots of the variables are used to reduce the weight of high rainfall intensities. The BALANCE index is used to quantify overestimation or underestimation of the reference rainfall estimate. The mathematical formulation is as follows:

$$BALANCE = \frac{\sum_{i=1}^n \hat{P}_i}{\sum_{i=1}^n P_i} \quad (4)$$

The BALANCE index is larger than 1 in case of reference rainfall overestimation, and smaller than 1 in case of reference rainfall underestimation. The two aspects of rainfall estimation described through indices GORE and BALANCE, *i.e.* time variability and amount, greatly influence the catchment model streamflow response.

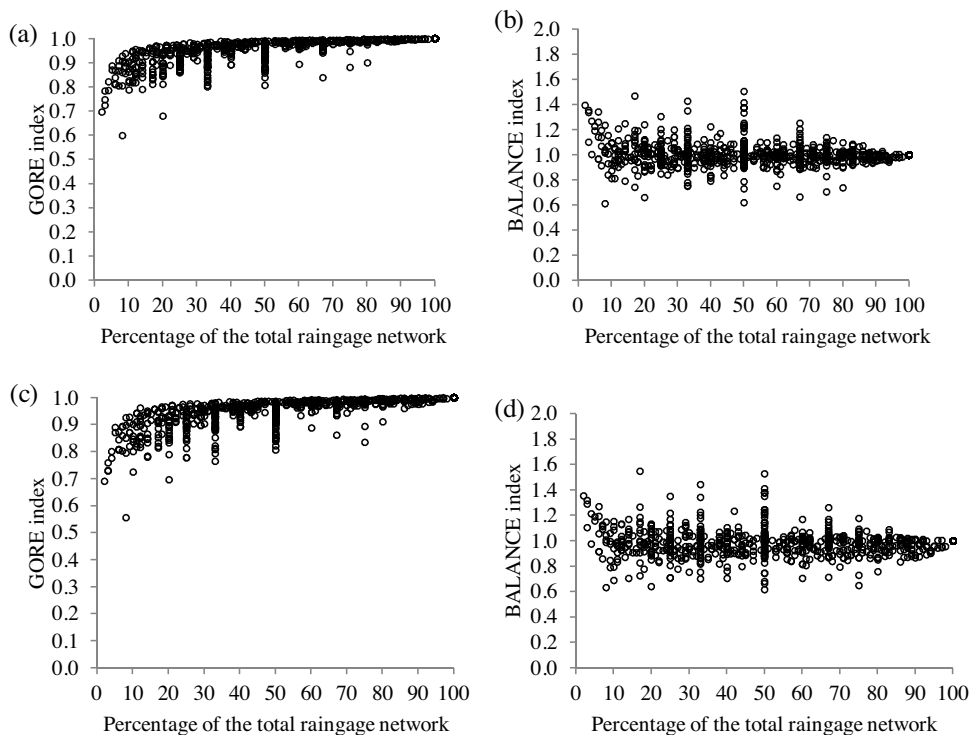


Fig. 7. Impact of the percentage of the total raingage network on the GORE index and the BALANCE index. Scatterplots (a) and (b) refer to the calibration period (1993–1997 in this case); scatterplots (c) and (d) refer to the validation period (1998–2002 in this case). Results are given for 133 catchments and the 869 combinations of k raingages leading to the best model efficiency in validation.

4. Results

4.1. Impact of the raingage network sub-sampling on the representativeness of the rainfall input

Fig. 7 depicts the change of the GORE and BALANCE indices according to the percentage of the total raingage network in calibration and validation. The percentage of the total raingage network is calculated for each catchment based on the number of raingages in the catchment over the total number. The behaviour of the indices is comparable between periods of calibration and validation. It is interesting to note that for some catchments, a very weak reduction of the total raingage network (*i.e.* a withdrawal of one or two raingages per catchment) can be enough to produce poor rainfall estimates in comparison to the reference one. This leads to low values of the GORE index (see Fig. 7a and c). As expected, the lowest values of GORE are obtained with a drastic reduction of the total raingage network (*i.e.* an exclusion of more than 80% of available raingages per catchment).

Another interesting common feature of Fig. 7a and c is that some of the 869 optimal subsets of raingages can produce values of GORE very close to 1 while including only a few raingages. It means that for some catchments, the spatial and temporal variability of the reference rainfall input can thus be captured with few specific well-located raingages. This observation is also valid for the BALANCE index (see Fig. 7b and d). No clear trend could be found between the percentage of the total raingage network and the BALANCE index: overestimation and underestimation of the reference rainfall input are evenly distributed according to the decrease of the network spatial density. One can also notice that the GR4J model tends to prefer larger amount of precipitation (actually a greater value than the reference rainfall input) for low percentage of the total raingage network (Fig. 7b and d). We believe that the explanation lies in the non symmetric behaviour of the X2 parameter according to systematic bias in rainfall input as demonstrated by Oudin *et al.* (2006b).

At the present stage, the usefulness of the reference rainfall input to the model is still questionable. This is why the next section of the paper is dedicated to some results on the relationship between subsets of raingages and model behaviour at gauged catchments.

4.2. Impact of raingage network sub-sampling on the model parameters and efficiency at gauged catchments

Fig. 8 shows for a set of contrasted catchments in terms of size and physical conditions, the GORE and BALANCE indices plotted against the value of k , that is the number of raingage(s) in the subset. Fig. 8 also presents the clusters of X1, X2, X3 and X4 GR4J parameters against the value of k . Interesting features come up from the analysis of Fig. 8:

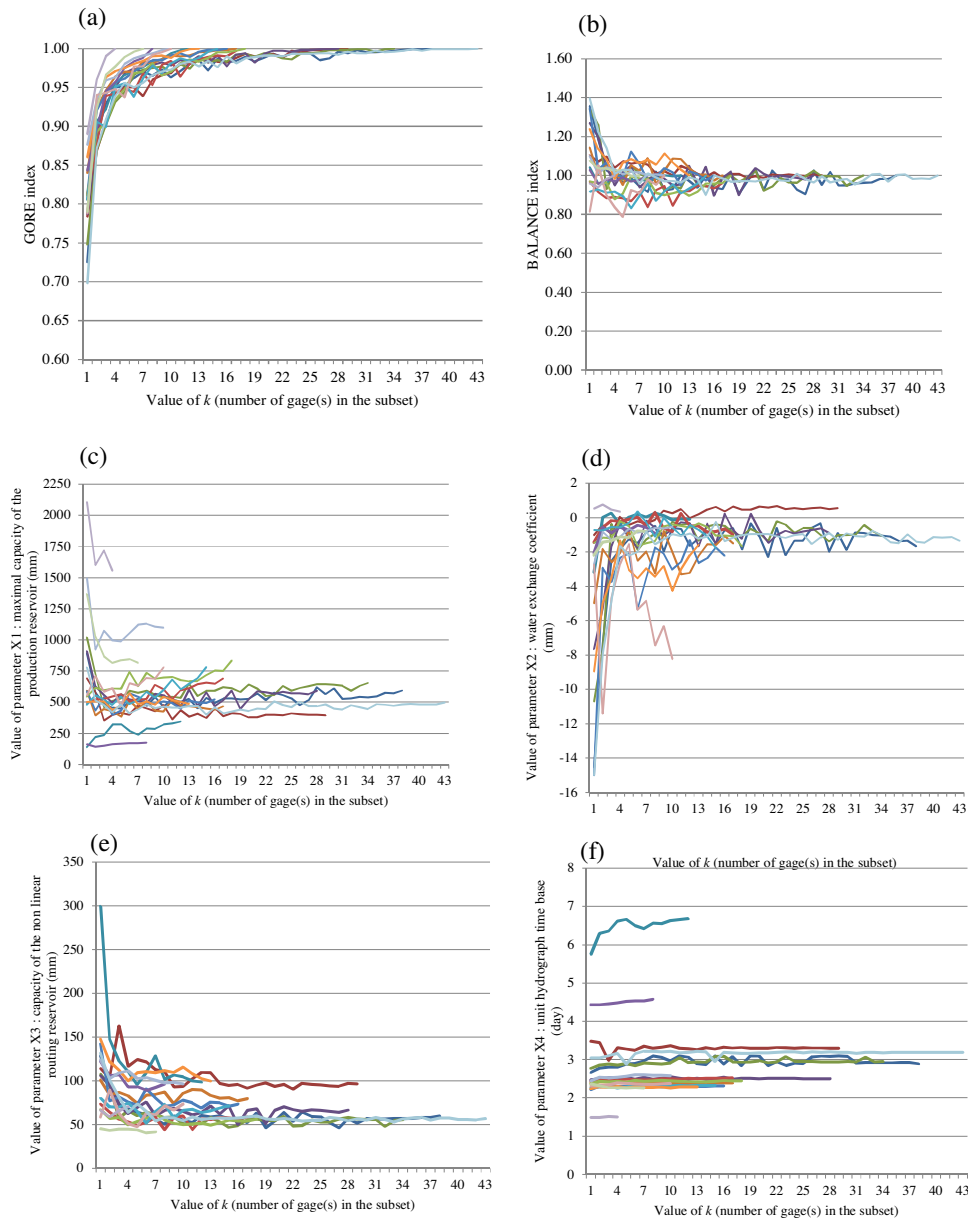


Fig. 8. Impact of the number of raingage(s) on the values of the GORE index (a), the BALANCE index (b) and the GR4J parameters: X1 (c), X2 (d), X3 (e) X4 (f). Results are given for a sample of 17 physically-contrasted catchments and the subsets of k raingage(s) leading to the best model efficiency in validation (1998–2002 in this case).

- For most of the catchments, low GORE values (see Fig. 8a), which represent a poor estimation of the reference rainfall input, increase variability of the parameters X1 (see Fig. 8c), X2 (see Fig. 8d) and X3 (see Fig. 8e). The GR4J model generally reacts to poor estimations of the reference areal rainfall by decreasing the GR4J X1 and X3 parameters while increasing the X2 parameter. However, for some catchments, the range of variation of these two parameters against the GORE index is very limited.
- Most of the time, parameters X1, X2 and X3 are also sensitive to overestimation and underestimation of reference rainfall input (see Fig. 8b vs c–e). The GR4J model reacts to the overestimation of areal rainfall (*i.e.* values of the BALANCE index greater than one) by increasing the production parameter X3 simulating greater water losses.
- Parameter X4 that relates to the response time of the catchment is almost unsensitive to change in the reference rainfall input (Fig. 8f).

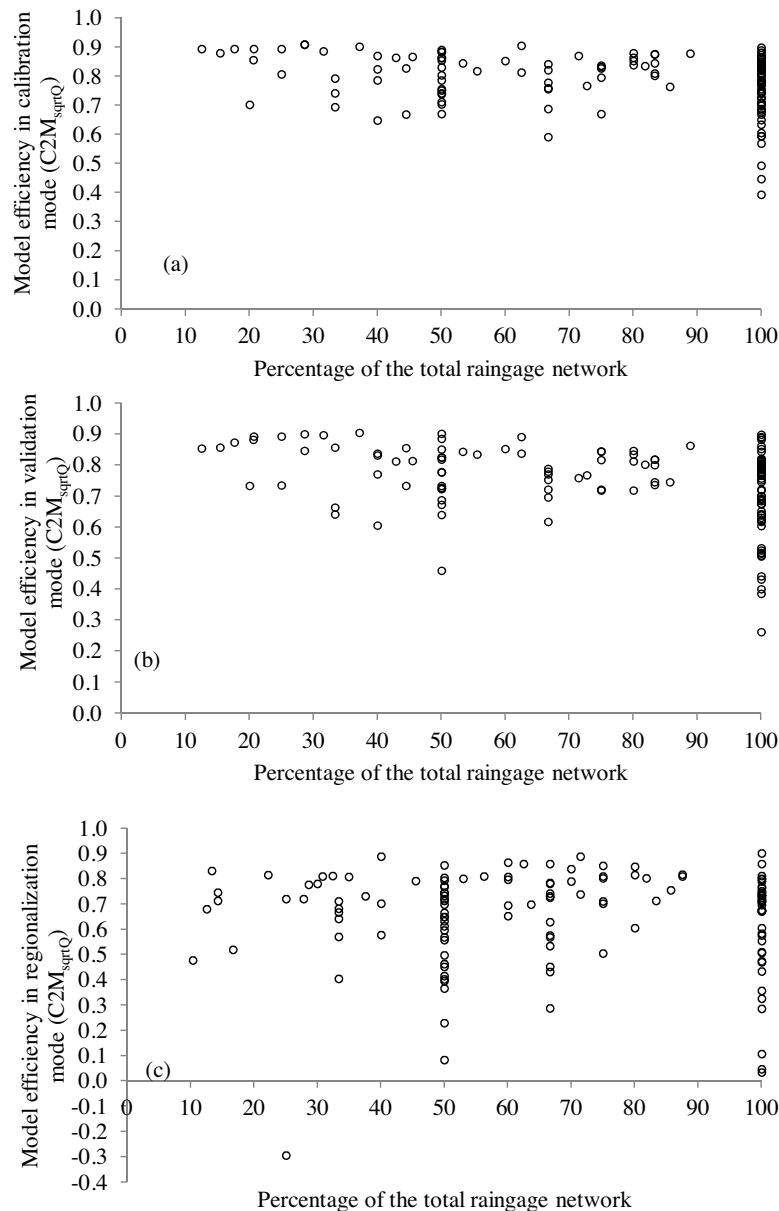


Fig. 9. Relationship between the percentage of the total raingage network and the performance of the GR4J model. (a) In calibration mode (1993–1997 in this case). (b) In validation mode (1998–2002 in this case). (c) In ungauged conditions (1998–2002 in this case). Results are given for 133 upon 148 catchments used for this study.

These results confirm that the parameters related to the GR4J production functions, that is X_1 , X_2 and X_3 , are more sensitive to the rainfall inputs than the parameter X_4 . This one is more conditioned by the size of the catchment and/or the river network length than by the rainfall input. Hence, for most of the catchments, the GR4J model is able to adapt its parameters to a change in rainfall input during the calibration process thanks to a distortion of the model parameters. In some rare cases, however, a more consistent estimation of rainfall input does not lead to a change in model parameters (see e.g. the deep purple curve in Fig. 8c). Whatever it be, that means that the model is able to identify the optimal parameter set with a very limited number of raingages.

To illustrate the impact of raingage network sub-sampling on model efficiency we represented the percentage of the total rainfall network that is necessary to reach the maximum model efficiency in calibration mode (Fig. 9a), in validation mode (Fig. 9b) and in regionalisation mode (Fig. 9c). Note that for a given catchment, the same optimal level of performance could be reached for various subsets of raingages. In this case, as a matter of parsimony, the smallest subset is retained. When looking at Fig. 9a–c two major features can be observed:

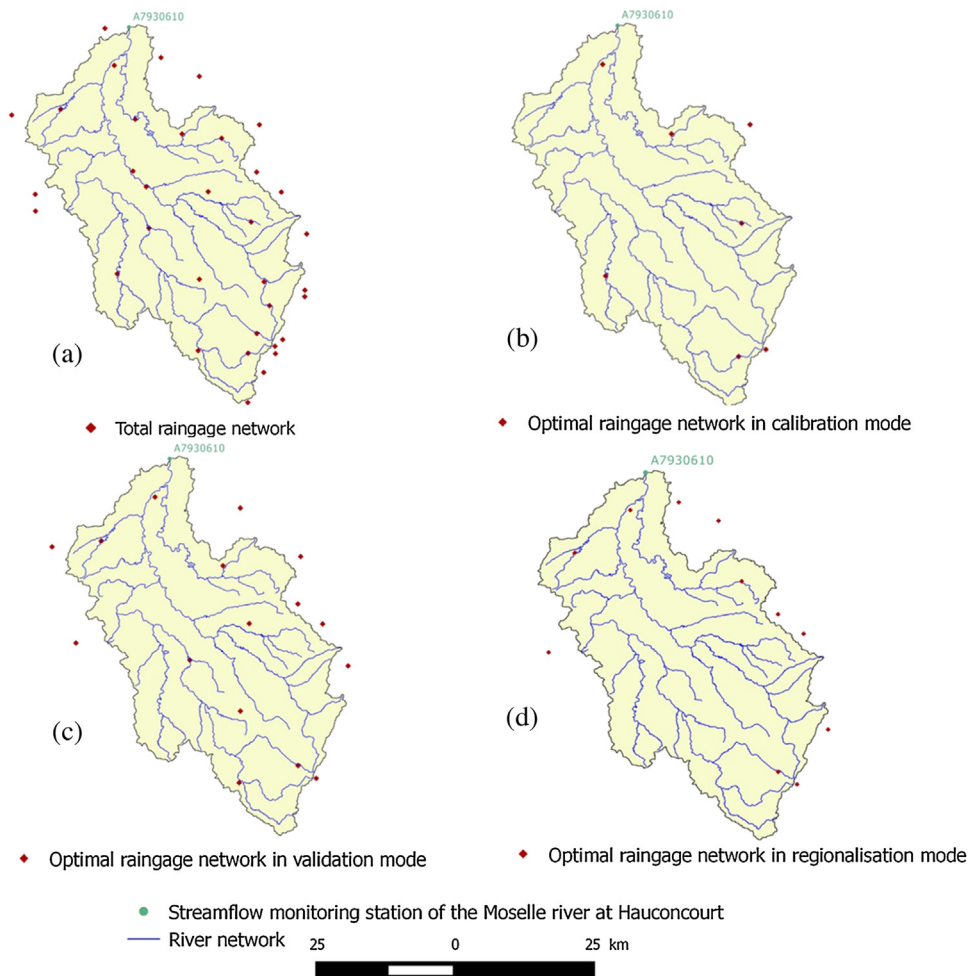


Fig. 10. Cartography of the total raingage network (a), the optimal raingage network in calibration mode (1993–1997 in this case) (b), the optimal raingage network in validation mode (1998–2002 in this case) (c) and the optimal raingage network in regionalisation mode (1998–2002 in this case) (d). Results are given for the Moselle river at Hauconcourt (9384 km²).

- For a majority of catchments (70 upon 133 in calibration mode; 97 upon 133 in validation mode; 94 upon 133 in regionalisation mode), the highest level of model efficiency is obtained with a more or less reduced percentage of the total raingage network. Therefore, for some catchments, the assumption that the reference rainfall estimate is the best descriptor of rainfall input should be questioned. Some subsets of raingages are apparently more informative for the calibrated and the regionalized model than using all raingages per catchment, which can even be disinformative. These subsets of raingages provide a simple way to avoid poor simulations, which should be one of the objectives of any hydrograph simulation experiment. For example, Fig. 10 provides the pattern of the total raingage network of a medium-size catchment used in this study. The subsets of raingages leading to the best model efficiency in calibration (Fig. 10b), in validation (Fig. 10c) and in regionalization (Fig. 10d) are also provided. In calibration, using a set of 7 optimal raingages, the $C2M_{\text{sqrtQ}}$ coefficient takes value of 0.856 against 0.875 in validation using 16 optimal raingages, 0.813 in regionalization using 11 raingages and 0.844 in validation using the total raingage network (*i.e.* 34 raingages). In this example, optimal raingages are preferentially located in headwaters and rain-rich areas close to the Vosges Mountains.
- For some catchments, the best model efficiency is obtained using the total raingage network per catchment (*i.e.* without applying any spatial density reduction). It shows that the calibrated model and the regionalized model could still gain in efficiency if it was possible to increase the spatial density of the total raingage network.

Fig. 11, which presents the distributions of the number of optimal raingages when changing the calibration period, speaks for itself: there is a poor matching between subsets of raingages for the two selected calibration periods (*i.e.* 1993–1997 and 1998–2002) having moderate contrasted rainfall amounts (Fig. 3). Incidentally, one can notice that the number of raingages required to reach the maximum model efficiency in calibration mode is highest for the « wet » calibration period

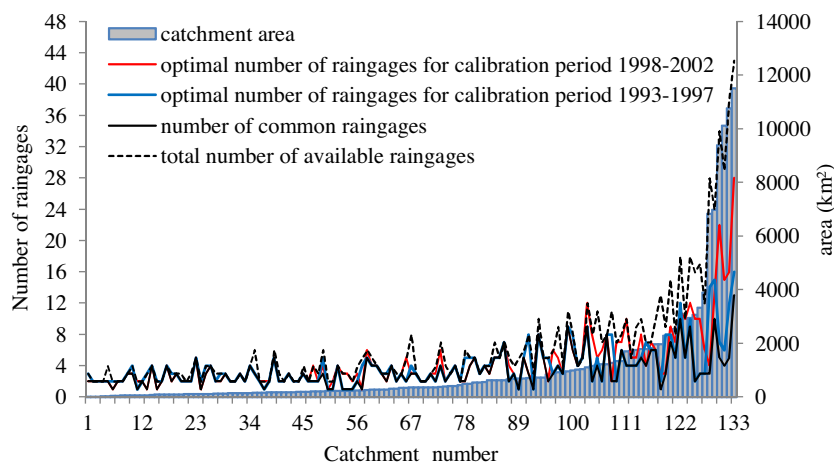


Fig. 11. Optimal number of raingages for the two consecutive calibration periods and number of common raingages between optimal subsets. For each catchment, the number of available raingages and the area are also given.

Table 1

Variants of rainfall input estimation used to assess the sensitivity of the regionalized model to rainfall input.

Variant number	Type of raingage network used in donor catchments	Type of raingage network used in the receiver catchment
Variant 1	Optimal (subsets)	Total (complete set)
Variant 2	Total (complete set)	Total (complete set)
Variant 3	Total (complete set)	Optimal (subsets)
Variant 4	Optimal (subsets)	Optimal (subsets)

(i.e. 1998–2002) in comparison to the drier calibration period (i.e. 1993–1997). Same conclusions can be drawn from the comparison of subsets of raingages in validation mode (not shown).

4.3. Impact of the raingage network sub-sampling on the regionalized model

In this section, we want to investigate the following two questions: (i) Does a better description of the rainfall input in calibration catchments lead to a better estimation of the flow at pseudo-ungauged catchments? (ii) How eliminating the undesirable raingages (if so) from the total raingage network when streamflow is unknown owing to the fact that the catchment model cannot be used to filter out the undesirable raingages through recalibration?

To answer the first question, we transferred the best parameter sets (that is parameter sets optimized with raingages maximizing the performance of the model in validation) of the four nearest catchments on the receiver catchment. According to our regionalization scheme, the model was then run on the receiver catchment for the two selected validation periods using rainfall input calculated with all raingages (see variant 1 in Table 1). In order to assess the impact of the regionalized model on the streamflow error at the outlet of a target catchment, we also calculate the model efficiency of the calibrated model in validation using rainfall input calculated with subsets of raingages (we call this an « optimal at-site calibration »). Looking at Fig. 12a and b we can see that:

- When a better description of rainfall input is ascribed to the model on donor catchments (i.e. variant 1 is used), the performance of the regionalized model is not significantly different than when all raingages are used for both donor and receiver catchments (see variant 2 in Table 1). This is counterintuitive as we would expect that a better modelling of neighbor catchments would lead to a better model hydrograph estimation at the outlet of a target catchment where streamflow is unknown.
- The optimal at-site calibrated model is much more performant than the regionalized model whatever be the rainfall input over donor catchments (variant 1 or variant 2). Knowing streamflow at the point of interest is by far the most useful information for the GR4J model in comparison to the knowledge of regional rainfall input and streamflow.
- The distributions of efficiency are almost similar between the two selected validation periods. The mean efficiency is slightly higher (0.731 against 0.714) when the model is calibrated over the « wet » segment (i.e. 1998–2002) and validated over the « dry » segment (i.e. 1993–1997).

To answer the second question, we test the following simple assumption: one could argue that the rainfall input leading to the smallest catchment model errors at neighbor gauged catchments could be the best available indicator of the rainfall

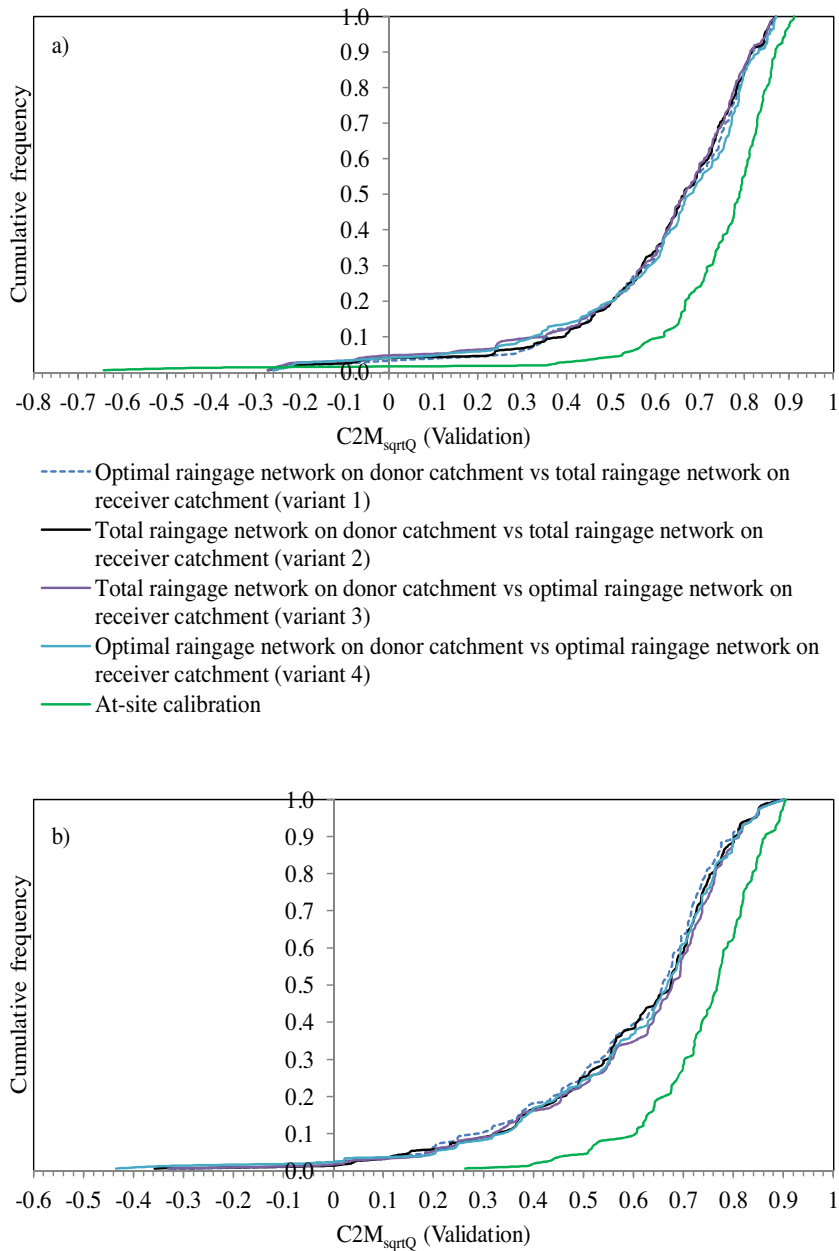


Fig. 12. Cumulative distribution functions (CDFs) of GR4J model efficiencies in pseudo-ungauged conditions using different solutions for the rainfall input. The CDF for at-site calibration model efficiencies is also shown. Results are given in validation mode: (a) 1993–1997; (b) 1998–2002.

input over a catchment controlled by a target ungauged location. To evaluate how realistic this assumption is, we performed a two-step Method:

- Step 1: We analysed the overlap between the total raingage network per catchment and the optimal raingage network for the neighbor catchments. We used the same method for selecting the neighbor catchments as that presented in the section 3.3. At this stage, for a given catchment, it is possible to know among all available raingages which are optimal raingages over neighbor catchments.
- Step 2: For a given catchment, we compute the rainfall input as the average of the rainfall records provided by the optimal raingages identified in step 1 or by the total raingage network in case of non-overlapping networks.

Fig. 13 shows the matching of the available raingage network of a receiver catchment and optimal raingages of neighbor catchments identified in calibration mode (i.e. in 1993–1997) and validation mode (i.e. in 1998–2002). For both modes, the

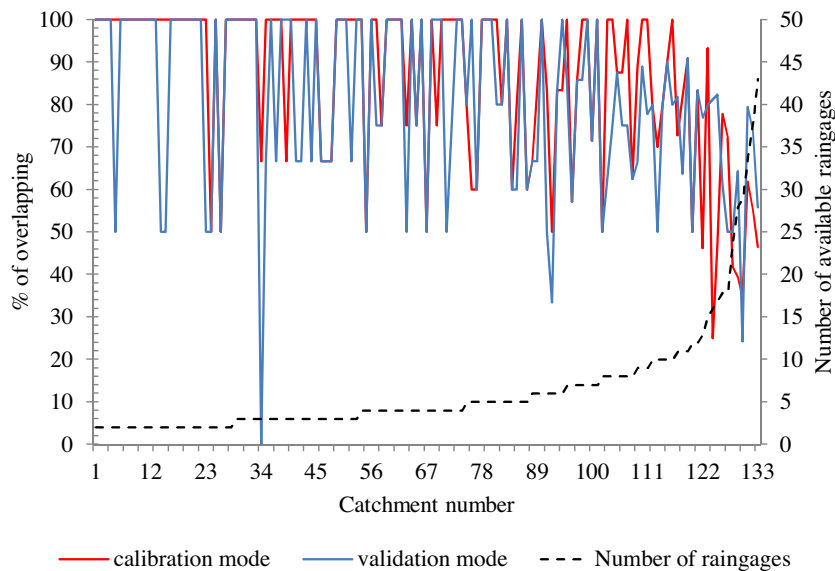


Fig. 13. Percentage of common raingages between the total raingage network of a receiver catchment and the optimal raingage network of the four closest catchments in calibration mode (1993–1997 in this case) and validation mode (1998–2002 in this case). For each catchment, the number of available raingages is also given.

degree of matching usually ranges from 50 to 100% when the number of available raingages is small and tend to decrease when the number of raingages increases. As the hydro-meteorological network for the study area is quite dense, only one catchment has no common raingage with its neighbor catchments. The same observation is valid when calibration period and validation period are reversed. Therefore, the variant 3 (Table 1) where optimal raingages from donor catchments are used to eliminate undesirable (*i.e.* non optimal) raingages on the receiver catchment can be tested. Variant 4 is obtained by using optimal raingages for both donor and receiver catchments (Table 1).

Fig. 12 illustrates the efficiency distributions computed for the regionalization approach with four variants of rainfall input. Fig. 12a and Fig. 12b clearly show that: (i) none of the rainfall input variants (*i.e.* variants 2, 3 and 4) are more competitive than variant 1, using all available raingages for both donor and receiver catchments; (ii) this report is independent to the validation period and appears to be climate-proof.

Further analysis of efficiency values shows that short lists of catchments with poor results (*i.e.* having a $C2M_{\text{sqrtQ}}$ less than 0.4 in validation) have physical singularities (*e.g.* sandstone aquifers in the Ardennes and the northern part of the Vosges Massif; karstic influences in the upper part of the Meuse catchment) or a poorly defined stage-discharge relationship.

5. Discussion and conclusions

Appropriate streamflow knowledge is a key-issue at river points where freshwater quality studies and programmes are undergone. To address this issue, we carried out a regional-scale assessment of a rainfall-runoff estimation method with optimized rainfall input and spatially transferred model parameter values. This estimation method uses model parameter sets provided by the four nearest neighbours of the target catchment. A multiple stages methodology allows producing a series of raingage subsets. As we implemented a sensitivity analysis searching for an optimization scheme, rainfall input was estimated in a voluntarily simple way as the arithmetic mean of the available rainfall records.

When streamflow is observed at the outlet of a catchment, we found that, for most of the catchments, especially the largest ones, the GR4J model is able to better define its parameters thanks to a more relevant rainfall input provided by subsets of raingages exceeding a critical number of raingages. This is a general property of the GR4J model which has a remarkable ability to cope with poor rainfall inputs while having less degrees of freedom than more complex lumped models (see also Andreassian *et al.*, 2001). Also, in light of a differential split-sample test (with moderately climate-contrasted periods), composition of subsets of raingages appears to be climate sensitive. Note that we could not find any obvious geographical features (such as the distance from the catchment outlet, the distance from the catchment centroid and the raingage altitudes) to explain the preferential location of optimal raingages. Aside from being located in areas where rainfall contributes to the streamflow at the outlet of a catchment, we believe that optimal raingage subsets are at almost unpredictable locations.

For ungauged catchments, removing non optimal raingages for such catchments is impossible as it requires flow observations. That is why, in this paper, we proposed to test an empirical neighbor catchment-based approach for computing the optimal rainfall input in ungauged catchments.

Thus, the regionalized GR4J model was provided with four variants of rainfall input combining optimal and non optimal rainfall estimates. On the basis of a differential split-sample test, we come to the conclusion that the predictive capacity

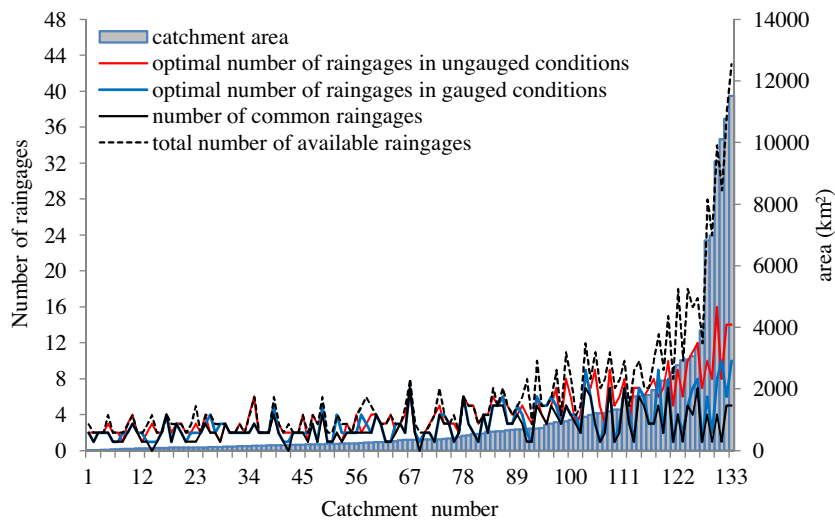


Fig. 14. Optimal number of raingages obtained with the regionalized model in ungauged and in gauged conditions. Results are provided for the validation period 1993–1997. For each catchment, the number of common raingages between optimal subsets, the total number of available raingages and the area are also given.

of the model does not take benefits from the most informative subset of raingages available for calibrating the model on neighbor catchments and/or for estimating rainfall input on the target catchment. For neighbor calibration catchments, the most plausible explanation is that, while improving the rainfall input and the model performance, sub-sampling of raingages produces more catchment-specific sets of optimal parameters what finally leads to « overcalibration » (Andreassian et al., 2012a). Whereas these sets are better locally defined with subsets of raingages, they seem to lose in spatial and temporal transferability to ungauged catchments. By increasing the performance of the model on calibration catchments thanks to a better rainfall input, one thus reduces the robustness and the genericity of the model parameters what leads to a loss in model efficiency at ungauged catchments. At receiver catchments, in order to check the regional validity of raingages we compared two subsets of optimal raingages obtained with the regionalized model considering that streamflow is known or unknown. Fig. 14 shows that the optimal number of raingages which should be used to maximize the predictive capacity of the regionalized model is always overestimated. The same result has been obtained for the 1998–2002 validation period (not shown). One can conclude that even though the number of common raingages is quite high between gauged and ungauged conditions (see the blue curve on Fig. 14), the proposed method for selecting optimal raingages in truly ungauged conditions is not accurate enough to capture the right subset of raingages. We believe that this is the reason why the regionalized GR4J model is not able to better simulate streamflow time series at ungauged location.

In a more general way, we believe that even though the regionalized model was fed with the right optimized rainfall input, the latter still does not represent the *real* rainfall input, hence suffers from a lack of representativeness.

One can argue that the implemented methodology to compute rainfall input could have been more sophisticated. As an alternative method to the arithmetic mean we tested the inverse-distance weighting method for computing the rainfall input. But the application of this simple interpolation method leads to similar conclusions to those obtained with the use of the arithmetic mean. So we are confident that our findings hold for truly non regulated ungauged catchments lying in similar hydro-meteorological and physical conditions.

Additionally, we found that catchments are better modelled with a calibrated catchment model that with a regionalized catchment model. That pleads in favor of the recommendation of Blöschl (2005) who supports that “the best way to handle the issue of rainfall-runoff modelling in ungauged catchments would be to install a stream gauge. Indeed, limited or incomplete data can still be extremely valuable because one can use it to constrain model calibrations”. This statement was confirmed at many occasions in the hydrological literature dedicated to quantitative streamflow estimation at ungauged catchments (see e.g. Oudin et al., 2008; Drogue and Plasse, 2014; Viviroli and Seibert, 2015).

As a future perspective in the course of our researches we could test other regionalization approaches which are based on a transfer of streamflow observations to the target location like top kriging (Skøien and Blöschl, 2007) and/or a regionalized version of the neighbor catchment model of Andreassian et al. (2012b). These sophisticated methods, as they avoid an explicit use of measured rainfall to estimate streamflow at an ungauged location, would certainly allow to enhance the efficiency of streamflow regionalization for well modeled catchments. However, we are quite skeptical regarding their ability to produce better streamflow simulations for outlier catchments because the application of the methods will rely on the same available catchment-set. Outlier catchments require a more specific work to improve the knowledge of their hydrological behaviour and to test an other model so that it would represent reality better. Finally, any conclusions drawn here on regionalization

might be very different on other geographical locations (e.g. Mediterranean catchments; snow-covered catchments) and observational conditions (e.g. low raingage and streamgage network density).

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at <http://dx.doi.org/10.1016/j.ejrh.2016.07.002>.

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