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Classification of heterogeneous precipitation fields for the assessment and possible improvement of lumped neural network models for streamflow forecasts

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Abstract

This work addresses the issue of better considering the heterogeneity of precipitation fields within lumped rainfall-runoff models where only areal mean precipitation is usually used as an input. A method using a Kohonen neural network is proposed for the classification of precipitation fields. The evaluation and improvement of the performance of a lumped rainfall-runoff model for one-day ahead predictions is then established based on this classification. Multilayer perceptron neural networks are employed as lumped rainfall-runoff models. The Bas-en-Basset watershed in France, which is equipped with 23 rain gauges with data for a 21-year period, is employed as the application case. The results demonstrate the relevance of the proposed classification method, which produces groups of precipitation fields that are in agreement with the global climatological features affecting the region, as well as with the topographic constraints of the watershed (i.e., orography). The strengths and weaknesses of the rainfall-runoff models are highlighted by the analysis of their performance vis-à-vis the classification of precipitation fields. The results also show the capability of multilayer perceptron neural networks to account for the heterogeneity of precipitation, even when built as lumped rainfall-runoff models.

1 Introduction

Lumped rainfall-runoff models, as opposed to distributed ones, continue to constitute a viable solution for the operational needs of estimating flows in watersheds. They are inexpensive, are relatively easy to operate, have low computing requirements, and can provide quick and reasonably accurate estimations at the watershed outlet. Such models are expected to be widely used well into the future. This paper proposes a method to better analyze one of the shortfalls of lumped hydrological models, which is that heterogeneous precipitation over a watershed cannot not be considered. Indeed, only the mean areal precipitation is usually considered as an input to lumped models, unless a specific subdivision of the watershed can be made and accommodated by the model. In their review of rainfall-runoff models, Singh and Woolhiser (2002) stress the effect of the spatial variability of precipitation on the production of streamflow in a watershed, and this effect has been a long standing issue in hydrology as demonstrated in the work of Naden (1992), and Faures et al. (1995). Dawdy and Bergman (1969), and Wilson et al. (1979) indicate that errors in the estimation of rainfall intensity are very likely to limit the accuracy of rainfall-runoff models, and this would be particularly prevalent for lumped models.

This study involves the use of a classification algorithm based on the Kohonen neural network for discriminating daily precipitation fields in a watershed into coherent groups. The performance of lumped multilayer perceptron neural network models for the estimation of streamflow on this watershed is afterward assessed with respect to each of the identified groups of precipitation fields. Through this work, three issues are addressed: 1) the relevance of the classification algorithm for the discrimination of precipitation fields from day to day, 2) the value of evaluating the performance of rainfall-runoff models with respect to precipitation field groups, and 3) the possibility of improving rainfall-runoff modelling performance through more specific identification of inputs as highlighted by the classification.

In terms of precipitation field classification, any form of clustering technique may be appropriate. For meteorological data in general, and for precipitation in particular, there is a large range of classification algorithms that have been employed. The simplest cases involve subjective inferences based on observations on synoptic maps (Bardossy and Plate, 1992; Siew-Yan-Yu et al., 1998). More objective methods normally include one simple discrimination rule such as the Euclidian distance between the features of two events (Shoof and Pryor, 2001) or a probabilistic criterion (Benzie et al., 1997). The level of objectivity can then be increased by including several discrimination rules, as is the case with the Classification and Regression Trees (CART) employed by Hughes et al. (1993), Zorita et al. (1995), and Shnur and Lettenmaier (1998). For the assignation of rules, the work of Bardossy et al. (1994) and Ozelkan et al. (1996) make use of fuzzy logic, which is an alternative to classification methods with fixed rules. Even the most objective methods contain some level of subjectivity that may induce some uncertainty on the validity of the generated classification. It must be noted as well that computing requirements increase as the number of rules increases, particularly with large databases (Zorita and Storch, 1999). The Kohonen neural network employed as the classification algorithm in this study possesses some amount of subjectivity. However, its process for the determination of classes (i.e., calibration) may be less demanding in terms of computing requirements than more traditional and common classification techniques, such as those presented in Dillon and Goldstein (1984), as shown for a large classification study by Lauzon (2003).

Multilayer perceptron neural networks are employed here as rainfall-runoff models. They have been widely acknowledged as being appropriate for rainfall-runoff modelling (ASCE, 2000a and b; Singh and Woolhiser, 2002), and such lumped models are easy to build and implement on an operational basis. They are employed here for one-day ahead streamflow forecasts.

The selection of an appropriate study watershed is essential to achieve the objectives of this work. In order to produce variability in the areal precipitation estimates, the watershed must have heterogeneous precipitation fields. For the same reason, the rain gauge network must include a large number of stations. Finally, the watershed must be selected so that forecasting uncertainties are mainly due to precipitation.

In the following section of this paper, a brief description of the Kohonen and multilayer perceptron neural networks, used for the classification of precipitation fields and rainfall-runoff modelling, is given. In subsequent sections, the context of application, including the description of the Bas-en-Basset (France) watershed and its database, as well as the details on the experimental protocol, is presented. This is followed by the analysis of the results, with an emphasis on the issues of interest: 1) the relevance of the classification algortithm, 2) the analysis in rainfall-runoff modelling performance based on the classification, and 3) the improvement of modelling performance. Finally, a conclusion highlighting the relevant findings is presented.

2 Description of the neural networks

2.1 Descriptive neural networks

The structure of a Kohonen neural network is designed so as to identify patterns in data, as with multivariate statistical clustering techniques. This network is therefore a descriptive tool that is used increasingly in hydrology and water resources, in applications such as the classification of watershed conditions (Liong et al., 2000); the determination of hydrological homogeneous regions (Hall and Minns, 1999); the identification of river pollutant sources (Gotz et al., 1998); and the study of algae bloom (Bowden et al., 2002). The network is made of an input layer of neurons that receives the data and an output layer, often structured in a planar surface, as depicted in Fig. 1. The weight vector of each output neuron is of the same scale as the input, and consequently can be considered as a mass center of a class. Each output neuron is thus the equivalent of a class, and it is said to be activated when its weight vector is the closest in distance to the input vector given to the network.

The elements of all the weight vectors must be calibrated so as to cover the whole data domain. The calibration is an iterative process, where one input vector is fed to the network at every iteration. Following the feeding of an input vector I at a given iteration, the weight vector (W_j) of each of the output neurons is updated as follows (Kohonen, 1990):

$$W_j^{(t)} = W_j^{(t-1)} + h_j \left(I - W_j^{(t-1)} \right) \tag{1}$$

This formulation simply drives the weight vector to be closer to the input vector, where h_j is expressed in this application as:

$$h_j = h_0 \exp\left(- \left(d_{j,a} / \sigma \right)^2 \right) \tag{2}$$

In this expression, $d_{j,a}$ is the distance between the most suitable output neuron (a) and another output neuron j as determined on the output map (layer). When j=a, the exponential equals 1 and the value of h_j is at its maximum value (h_0). The value of h_j decreases as the distance between activated neuron a and neuron j increases. Parameter h_0 gives the magnitude of the updating, while parameter σ is a scaling factor on the distance, and indicates the extent of the output map affected by the updating. Both parameters are set at a high value at the start of the calibration process to ensure a rapid spreading of the output neurons over the data domain, and are reduced gradually so that only small adjustments are performed at the end of the calibration process. A large number of iterations ensures that all input vectors are employed a significant number of times on the average at all times of the calibration process.

The calibration process ensures that all the patterns present in the data are defined in a meaningful coordinate system, and this is why the Kohonen neural network is often called a self-organized map. The Kohonen neural network reduces the dimension of a problem, from an n-dimension input vector to 2-dimension solution, so as to produce a clearer view of the data patterns (Kohonen, 1990).

2.2 Predictive neural networks

As a predictive tool, the multilayer perceptron network with biases, an input layer, a single hidden sigmoid layer, and a linear output layer (see Fig. 2) is by far the most commonly used network topology in the field of water resources (Coulibaly et al., 1999; Maier and Dandy, 2000). They are able to approximate any function with a finite number of discontinuities (Cybenko, 1989; Hornik et al., 1989), provided that the training is sufficient. The Levenberg-Marquardt backpropagation algorithm (Hagan and Menhaj, 1994), a second-order non-linear optimization technique, is selected for the calibration or training of the network weights, because this technique is usually faster and more reliable than any other backpropagation variants (Tan and Van Cauwenberghe, 1999).

Generalization, which is the ability to provide accurate output values for input values that have never been seen by the network, is achieved by the combination of two complementary approaches. The first approach, Bayesian regularization, relates to the training procedure. It involves a multiple objective optimization by which both the sum of the squared errors and the sum of the squared weights must be minimized (MacKay, 1992; Foresee and Hagan, 1997). Bayesian regularization is particularly suited to reduce variance errors, because the minimization constrains the weight to small values, making less likely the possibility of large fluctuations in the response of the network given inputs of large magnitude. An application of this approach in hydrology can be found in Anctil et al. (2004a). The second approach, bagging (Breiman, 1996), relates to techniques used for constructing training data sets. Several training data sets are created from the original data set by bootstrap, which is random picking with replacement. Each of these training sets is employed to train a neural network. Hence a pool of models is created, and a global predictor can be obtained by the mean of their estimates for a given input vector. It has been demonstrated that bagging can reduce variance errors, since aggregation has the effect of smoothing fluctuations from the estimates of all the models (Breiman, 1996, 2001). An application of this approach in hydrology can be found in Canon and Whitfield (2002).

Predictive neural networks are developed for one-day ahead streamflow forecasts, and predictive performance is globally assessed in this application by the sum of squared errors:

$$\mathrm{SSE} = \sum_{t=1}^{n} \left(Q_{\mathrm{obs},t+L} - Q_{\mathrm{est},t+L}\right)^2 \tag{3}$$

the root mean squared errors:

$$\mathrm{RMSE} = \left(\frac{\mathrm{SSE}}{n}\right)^{0.5} \tag{4}$$

ant the persistence index (Kitanidis and Bras, 1980):

$$\mathrm{PERS} = 1 - \frac{\mathrm{SSE}}{\mathrm{SSE}_{\mathrm{naive}}} \tag{5}$$

where $\mathrm{SSE}_{\mathrm{naive}}$ is a scaling factor expressed as:

$$\mathrm{SSE}_{\mathrm{naive}} = \sum_{t=1}^{n} \left(Q_{\mathrm{obs},t+L} - Q_{\mathrm{obs},t}\right)^2 \tag{6}$$

In Eqs. 3 to 6, $Q_{\mathrm{est},t}$ is the neural network forecast of the observed streamflow $Q_{\mathrm{obs},t}$ at time step t where t=1,2,...,n, L is the lead time (L=1 for one day-ahead forecast), and n is the number of time steps where model error can be calculated. A PERS value of 1 reflects a perfect fit between predicted and observed values, but 0 is reached when SSE=$\mathrm{SSE}_{\mathrm{naive}}$, which is equivalent to saying that the rainfall-runoff model is no better than the naïve model. PERS statistics are particularly well suited for assessing forecasts, considering that the previous streamflow is usually one of the neural network input vectors. Negative PERS values would thus signify that the model is degrading the provided information.

3 Context of application

3.1 The Bas-en-Basset watershed

This study focuses on the Bas-en-Basset watershed, 3234 km^2, located in the Western Mediterranean region, in Southern France. Figure 3 provides a schematic of this watershed. Its main stream is actually the upstream reach of the Loire River, encased in mountain formations that separate the large hydrographic systems of the Loire, Rhone, and Garonne rivers. The Western Mediterranean region is an interesting domain for the study of precipitation fields, because the climate is prone to high precipitation rates, such as daily rainfalls in excess of 200 mm. This is especially true during fall when the Mediterranean Sea surface temperatures are still high from the summer heating while the onset of fall increases the chances of strong synoptic forcing. Convection also plays an important role in a good number of these events, mostly from the Mediterranean Sea itself and the complex terrain features surrounding it. Detailed analyses of some major Western Mediterranean rainstorms are provided by Sénési et al. (1996), Doswell et al. (1998), and Bechtold and Bazile (2001), some of which lead to flash floods that caused fatalities and large property damage.

Daily streamflow is observed at the Bas-en-Basset watershed outlet, and a total of 23 rain gauges, identified by diamonds in Fig. 3, have been available for the observation of daily rainfall from 1980 to 2000. For the purpose of the classification of precipitations fields, only the days with no missing observations in the set of rain gauges are considered. A total of 5100 days are thus available for the application, 3931 of which being days when precipitation is observed at one or more rain gauges. The numbers in Fig. 3 represent the average daily precipitation at each rain gauge, calculated with the 5100 available days.

3.2 Protocol of experiment

In a first step, the classification of the daily precipitation fields is performed using Kohonen neural networks. Several initial tests have been conducted to classify the precipitation fields, with the number of evaluated classes or groups set between 2 and 12 groups. The number of available data records is the major constraint limiting the number of groups that can be defined. For this application, the 3- and 6-group classifications are deemed adequate, being small enough to offer an easy analysis while being large enough to allow a good discrimination of precipitation fields. The input vectors for the Kohonen network are composed of the daily observations at each of the 23 rain gauges. Prior to being fed to the network, the input vectors are normalised on a daily basis. Hence, a given vector provides the daily precipitation observations, minus the daily precipitation average, divided by the daily standard deviation. This normalisation ensures that all input vectors are on the same scale while preserving the spatial distribution of the daily precipitation fields, which is the feature that is discriminated in the classification.

In a second step, multilayer perceptron neural networks are trained for the prediction of one-day ahead streamflow values for the Bas-en-Basset watershed. The method for the construction of training and validation sets proposed here makes use of the Kohonen classification of precipitation fields. Through random selection, two-thirds of the input vectors available are allocated for training, while the other third is left for validation. The selection process is structured so that, for any given group of precipitation fields, two-thirds of the associated input vectors go for training and the other third is assigned for validation. This two-thirds/one third ratio selection is accomplished with the 6-group classification, and the selection is such that the ratio is also respected for the 3-group classification. A 1-group classification, where rainy days are all gathered in one single group, is considered and used in the results section as a reference.

Three input vector configurations, which are designed to define the heterogeneity of precipitation fields, are tested. All configurations use streamflow at day t for the prediction of streamflow at day $t+1$. The first configuration, which is the reference, uses the areal mean precipitation at day t (i.e., all 23 rain gauges) as an input. In the second configuration, the watershed is divided into two regions based on the classification of precipitation fields, and the mean areal precipitation of each of these regions is employed as inputs. In the third configuration, the watershed is divided into four regions, yielding four areal mean precipitation inputs. The performance of the neural networks is analysed with respect to each group of precipitation fields for each classification (1-, 3- and 6-group).

4 Results

4.1 Classification of precipitation fields

The daily mean precipitation at the rain gauges presented in Fig. 3, over the whole database and regardless of any classification, indicates higher precipitation in the north and the south of the watershed, due to orographic effects. A figure illustrating the standard deviation instead of the mean would show the same spatial heterogeneity as a result of the mountains in the north and south of the watershed. There may be several types of heterogeneous precipitation events on this watershed, and the goal of the classification applied here is to identify them from day to day.

The classification into three groups (see Fig. 4) fulfills expectations on the aspect of the discrimination of precipitation fields. Similar in format to Fig. 3, Fig. 4 gives the daily mean precipitation at the rain gauges on rainy days, for each group of precipitation fields. The first group (Fig. 4a) contains the daily events with high precipitation observed in the northern part of the watershed as a result of the orographic effect. The precipitation cells during these events appear firmly located in the north, for little precipitation is observed in the south, including in the southern mountainous part. The third group (see Fig. 4c) includes the daily events with heavy precipitation in the southern part of the watershed. In all likelihood, this group gathers the precipitation events originating from the Mediterranean Sea and the events of lumped heavy precipitation, as demonstrated by the high daily mean at all rain gauges on the watershed. As for the second group (see Fig. 4b), it represents the daily low precipitation events that are relatively homogeneous spatially. The daily mean precipitation is rather similar from one rain gauge to another and the standard deviations are low as well, and this is indicative of a low spatial variability for the events of this group. The results of the classification into three groups are satisfying in that it produces groups of precipitation fields that are expected for the Bas-en-Basset watershed. There is one group for the northern orographic effect, another for the southern orographic effect and heavy precipitation overall, and one last group for the relatively low and homogeneous precipitation events. On a hydrologic standpoint, it is likely that each of these groups generates a distinct response from the watershed, and this is partly highlighted by the analysis of the rainfall-runoff relationship.

The results of the classification into six groups confirm those of the classification into three groups while refining the discrimination of the daily precipitation events. Figure 5 is similar to Figs. 3 and 4, and summarizes the results of the classification into six groups. Some groups are typical and already observed in the classification into three groups. There is one group for the heavy precipitation events due to the mountains in the northern part of the watershed (Fig. 5d), and another one for heavy events due to the mountains and the Mediterranean climate in the southern part of the watershed (Fig. 5c). Groups 3 and 4 (Figs. 5c and d) of the six group classification include the most extreme precipitation events and therefore the most heterogeneous in all likelihood.

As an indication of the agreement between the two classifications, Table 1 gives the distribution of the daily precipitation events following the classifications into three and six groups. It is noted that almost all of the events in groups 3 and 4 of the 6-group classification are respectively located in groups 3 and 1 in the 3-group classification. Mostly, for all of the groups of the 6-group classification, the events are distributed either into groups 1 and 2 or into groups 2 and 3 in the 3-group classification. There is no distribution into groups 1 and 3 (3-group classification) from any group of the 6-group classification. Groups 5 and 6 (Figs. 5e and f) of the 6-group classification show not only a north-south variation in the location of the precipitation cell, but also an east-west variation as well, which cannot be noticed in the 3-group classification. Groups 1 and 2 (Figs. 5a and b) in the 6-group classification should be considered as containing relatively low and homogeneous precipitation events.

As a general rule for this watershed, the heavier is the precipitation event, the more heterogeneous it is susceptible to be. This is confirmed by Fig. 6, which show the distribution of the (a) mean and (b) standard deviation of the precipitation events according to each group for the 6-group classification. Similar results are obtained for the 3-group classification. There is a clear distinction between group 3, which contains the heaviest and most heterogeneous daily precipitation events, and all the other groups. The events of group 3 are very likely to produce a response in terms of streamflow production that may significantly differ from that of the other groups. The other groups may well each generate a distinct response from the watershed, although it might not be easy to clearly distinguish each one from the others. Assessing the response of the watershed to precipitation events is implicitly accomplished here through the analysis of the performance of rainfall-runoff models with respect to the groups identified in both classifications.

4.2 Rainfall-runoff relationship

Pertinent input vectors for Bas-en-Basset one day-ahead streamflow forecasts are the streamflow and the precipitation of the previous day. These have been identified in a step-wise manner, as in Anctil et al. (2004b), from a pool of candidates consisting of streamflow, mean areal rainfall and potential evapotranspiration with time-lags of one to three days. The goal of input selection is to maximize the PERS for the validation dataset (one third of the database), while the network weights are optimized for the training dataset (two thirds of the database). At this stage of input selection, the number of hidden neurons is set at 5. After the input selection, the number of hidden neurons is optimized by trial and error from 2 to 35. The network architecture and the number of parameters (weights and drifts) to calibrate for each of the models are given in Table 2.

As for the use of precipitation inputs, three cases are considered. The first case employs the areal mean precipitation, calculated with all 23 rain gauges. The other two cases divide the watershed into 2 and 4 regions, respectively, and the mean precipitation of each of the regions are used as inputs. Figure 7 illustrates these regions. In case 2 (2 mean precipitation inputs), the southern region includes the rain gauges with the heaviest precipitation measurements observed. In case 3 (4 mean precipitation inputs), the regions are set to account for both the north-south and east-west precipitation field variability observed during the classification. Case 1 represents the reference while cases 2 and 3 constitute attempts to improve rainfall-runoff modelling performance. One rainfall-runoff model is developed for each case, and their performance is summarized in Table 2 with respect to SSE, RMSE and PERS. The results show that adding precipitation inputs does not lead to improved performance. A priori, performance decreases as the network becomes less parsimonious, although a final conclusion can only be made after modelling performance is analyzed with respect to the groups of precipitation fields.

Table 3 details model performance with respect to both the modelling cases (1, 2 or 4 precipitation inputs) and the groups from Kohonen classifications, for all three performance indicators (SSE, RMSE and PERS). The best modelling scenarios are those that yield an SSE and a RMSE that are closer to 0 and a PERS that is closer to 1. The situation where no classification is performed, gathering all precipitation fields in one single group, is also given in Table 3 for comparison. Note that group 0 represents the days when no precipitation is recorded at any of the rain gauges.

In terms of the SSE, group 3 (i.e., southern orography and heavy precipitation) in both classifications is the highest, with group 1 in the 3-group classification and group 4 in the 6-group classification (i.e., northern orography) possessing the second largest SSE on most occasions. The RMSE obviously confirms the conclusion about the SSE, as it translates the sum of errors into an average error associated to a single day. It is to be expected that lumped conceptual models are not able to take into account precipitation heterogeneity over a watershed. The results of Table 3 exemplify this with the multilayer perceptron neural networks (lumped, although not conceptual models). The SSEs and RMSEs are typically small for situations with relatively homogeneous precipitation fields spatially (e.g., group 2 in the 3-group classification, and groups 1 and 2 in the 6-group classification), while they are quite high for situations with moderately to highly heterogeneous precipitation fields (e.g., groups 1 and 3 in the 3-group classification, and groups 3 and 4 in the 6-group classification). The SSEs and RMSEs must also be weighted with respect to the amount of precipitation and streamflow level (e.g. group 3 in both the 3- and 6-group classifications), as they usually become larger as the average precipitation and streamflow increase.

Larger SSEs and RMSEs do not necessarily translate into poor performance in terms of PERS. The neural network models for the situation involving group 3 precipitation fields for both classifications possess large SSE and RMSE compared with the other groups, but also a large PERS compared with the other groups. It indicates that neural networks are far better alternative than the reference model for PERS (i.e., the naïve model) in the cases of highly heterogeneous precipitation fields, compared with cases of relatively homogeneous precipitation fields or cases where no precipitation is observed. It is expected, for any hydrological model, that large errors are produced in the events of large streamflow or precipitation.

The use of more than one precipitation input, either 2 or 4, has been justified by the expectation of improving modelling performance, although the results in Table 3 do not show this to be the case. Improvement is noticed (e.g., group 2 in the 3-group classification or group 5 in the 6-group classification), but it is only marginal and offset by the degradation of performance for the group with the largest SSE (i.e., group 3 in both classifications). The definition of good inputs is critical for modelling performance, and the division into regions as performed here has been subjective. The use of a more objective approach, based on a systemic exploration of the combinations of rain gauges available for the calculation of areal mean precipitation, is recommended here. Another alternative for modelling improvement would be to develop a distinct model for each of the groups, which is feasible if the database is large enough to accommodate this community of models. The preliminary tests performed on this watershed indicate that the available database needs to be larger, as no significant improvement is noticed. In the present situation, input parsimony is advantageous to the performance of the networks.

With respect to the advantage of multilayer perceptron neural networks, the results demonstrate that they have a capacity to accommodate heterogeneous precipitation fields. The training process may generate a network topology that can distinguish between precipitation events, even if only two inputs, streamflow and mean areal precipitation, are given. In the case of Bas-en-Basset, it can be assumed that two significantly different precipitation fields exist, that is, those in group 3 for both classifications (southern orography and heavy precipitation) and all the others combined (Fig. 6). In a classification tree, only one input is necessary to separate a data domain into two groups (e.g., smaller or bigger than a given threshold), and this is why only one precipitation input may be enough to differentiate between two different precipitation fields in the Bas-en-Basset watershed. In the situation where more than two precipitation fields are present, more than two precipitation inputs would be necessary to give the network topology a chance to make a distinction among the fields.

5 Conclusion

The goal of this work has been to accomplish a classification of precipitation fields so as to distinguish between homogeneous and heterogeneous precipitation events and hence collect information to better support rainfall-runoff modelling efforts on the Bas-en-Basset watershed from which the precipitation data come from. Kohonen neural networks are used as the classification tool while multilayer preceptron neural networks are employed as lumped models for one-day ahead streamflow prediction. The results of the classification validate the use of the Kohonen network as a classifier of precipitation fields. The classification generates groups of precipitation fields that are expected to exist on the Bas-en-Basset watershed considering the general climate patterns of the region and the physical constraints (orography). The classification can help afterward to refine the analysis of the performance of rainfall-runoff models. Performance can be analysed with respect to each group of precipitation fields. The performance analysis accomplished on the Bas-en-Basset watershed has shown that rainfall-runoff models produce the largest errors for cases of moderately to highly heterogeneous precipitation fields, which is to be expected of conventional hydrological models. On the basis of this analysis with respect to group of precipitation fields, solutions such as the addition of precipitation inputs or the development of specific models per group can be envisioned. The use of more than one precipitation input has not led to performance improvement in rainfall-runoff modelling for this application. With respect to the advantage of multilayer perceptron neural networks, it can be said that they can account for heterogeneous precipitation, providing that enough inputs are given to the models to allow for the distinction between the existing precipitation fields. In the case of the Bas-en-Basset watershed, it can be assumed that only two significantly distinct precipitation fields actually exist, and consequently only one precipitation input is required. Further development on this application would involve the exploration of combinations of rain gauges from among the 23 available that would be better able to represent precipitation on the watershed and lead to improved rainfall-runoff modelling performance.

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Table 1. Discrimination of precipitation fields with respect to the classifications into 3 and 6 groups.

3-group classification	6-group classification 1	2	3	4	5	6	Total
1	270	3	0	815	249	0	1337
2	299	525	1	4	337	233	1399
3	1	101	755	0	2	336	1195
Total	570	629	756	819	588	569	3931

Table 2. Summary of performance for the three cases of rainfall-runoff modelling according to precipitation inputs.

Number of precipitation inputs	Network architecture	Number of parameters	SSE (mm^2)	RMSE (mm)	PERS
1	2-7-1	29	171.7	0.316	0.795
2	3-6-1	31	179.5	0.323	0.785
4	5-5-1	36	195.3	0.337	0.767

Table 3. Summary of rainfall-runoff modelling performance per group of precipitation fields.

Group number	No classification SSE (mm^2)	RMSE (mm)	PERS	3-group classification SSE (mm^2)	RMSE (mm)	PERS	6-group classification SSE (mm^2)	RMSE (mm)	PERS
				One precipitation input					
0	5.2	0.112	0.680	5.2	0.112	0.680	5.2	0.112	0.680
1	166.6	0.357	0.797	19.6	0.215	0.704	4.0	0.155	0.718
2				22.5	0.215	0.809	4.4	0.140	0.559
3				124.5	0.559	0.804	117.1	0.671	0.810
4							15.6	0.237	0.705
5							17.3	0.303	0.835
6							8.1	0.206	0.656
				Two precipitation inputs					
0	5.2	0.113	0.675	5.2	0.113	0.675	5.2	0.113	0.675
1	174.2	0.365	0.788	20.5	0.219	0.690	4.8	0.169	0.664
2				14.4	0.172	0.878	4.8	0.147	0.513
3				139.3	0.591	0.781	131.2	0.710	0.787
4							15.6	0.237	0.705
5							9.5	0.224	0.909
6							8.2	0.208	0.649
				Four precipitation inputs					
0	5.0	0.110	0.692	5.0	0.110	0.692	5.0	0.110	0.692
1	190.3	0.381	0.768	22.1	0.228	0.667	5.9	0.187	0.587
2				16.4	0.184	0.860	3.5	0.125	0.646
3				151.9	0.617	0.761	144.4	0.745	0.765
4							18.0	0.254	0.661
5							9.1	0.219	0.913
6							9.4	0.222	0.599

Note: the 0 group represent the days when no precipitation is recorded at any of the rain gauges.

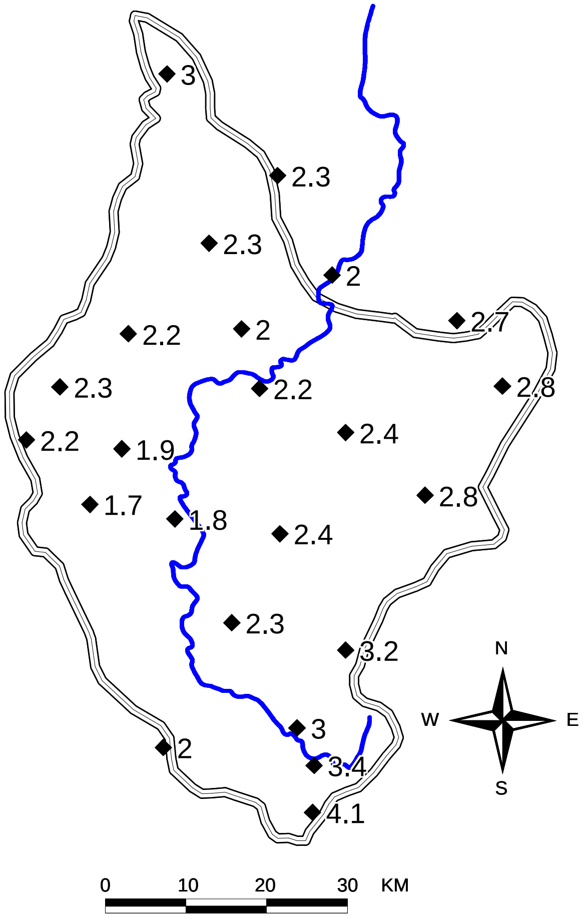

Fig. 1. Schema of the Bas-en-Basset watershed, with precipitation average at each of the rain gauges (including non-rainy days).

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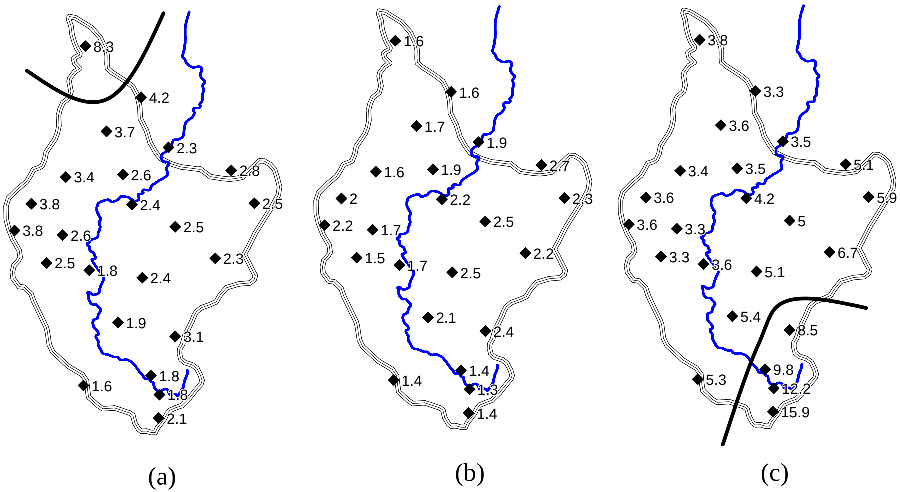

Fig. 2. Average daily precipitation at every rain gauge, per group, for the classification of precipitation fields into 3 groups.

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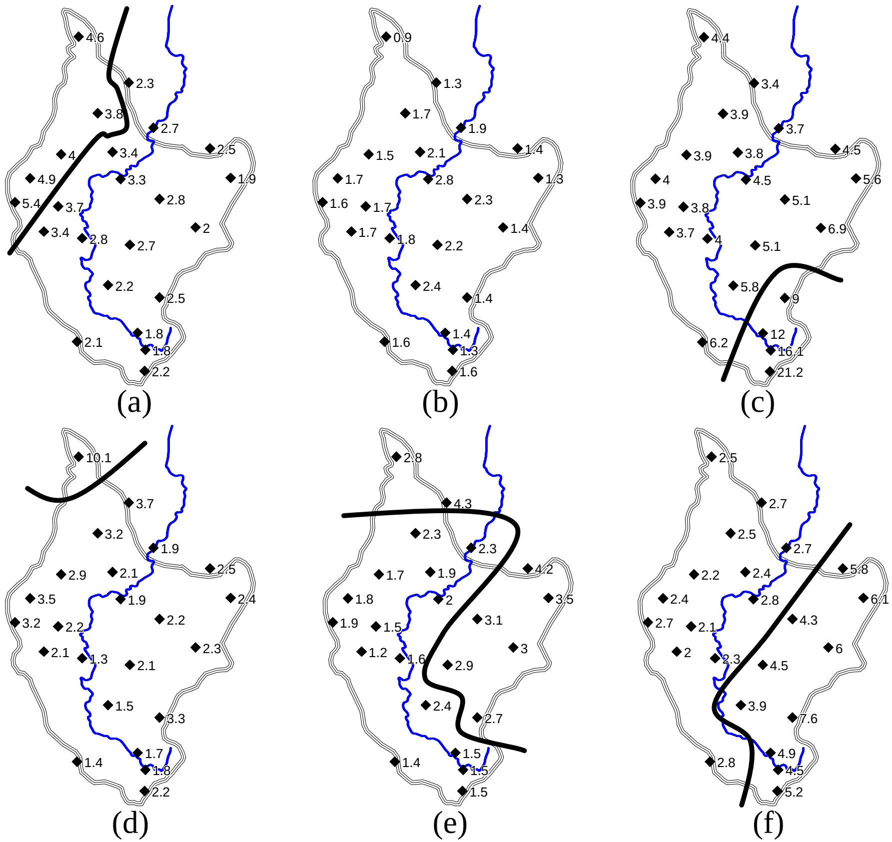

Fig. 3. Average daily precipitation at every rain gauge, per group, for the classification of precipitation fields into 6 groups.

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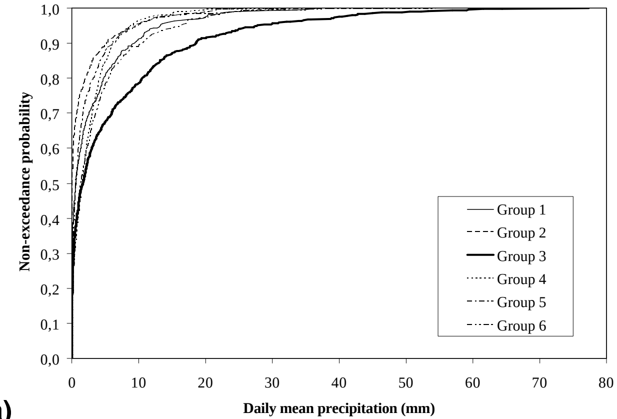
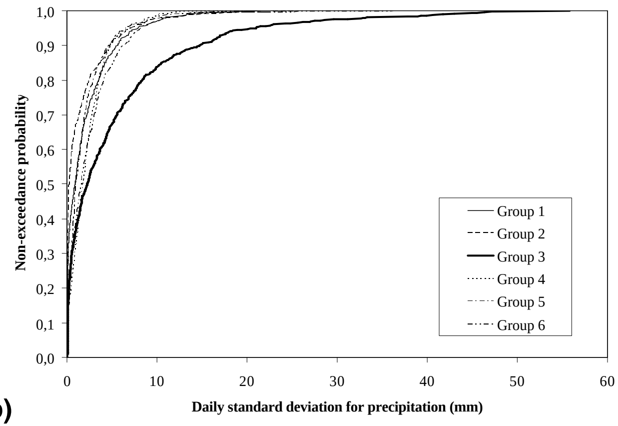


(a)



(b)

Fig. 4. Distribution of the daily mean precipitation **(a)** and daily standard deviation of precipitation **(b)** with respect to each group for the classification into 6 groups.

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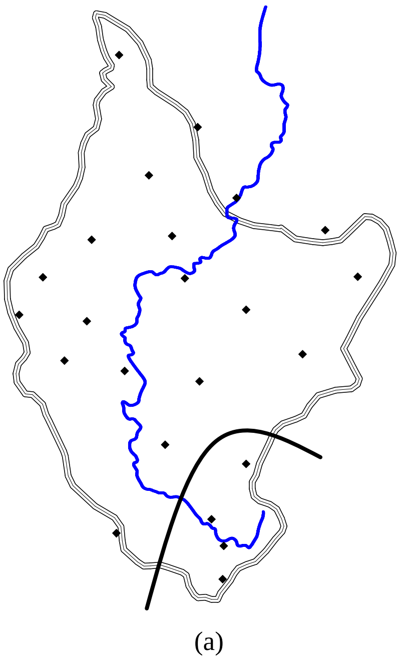

Fig. 5. Division of the watershed into **(a)** two and **(b)** four regions for the determination of precipitation inputs for the rainfall-runoff models.