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Classification of hydro-meteorological conditions and multiple artificial neural networks for streamflow forecasting

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Abstract

This paper presents the application of a modular approach for real-time streamflow forecasting, that uses different system-theoretic rainfall-runoff models according to the situation characterising the forecast instant. For each forecast instant, a specific model is applied, parameterised on the basis of the data of the similar hydrological and meteorological conditions observed in the past. In particular, the hydro-meteorological conditions are here classified with a clustering technique based on Self-Organising Maps (SOM) and, in correspondence of each specific case, different feed-forward artificial neural networks issue the streamflow forecasts one to six hours ahead, for a mid-sized case study watershed. The SOM method allows a consistent identification of the different parts of the hydrograph, corresponding to current and future hydrological conditions, on the basis of the only information available in the forecast instant. The results show that an adequate distinction of the hydro-meteorological conditions characterising the basin, hence including additional knowledge on the forthcoming dominant hydrological processes, may considerably improve the rainfall-runoff modelling performance.

1 Introduction

Metric (or system-theoretic) and hybrid metric-conceptual (see Wheater et al., 1993) models have always represented a natural candidate for online forecasting of the rainfall-runoff transformation (WMO, 1992; Young, 2002), since the real-time framework gives more importance to the simplicity and robustness of the model implementation rather than to an accurate description of the various internal sub-processes.

System-theoretic models are based primarily on observations (data driven models) and seek to characterise the system response from extensive records of past input and output variables. They are, therefore, particularly sensitive to the set of data used for their calibration, which must be suitable for inferring an adequate input-output re-

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lationship. On the other hand, also the use of physically-based approaches cannot, yet, overcome the need to calibrate at least a part of the model parameters, so that the significance of calibration data is crucial in any kind of rainfall-runoff transformation model.

The significance of the data belonging to a particular period, and therefore the reliability of a model parameterised on that data set, are strictly linked to the hydrological processes taking place in the period. Such processes are in fact strongly variable in time: the physical phenomena governing the streamflow generation at the beginning of a storm are certainly extremely different from those dominating the falling limb of the same flood hydrograph, and even further from those responsible for the low flows.

This constatation is at the basis of the formulation of event-based models, where it is explicit the intention of modelling only the processes that are dominant during flood events. But the same consideration guides the calibration procedure of continuously-simulating models where the hydrologist has to choose which part of the observed hydrograph is most important to fit, either implicitly, through the visual agreement in manual calibration, or explicitly, through the choice of the objective function(s). Changing the objective functions it is in fact possible to emphasise different kind of errors, giving them more weight in the calibration phase, for example with functions distinguishing high and low flows (Coulibaly et al., 2001; de Vos and Rientjes, 2007), or with peak, time-to-peak or volume errors in case of flood events. In order to keep openly into account the fact that more aspects of the observed hydrograph should be adequately reproduced by the simulated flows, multi-objective calibration algorithms have been successfully developed in the recent years (e.g. Gupta et al., 1998; Madsen, 2000; Vrugt et al., 2003; Tang et al., 2006; de Vos and Rientjes, 2007), with the aim of helping the hydrologists to choose an optimum (even if always subjective) trade-off.

A different line will be followed in this study, consisting in the implementation of multiple models, that is a modular approach diversifying the rainfall-runoff models on the basis of the specific hydro-meteorological situation presenting itself in each forecast instant.

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The hydrological and meteorological conditions characterising the instant in which the forecast is issued determine in fact which hydrological processes will be dominant in the following period. The future evolution of the streamflow values is therefore simulated with a different model for each forecast instant, chosen in function of the hydro-meteorological situation and parameterised on the basis of the evolution of the similar situations observed in the past. This approach is particularly suitable for system-theoretic, data-driven models: in this work, multi-layer Artificial Neural Networks (ANN) will be used, where there is no explicit a priori representation of the known physical processes and the models are set up exclusively on the basis of the available data.

The identification of the different hydro-meteorological conditions corresponding to each forecast instant will be done with a classification technique based on the use of Self-Organising Maps (SOMs, Kohonen, 1982, 2001). The SOMs were originally used principally for signal recognition, organization of large collections of data and information processing, but they are now acknowledged as a powerful clustering technique (Mangiameli et al., 1996; Astel et al., 2007) and have been recently used also in a variety of water resources studies (see Kalteh et al., 2008, for an exhaustive review). The main advantages of the SOM clustering algorithm are that it is non-linear and it has an ability to preserve the topological structure of the data (ASCE Task Committee, 2000a), thus allowing also an evaluation of the affinity between the clusters, as explained in the following.

2 The Sieve River case study

The case study herein considered is referred to the Sieve River basin, a first tributary of the Arno River, located on the Apennines Mountains in Tuscany, North-Central Italy. The Sieve River basin is elongated in shape and the drainage area is around 830 km^2 at the outlet section of Fornacina, where the time of concentration is approximately 10 h.

At the closure section, hourly discharge observations were collected between 1 January 1992 and 31 December 1996. For the same observation period, hourly rainfall depths at 12 raingauges are available, thus allowing the computation of the average areal precipitation over the watershed with an inverse squared distance weighting of the raingauges observations. The calibration procedures described in the following are based on the data belonging to the first three hydrological years of the observation period, from 1 September 1992 to 31 August 1995. The last 16 months, from 1 September 1995 to 31 December 1996, are used for validation purposes. In correspondence of each time instant, six forecasts are issued, corresponding to a lead-time varying from 1 to 6 h.

3 Artificial neural networks for streamflow forecasting

The appeal of the use of Artificial Neural Networks (ANNs) as hydrological models lies mainly in their capability to flexibly and rapidly reproduce the highly non-linear nature of the relationship between input and output variables, and it is certainly worthy considering ANN models as powerful tools for real-time short-term runoff forecasts.

An extensive review of the potentiality of ANNs in hydrological modeling was given, for example, by the ASCE Task Committee (2000b) and by Maier and Dandy (2000). The majority of the applications for river flow prediction consists in modeling the rainfall-runoff transformation, providing in input past flows and past precipitation observations: extremely encouraging results have been obtained in literature on both real and synthetic rainfall-runoff data (among the many others, in the recent years: Cameron et al., 2002; Solomatine and Dulal, 2003; Jain et al., 2004; Khan and Coulibaly, 2006; Shamseldin et al., 2007; Srivastav et al., 2007). Despite the importance of calibration information in a data-driven technique, little attention has been paid, so far, to the influence that the calibration period has on the forecasting performances of ANN rainfall-runoff modeling. Even if it is acknowledged that the choice of the training set has a fundamental weight (see, for instance, Minns and Hall, 1996; Campolo et al., 1999), only a few studies have presented, so far, an analysis of the impact of the use of different training data sets on ANN performances in validation (e.g. Dawson and Wilby, 1998; Anctil et al. 2004; Toth and Brath, 2007).

ANNs distribute computations to processing units called neurons, grouped in layers and densely interconnected. In the supervised feed-forward multilayer networks, three different layer types can be distinguished: an input layer, connecting the input information to the network (and not carrying out any computation), one or more hidden layers, acting as intermediate computational layers, and an output layer, producing the final output. In correspondence of a computational node, each one of the entering values is multiplied by a connection weight. Such products are then all summed with a neuron-specific parameter, called bias, used to scale the sum of products into a useful range. The computational node finally applies an activation function to the above sum producing the node output. The ANNs applied in the present work have only one hidden layer: tan-sigmoidal activation functions were chosen for the hidden layer and linear transfer functions for the output layer.

Weights and biases are determined by means of the quasi-Newton Levenberg-Marquardt BackPropagation optimisation procedure (Hagan and Menhaj, 1994), minimising a learning function expressing the closeness between observations and ANN outputs, in the present case the mean squared error. To mitigate overfitting and to improve generalization, a Bayesian regularization of the learning function (Foresee and Hagan, 1997; Anctil et al., 2004) was applied.

For each lead-time, a distinct mono-output network will be implemented: the output of each network, $Q_{\text{sim}}(t+L)$, corresponds to the streamflow forecast issued, in the forecast instant t, for each lead-time L.

The input data consist of the most relevant information that is generally available in a real-time flow forecasting system, that is past rainfall and streamflow observations.

The optimal number of input nodes (corresponding to past streamflow and mean areal precipitation values) and of hidden nodes to be included in the network is strongly case-dependent: the investigation of the performances of several combinations of input and hidden layers dimensions was performed (through a trial-and-error procedure based on a "forward selection method", consisting in beginning by selecting a small number of neurons and then increasing it) in past researches on the same study watershed (partly reported in Toth and Brath, 2007) and will not be described here for sake of brevity. The architecture providing the best trade-off between parsimony and forecasting performances resulted the one feeding to the input layer four streamflow and three precipitation values preceding the forecast instant t, $\{Q_{\text{obs}}(t-3), Q_{\text{obs}}(t-2), Q_{\text{obs}}(t-1), Q_{\text{obs}}(t), P(t-2), P(t-1), P(t)\}$, with three nodes in the hidden layer and one output node $Q_{\text{sim}}\ (t+L)$. It was examined the possibility to implement a different architecture for each network, that is for each lead-time L, but the validation results showed, for each L, an analogous behaviour when varying the dimension of the layers.

4 Multi-network modeling

Extremely different methods for combining the river flow forecasts issued by a set of different rainfall-runoff models have been recently proposed in the literature, for example by Shamseldin et al. (1997, 2002, 2007), Abrahart and See (2002), Georgakakos et al. (2004), Solomatine and Siek (2006). This work, in particular, presents an implementation of multiple, alternative models, that is a modular approach that uses different, specialised rainfall-runoff models, chosen on the basis of the specific hydro-meteorological situation presenting itself in each forecast instant. Modular neural networks (or multi-network models) for streamflow forecasting have been successfully applied in the hydrological literature in the most recent years: interesting applications, considering different input variables and different methods for identifying the model appropriate to each case, have been recently presented with the objective of forecasting future streamflow at extremely variable time-scales (from hourly to monthly).

Furundzic (1998) was the first to propose a multi-network approach with decomposition of the modelling domain in a study on the relevancy of input variables. Zhang and

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Govindaraju (2000) introduced a modular architecture where different modules within the network were trained to learn subsets of the input space in an expert fashion: a gating network was used to mediate the responses of all the experts and the model was applied for forecasting monthly runoff values. An hybrid structure of Artificial Neural Networks, SORB, was proposed by Moradkhani et al. (2004): the architecture employed consisted of a Self-Organising Map (SOM) as an unsupervised training scheme for data clustering, which correspondingly provided the parameters required for the Gaussian functions in a Radial Basis Function (RBF) neural network. Such scheme was inspired by the Self Organizing Linear Output mapping (SOLO) proposed by Hsu et al. (2002): SOLO classifies the input information using a SOM and then maps the inputs into the outputs using multivariate linear regression. Parasuraman and Elshorbagy (2007) clustered the data set in two groups with a K-means algorithm before applying two different networks for forecasting monthly runoff values, obtaining a better reproduction of the dynamics of high flows. Gopakumar et al. (2007) used Self-Organising Maps (SOMs) for identifying a seasonal pattern classifying the monthly rainfall and runoff values: subsequently an ANN was developed for daily flow forecasting using only the data of the identified rainy season. A pioneer work that proposed clustering algorithms for grouping high-resolution streamflow data (at hourly time scale), thus explicitly decomposing the hydrograph in separate parts, for ANN multinetwork modelling, is that by Abrahart and See (2000): they implemented two separate ANN models, specifically developed for two rising limbs clusters. In their work, as also in the one by Wang et al. (2006), the classification was based on past river flow only, whereas information on the recent precipitation depths are precious for the identification of the streamflow evolution: in the period immediately following the forecast, a rising limb, for example, will keep increasing or will reach the peak and begin to decrease depending if the rainfall is continuing or if it has already stopped. Jain and Srinivasulu (2006) used both rainfall and flow values for decomposing the flow hydrograph and then forecasting one-step ahead daily streamflow with a multinetwork approach: the decomposition was performed with methods based on physical concepts and with a small SOM network, which classified the flows in low, medium and high ranges. Corzo and Solomatine (2007) applied a modular architecture based on the distinction of baseflow and excess flow obtained with i) a K-means clustering algorithm, ii) a semi-empirical constant slope method or iii) filtering algorithms of the hydrographs (where i) and ii) are again based on past flows only).

The objective of the study presented in this paper is to forecast the future hourly streamflow not only one-step ahead but for increasing lead-times, thoroughly exploring the potential of SOMs for identifying the different meteorological and hydrological conditions of each forecasting instant, and therefore the future dominant hydrological processes, thus improving the rainfall-runoff ANN modelling.

5 Classification of hydro-meteorological conditions

The classification of the conditions of the watershed in each forecast instant will be based on the most relevant available information, that is past rainfall and flow observations, assuming that such variables are able to characterise both the current situation and its near-future evolution. It is important to underline that the ongoing runoff in the forecasting section represents a precious information on the state of saturation of the basin before the forecast instant, and therefore on the capability of the system to respond to recent and current rainfall perturbation. The vector chosen for representing each forecast instant is therefore the same that will be provided in input to the multilayer feedforward ANNs modelling the future streamflow values: $\{Q_{obs}(t-3), Q_{obs}(t-2), Q_{obs}(t-1), Q_{obs}(t), P(t-2), P(t-1), P(t)\}$.

The classification is based on the use of a SOM (Self Organised Map), which organises the data according to their similarity.

5.1 Self organising maps

SOMs, or Kohonen networks (Kohonen, 1982, 2001), are artificial neural networks of the unsupervised type: as opposite to supervised networks (like the multilayer networks introduced in Sect. 3 for rainfall-runoff modelling) there is no known user-defined target that the output vector should reproduce: the desired solutions are not given and the network learns to cluster the input data by recognizing different patterns.

A SOM is formed by only two layers of nodes: the input layer contains a node for each of the n variables characterising the unit to classify and the output layer is an array, generally two-dimensional for the convenience of visual understanding, whose nodes are connected, by weighted connections, to the input layer. Each input vector "activates" only one output node, representing its class, using the Kohonen competitive learning rule.

Initially the weights are randomly assigned. When the n-dimensional input vector ($\boldsymbol{x}$) is sent through the network, each neuron of the network computes a distance measure, an Euclidean distance was here chosen, between the weight ($\boldsymbol{W}$) and the input:

$$\|\boldsymbol{x} - \boldsymbol{W}\| = \sqrt{\sum_{i=1}^{n} (x_i - W_i)^2} \, . \tag{1}$$

The neuron responding maximally to the given input vector, that is the weight vector having the minimum distance from the input vector, is chosen to be the winning neuron. The winning neuron and its neighbouring neurons are allowed to learn by changing the weights at each training iteration t, in a manner to further reduce the distance between the weights and the input vector:

$$\boldsymbol{W}(t+1) = \boldsymbol{W}(t) + \alpha(t) h_{lm} (\boldsymbol{x} - \boldsymbol{W}(t)) \, , \tag{2}$$

where α the learning rate, $\in [0 \;\, 1]$, l and m are the positions of the winning and its neighbouring output nodes and h_{lm} is the neighbourhood shape, that reduces the ad-

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justment for increasing distance:

$$h_{lm} = \exp\left(-\frac{\|l-m\|^2}{2\sigma(t)^2}\right), \tag{3}$$

where $\|l-m\|$ is the lateral distance between l and m on the output grid and σ is the width of the topological neighbourhood.

Lateral interaction between neighbouring output nodes ensures that learning is a topology-preserving process in which the network adapts to respond in different locations of the output layer for inputs that differ, while similar input patterns activate units that are close together. In this way, a SOM produces a topologically ordered output that displays the similarity between the samples presented to it (Foody, 1999). The network, once it has been trained, will decide which output node to activate in correspondence of each input vector: all the input vectors that activate the same node belong to the same class.

5.2 Results of the classification of hydro-meteorological conditions

The use of a SOM in the proposed research activity entails the association of each of the input variables defining the current hydro-meteorological condition, $\{Q_{obs}(t-3), Q_{obs}(t-2), Q_{obs}(t-1), Q_{obs}(t), P(t-2), P(t-1), P(t)\}$, to an input node. In the classification phase, such values are standardised to have mean equal to 0 and variance equal to 1, in order to give them the same importance in the distance measure.

It was chosen an output layer formed by 3 rows by 3 columns, for a total of 9 nodes, each one corresponding to a class, believing that such number is sufficient for representing a variety of hydro-meteorological conditions without preventing their following interpretation. The output layer topology is hexagonal, rather than rectangular, so that diagonal neighbours have the same distance as horizontal and vertical neighbours. The trained network will indicate, for any input vector, the class of the corresponding forecast instant, along with the affinity with other classes.

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The SOM was initially applied to the calibration set, that is to the first three hydrological years of the observation period, from 1 September 1992 to 31 August 1995. The vectors charactering each one of the instants of such period, formed by the precipitation and streamflow data preceding each instant, for a total of 26 280 vectors, were iteratively given in input to the SOM: at the end of the tuning phase, these vectors were classified in 9 homogeneous groups, formed by all the vectors resulting assigned to the same node on the output layer.

The hexagonal output layer is shown in Fig. 1, using markers that have similar colour and shape for the neighbouring nodes. The figure displays also a part of the observed hydrograph where, at each time t, representing each instant in which a forecast (or better, six forecasts for the varying lead-times) will be issued, the flow value is indicated by a marker having the colour and shape of the class to which the forecast instant is assigned. It is therefore possible to visualise which parts of the hydrograph are associated to the different classes. It should be noted that the hydro-meteorological condition, that is the class, of each forecast instant is the same, independent of the lead-time that will be successively considered for the forecast.

It may be observed in Fig. 1 that classes 1 and 2 (whose node are adjacent on the output layer) correspond to the rising limbs (beginning of the rising for class 1, values closer to the peak for class 2), whereas nodes 3 and 6 (contiguous as well, even if diagonally, on the hexagonal map) correspond to the maximum flow values, respectively around the peak and at the beginning of the falling limb. Nodes 7 and 8, even if it is less evident in the hydrograph zoom reported in the figure, are associated to recession low flows. The hydro-meteorological conditions corresponding to the remaining nodes (4, 5 and 9) are instead intermediate between the previously described classes and less easily identifiable.

The nature of the various classes pictured in Fig. 1 is recognisable also by analysing the numerousness of the classes and the mean values of the different variables in each class, reported in Table 1.

The table highlights that classes 1 and 2 are characterised by the highest precipitation values, as expectable along rising limbs, while the highest streamflow values are associated to nodes 3 and 6. Minimum streamflow values and precipitation practically null correspond to nodes 7 and 8 and it may also be noted that such conditions are largely dominant in terms of class numerousness.

Overall, the SOM allows to clearly recognize the different conditions, distinguishing the parts of the hydrograph not only in terms of the flow value corresponding to the forecast instant and to the previous ones, but, keeping into account also the recent meteorological forcing, it seems able to discern the near-future trend of the hydrograph evolution.

6 Rainfall-runoff modelling

Preliminary to the design of the modular approach, in order to have a term of comparison for the multi-network results, one traditional, global rainfall-runoff ANN model is implemented, trained on all the data belonging to the calibration period. As a matter of fact, as described in Sect. 3, six different mono-output feed-forward networks, with seven nodes in the input layer and three hidden nodes, were implemented for forecasting the future streamflow from one to six hours ahead, $Q_{\mathrm{sim}}(t+L)$.

Having identified, in Sect. 5, the nature of the different hydro-meteorological conditions and the corresponding classes of forecast instants, it is possible to build the modular rainfall-runoff system: nine ANN models, each one formed by six mono-output networks for the varying lead-times, are implemented. Every model is parameterised through a training procedure that uses exclusively the input-output vectors, of the calibration period, belonging to the same class. In this way, a different model is built for each class, to be used in correspondence of each particular hydro-meteorological condition.

In the validation phase, streamflow forecasts are issued for every instant belonging to the last 16 months of the observation period, whose data was not used in any way nor in the tuning of the SOM, nor in the parameterisation of the rainfall-runoff models. In the modular approach, the tuned SOM already used to classify the calibration data is first used to associate every instant of the validation period to one of the identified nine classes. The rainfall-runoff module corresponding to that class is then chosen for issuing the streamflow forecasts.

The validation performances of the forecasts issued by the global and by the 9-class modular approach are evaluated by the Nash-Sutcliffe efficiency,

$$E_L = 1 - \frac{\sum_{t=1,N} \left[Q_{\text{obs}}(t+L) - Q_{\text{sim}}(t+L)\right]^2}{\sum_{t=1,N} \left[Q_{\text{obs}}(t+L) - \mu_{\text{obs}}\right]^2}, \quad L = 1 \div 6, \tag{4}$$

and also through an absolute error measure, namely the mean absolute error,

$$\text{MAE}_L = \frac{\sum_{t=1,N} \left|Q_{\text{obs}}(t+L) - Q_{\text{sim}}(t+L)\right|}{N} \tag{5}$$

where t is the forecast instant, μ_{obs} is the mean value of Q_{obs}, N is the total number of forecast instants and L is the lead-time, varying from 1 to 6 h in the present study. The efficiency coefficient varies in the range]–∞, 1], where 1 indicates a perfect agreement and negative values mean that the forecast is worse than assuming future occurrences equal to the mean value μ_{obs}. The range of MAE is [0∞[, with larger values indicating larger discrepancies.

As an additional benchmark, the forecasting performances are compared also with a naïve persistent model, where future streamflow is supposed to be equal to the last observed value over all the lead-times:

$$Q_{\text{pers}}(t+L) = Q_{\text{obs}}(t), \forall L \tag{6}$$

The error measures of the validation forecasts that are presented in Table 2 indicate, as expected, a remarkable improvement for both the global model and the modular one in comparison with the simple persistent model. It is, on the other hand, evident that the use of the 9-modules model allows an improvement of the MAE index, but it entails a deterioration of the efficiency coefficients, if compared to the global model.

It may be hypothesised that this deterioration is related to the number of data belonging to the classes: in fact, with the exception of classes 7 (and 8), the parameterisation of the rainfall-runoff models based on the only elements of each one of the remaining classes may result not adequate because of the numerousness, in some cases really meagre, of the classes. The reduced informative content of small-sized calibration sets may therefore be insufficient for a satisfactory characterisation of the input-output relationship in the calibration phase. This limit would particularly affect the classes different from 7 and 8, which in addition to be the most numerous are also those corresponding to the lowest streamflow values, and it would bring to less reliable performances in the prediction of the higher flows. Since the efficiency coefficient, like all quadratic measures, amplifies the highest errors, that generally correspond to the highest flows, this would justify the deterioration of such coefficient for the 9-classes modular model.

To overcome this problem, it was tested the opportunity to form wider (but always homogeneous from an hydrological point of view) classes of observations, so to ensure a greater numerousness of the data sets used in the calibration procedure. The SOM classification offers a straightforward solution for the formation of groups of similar classes. In fact, as said in Sect. 5, due to its topological properties, input vectors belonging to similar classes activate nodes that are adjoining on the output layer: in this way, nodes that are nearby may be considered representative of akin classes. Once identified, on the output map, an association of similar, adjacent nodes, it is therefore identified a new, broader class, formed by all the elements that activate each one of the neighbour nodes. One such possible association was already recognised in Sect. 5.2, based on the fusion of the following classes: 1 and 2 (rising limbs), 3 and 6 (flows close to the peak and beginning of falling limb), 7 and 8 (null precipitation and low flows) and the union of the remaining classes, corresponding to intermediate situations.

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A new classification is so obtained, formed by four larger classes: on the basis of these new classes a second modular system is built. Four different rainfall-runoff network models are calibrated using all and only the data belonging to each one of the larger classes of hydro-meteorological conditions.

The goodness-of-fit indexes of the forecasts in validation obtained with this second modular approach are reported in Table 2, as well. They show that this last approach appears the best performing one, providing efficiency coefficients analogous to those obtained with the global model and, at the same time, mean absolute errors as good as those of the first modular system, based on nine distinct classes.

7 Conclusions

The SOM method has proved to be an instrument suitable for an objective, automatic classification of the hydro-meteorological conditions of the watershed: its use allowed in fact a satisfactory identification of the different parts of the hydrograph corresponding to current and future hydrological conditions, on the basis of the only information available in the forecast instant.

As far as the real-time rainfall-runoff modelling is concerned, the performances of the first modular approach, based on the nine classes of hydro-meteorological situations, appear penalised by the dimension, in some cases really meagre, of the classes. The reduced informative content of not sufficiently numerous classes may in fact prevent an adequate characterisation of the input-output relationship in the calibration phase. Wider classes were therefore formed, but always hydrologically homogeneous since based on a reasoned association of the previously obtained classes, exploiting the property of the SOM, unique among the other clustering techniques, to provide indications on the similarity between the classes. The new modular system, differentiating the rainfall-runoff models according to the four associations of the original classes, allowed a remarkable improvement of the performances in validation, in comparison to both the first modular approach and to the global one. Overall, the results show that an adequate distinction of the hydro-meteorological conditions that characterise the basin at the forecast instant, thus including additional knowledge on the forthcoming hydrological processes, may considerably improve the rainfall-runoff modelling performance.

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Table 1. Numerousness of the nine classes obtained with the SOM and mean values, for each class, of the variables forming the input vectors of the calibration set.

Class	Members number	Mean value						
		Q_t (m^3/s)	Q_{t-1} (m^3/s)	Q_{t-2} (m^3/s)	Q_{t-3} (m^3/s)	P_t (mm/h)	P_{t-1} (mm/h)	P_{t-2} (mm/h)
1	1141	9.11	8.50	8.14	7.92	1.84	1.81	1.62
2	329	46.40	41.36	38.52	37.02	1.19	1.54	1.64
3	602	215.13	216.42	215.78	213.80	0.73	0.80	0.89
4	1295	5.87	5.79	5.74	5.69	0.28	0.23	0.29
5	1403	30.68	30.77	30.90	31.10	0.13	0.11	0.12
6	940	54.86	55.97	57.04	58.07	0.07	0.06	0.07
7	12 166	2.13	2.14	2.15	2.15	0.00	0.00	0.00
8	5462	9.09	9.12	9.16	9.20	0.01	0.00	0.01
9	2942	19.38	19.47	19.58	19.72	0.02	0.01	0.02

Table 2. Performance indexes of streamflow forecasts for the validation data set.

	Lead-time (hours)					
	1	2	3	4	5	6
	Mean Absolute Error (MAE), m^3/s					
Global model	0.53	1.11	1.52	2.03	3.07	2.85
1st modular approach (9 classes)	0.51	0.93	1.28	1.53	1.81	2.31
2nd modular approach (4 classes)	0.49	0.97	1.28	1.51	1.75	2.21
Persistent model	0.65	1.24	1.78	2.26	2.70	3.10
	Efficiency coefficient					
Global model	0.993	0.969	0.932	0.905	0.870	0.821
1st modular approach (9 classes)	0.988	0.961	0.914	0.890	0.836	0.747
2nd modular approach (4 classes)	0.993	0.963	0.924	0.911	0.874	0.824
Persistent model	0.974	0.910	0.824	0.734	0.648	0.573

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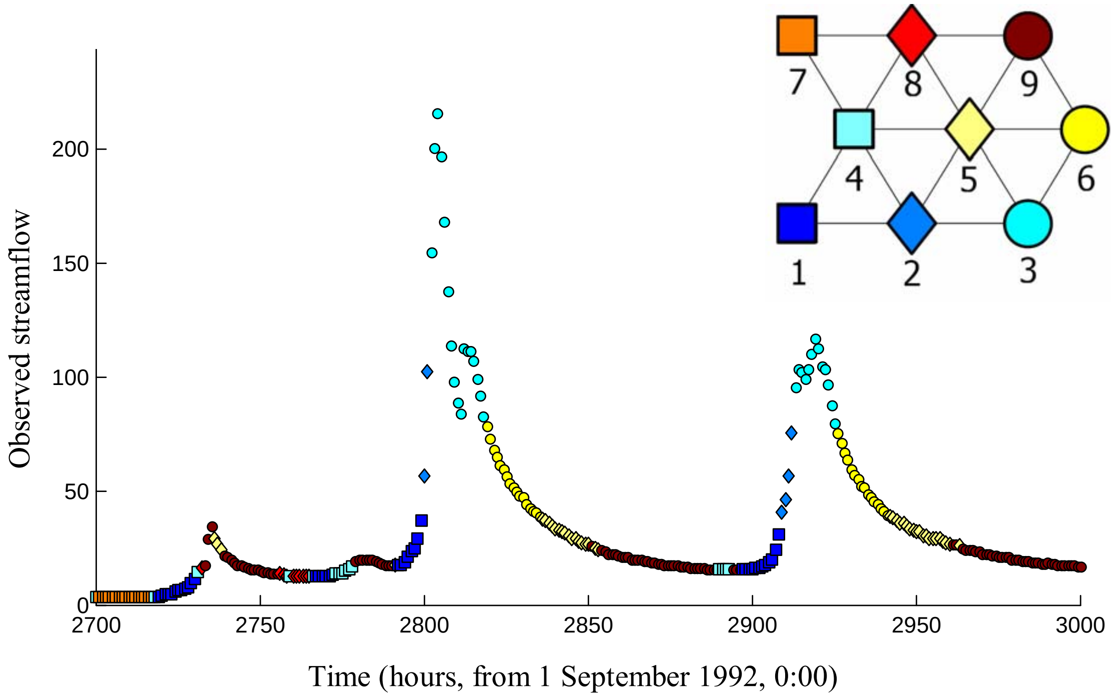

Fig. 1. Markers associated to the SOM output layer nodes (upper right-hand corner) and part of the observed hydrograph: the streamflow value relative to each forecast instant is indicated with the marker of the corresponding class.

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