Short-term rainfall prediction with time series analysis techniques for real-time flash flood forecasting

A. BRATH, A. MONTANARI and E. TOTH

Dipartimento di Ingegneria delle Strutture, dei Trasporti, delle Acque, del Rilevamento e del Territorio, University of Bologna, Viale Risorgimento 2, I-40136 Bologna, Italy. E-mail: elena.toth@mail.ing.unibo.it

ABSTRACT

The incorporation of quantitative precipitation forecasting has been recognised to play a key role in flash flood warning systems, allowing for an extension of the lead-time that enables a more timely implementation of the control measures. This study compares the performances of time-series methods for determining short-term rainfall forecasting in absence of meteorological information other than some historical rainfall data over the basin and the measurement of the current rainfall, so that the implementation of numerical weather prediction models or radar and satellite images extrapolation methods is not feasible. The examined rainfall time-series modeling approaches include linear stochastic models, artificial neural network models, and nearest-neighbour methods. The aim of the analysis is a comparison of the performances attainable by integrating the above methods in a runoff forecasting system applied to a real world case study, referred to the Sieve River basin on the Apennine Mountains in Italy. The time of concentration of the basin is around 10 hours and the drainage area is 830 km^2. The issued rainfall forecasts are routed through a conceptual, lumped, rainfall-runoff model and the efficiency of the forecasted river discharges are compared with those obtained with empirical approaches often adopted in the operational practice relying on the prediction of future rainfall based on heuristic methods.

1 INTRODUCTION

The importance of the incorporation of Quantitative Precipitation Forecasting in flood warning systems, thus allowing for longer lead-time and improved reliability of the warnings, is particularly strong for rapidly evolving floods, such as those developing in small and medium-sized basin typical of Mediterranean regions.

It is widely recognised that obtaining a reliable QPF is not an easy task, and great uncertainties still affect the performances of both stochastic and deterministic rainfall prediction models. This study compares the performances of time-series analysis techniques for determining short-term rainfall forecasting. Even if the predictive ability of these methods is limited because of the low persistence in time usually characterising rainfall time series, the possibility of implementing such methods in quick times and with moderate data availability makes their application attractive in the context of real-time flood forecasting.

The following time series methods have been considered: (1) linear stochastic AutoRegressive Moving Average (ARMA) and AutoRegressive Integrated Moving Average (ARIMA) models, which express the future rainfall as a linear function of past data. The approach is thus linear, model-driven and parametric, i.e. it first requires identification of the type of relationship among the variables (model identification) and then the estimation of model parameters; (2) Artificial Neural Network architectures (ANN), belonging to the non-linear, data-driven, approaches: the resulting model depends on the available data to be "learned", without any *a priori* hypothesis about the kind of relationship, which is allowed to be complex and non-linear; (3) K-Nearest Neighbours Method (K-NN), a non-parametric regression methodology, not implying any structured interaction but exploiting the closeness ("neighbourhood") between the most recent observations and K "similar" sets of observations chosen in an adequately large training sample.

The aim of our analysis is a comparison of the above methods from an operational point of view, considering an integrated rainfall and runoff forecasting system operated on a real world case study. The issued rainfall forecasts are routed through a lumped conceptual rainfall-runoff transformation model and the performances of the flow forecast are analysed and compared.

Given the predominance of the presence of null or very low values in the rainfall series and our interest in flood forecasting, we limited our analysis, both in the calibration and validation phase, to the rainfall values belonging to storm events, so to identify the temporal pattern characterising the storms, whose persistency properties are different from those of dry or low rainfall sequences.

2 CASE STUDY, DATA SETS AND CALIBRATION APPROACHES

The case study herein considered is referred to the Sieve River basin, a first tributary of the Arno River in Central Italy. The basin has a drainage area of 830 km^2 and the time of concentration is about 10 hours. The data set consists of five years of hourly discharges at the closure section of Fornacina and hourly precipitation in 12 raingauges, spatially averaged over the watershed. In the observation period a total of 84 storm events were identified and the corresponding precipitation and river discharge observations were collected.

Two alternative approaches were followed for estimating the parameters of the models: split-sample calibration and adaptive calibration. In the split-sample calibration the storm events were divided in two sets: a calibration (or training) set and a validation set, to test the performances of the calibrated model over out-of-sample occurrences. In the adaptive calibration no database of past significant observed events was supposed available for the calibration, but only the most recently observed values, so that the calibration of the model is implemented on-line, as soon as new observations become available. For both calibration approaches, in correspondence of each hourly time step belonging to the validation set, a rainfall forecast was issued for the subsequent 1 to 6 hours, using the most recent observations as inputs. The resulting forecasted rainfall values were processed as inputs to the rainfall-runoff transformation model thus providing the discharge forecast.

3 LINEAR STOCHASTIC MODELS (ARMA AND ARIMA)

Most of the time series techniques traditionally used for modeling water resources series fall within the framework of the AutoRegressive Moving Average class of linear stochastic processes. They are usually denoted as ARMA(p,q) models, where p and q, are, respectively, the autoregressive and moving average orders (Box and Jenkins, 1976; Brockwell and Davis, 1987). They describe each observation of the time series as a weighted sum of p previous data and the current and q previous values of a white noise process:

$$x_t = \phi_1(x_{t-1} - \mu_x) + \phi_2(x_{t-2} - \mu_x) + \ldots + \phi_p(x_{t-p} - \mu_x) + \eta_t + \theta_1\eta_{t-1} + \theta_2\eta_{t-2} + \ldots + \theta_q\eta_{t-q} + \mu_x \qquad (1)$$

where x_t, x_{t-1},… is the investigated time series; η_t is a white noise, i.e. a not-correlated, zero-mean random variable which is also not correlated with the past values of x_t; ϕ_1, ... , ϕ_p and θ_1, ... , θ_q are respectively the autoregressive and moving average parameters; μ_x is the mean of the time series.

The parameters of the models were estimated with an approximation in the spectral domain of the Gaussian maximum likelihood function, which was first proposed by Whittle (1953) for short-memory models.

The use of low-order ARMA processes to model short-term precipitation values was considered, following the modeling framework proposed by Brath et al. (1988) and Burlando et al (1993). The application of ARMA models requires the data to be stationary and this is often not the case for hourly rainfall observations, whose statistical properties may vary with the season. Nonetheless the limited number of rainfall events in the observation period prevented us, in the split-sample calibration, from grouping the events in monthly periods, as it is usually done in hydrology to circumvent non-stationarity. In the adaptive calibration application (corresponding to the "continuous" approach implemented by Burlando et al., 1993) non-stationarity is accounted for by allowing the model parameters to vary along time since the calibration is performed on the current event progress solely. Furthermore, we applied, in both split-sample and adaptive calibration approaches, the extension of ARMA models which permits the handling of non-stationary processes, denoted as AutoRegressive Integrated Moving Average (ARIMA) models, based on the differencing of the time series (Brockwell and Davis, 1987).

We preferred not to perform any preliminary transformation of the data in order to make them as close to Gaussian as possible. In fact, Gaussianity of the data is not required for the forecast application of ARMA and ARIMA models, since they provide the best linear prediction even in the non-Gaussian case (Brockwell and Davis, 1987).

The selection of the model autoregressive and moving average orders, p and q, was driven by some results available in literature. Obeysekera et al. (1987) determined an equivalence between the correlation structure of the ARMA(1,1) and ARMA(2,2) models and some widely known and satisfactorily used rainfall point process models, like the Poisson Rectangular Pulse, the Neyman-Scott White Noise models (Rodriguez-Iturbe et al, 1984) and the Neyman-Scott Rectangular Pulses model (Rodriguez-Iturbe, 1986). In both the split-sample and adaptive calibration we tested all the ARMA models with a total number of parameters less or equal to 6, and the ARIMA models corresponding to orders p and q ranging from 0 to 2 and order of differentiation d equal to 1 and 2.

In the adaptive calibration approach, the optimal number w of observations x_t immediately preceding the forecast time to be used for estimating the model parameters was chosen on the basis of the results of a previous study (Brath et al. 1998). The results showed that more than 3 days of hourly observations were needed for lead-times longer than 4 hours. Thus, we set the number of past rainfall hourly observations to be used in the adaptive calibration equal to 100.

4 Artificial Neural Networks (ANN)

Artificial Neural Networks have been widely studied and applied to a variety of problems, including hydro-meteorological variables simulation and forecasting. Several studies have been dedicated to the prediction of river flows both with and without exogenous inputs, that is with the only use of past flow observations or based on the knowledge of previous rainfall depths (and other meteorological variables) along with past observed flows (e.g. Karunanithi et al, 1994; Hsu et al., 1995; Shamseldin, 1997).

The use of ANN for rainfall forecasting has not been fully explored, yet. A pioneer work is the study by French et al. (1992), who applied a neural network to forecast 1 hour ahead, two-dimensional rainfall fields synthetically generated on a regular grid. Kuligowski and Barros (1998) generated QPF of point precipitation cumulated over the following 6-hours period using as inputs the antecedent rainfall depths measured in adjacent gauges and the radiosonde-based wind direction.

Neural networks emulate the human brain computational capacity by distributing computations to relatively simple processing units called *neurons*. The neurons are grouped in layers and adjacent layers are interconnected through synaptic links (*weights*). Three different layer types can be distinguished: *input layer*, connecting the input information, *output layer*, producing the final output, and one or more *hidden layers*, acting as intermediate computational layers between input and output. The input values are multiplied by the first interconnection weights, all such products are summed with a neuron-specific parameter, called *bias* (used to scale the sum of products into a useful range), and become inputs to the hidden layer nodes, which apply a non-linear *activation function* (usually a sigmoidal unit) to the above sum producing an hidden node output. These outputs are processed in the same way through the subsequent hidden layers (if existing) or through the output layer, generating the network output.

Neural networks are trained with a set of observed input and output (called *target* to be distinguished from the network final output) data pairs, the *training data set*, which is processed repeatedly, changing the values of the parameters until they converge to values such that each input vector produces output values as close as possible to the desired target vectors. The applied training technique is the popular and extensively tested BackPropagation (BP) training algorithm, a supervised learning method in which the output errors (differences between the network output and the target) is fed back trough the network, and the weights are gradually adjusted in the steepest gradient descent direction in the basic algorithm.

It has been proved that only one layer of hidden units «suffices to approximate any function with finitely many discontinuities to arbitrary precision», provided the activation functions of the hidden units are non-linear (the «*Universal Approximation Theorem*», see Hornik et al., 1989). Regarding the optimal number of nodes in the hidden layer, an ANN may suffer from either *underfitting* or *overfitting*. A network that is not sufficiently complex can fail to fully detect a complicated input-output relationship, leading to *underfitting*. A network with too large a number of hidden units will probably fit exactly the training set, but it may learn spurious relationships peculiar to the training data, becoming lacking in generalisation capability (*overfitting*).

Among the tested network architectures (changing the type of allowed connections between nodes) and variants to the basic BP algorithm, a classical multilayer feedforward network (see Fig.1) trained with the Levenberg-Marquardt algorithm (an optimisation method approximating a second order training speed), proved to be the best performing, quickest trained and less easily trapped in local minima.

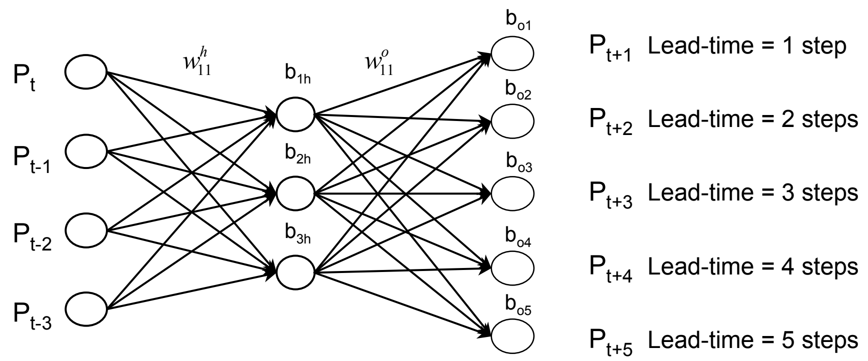

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Figure 1: Feed-forward direct multistep network. P_t is the precipitation process; t is the forecast instant, w_{ij}^h, w_{ij}^o are the connection weights towards the hidden and output layers and b_j are the nodes biases.

The most crucial disadvantage of ANN models is that the optimal network architecture is highly problem-dependent and no established methodology exists to deal with the neural network modelling problem. The complexity of the model, that is the number of input and hidden nodes, has therefore been determined with a trial-and-error approach.

In the split-sample application, networks with a number of input nodes ranging from 2 to 24 were tested. For each input layer dimension the number of hidden nodes was progressively increased from 2 to 8 and each time a deterioration of the forecasting performance on the validation set, indicating overfitting, was shown for very moderate dimensions of the hidden layer. In the adaptive calibration more parsimonious networks (from 2 to 4 nodes in each layer) were investigated, given the modest forecasting performance improvement allowed by increasing complexity, as highlighted by the split-sample calibration.

5 K-NEAREST-NEIGHBOUR METHOD (K-NN)

The K-Nearest-Neighbours method has its origins as a non-parametric statistical pattern recognition procedure. Yakowitz (1987) and Karlsson (Karlsson and Yakowitz, 1987a,b) did considerable work in extending the K-NN method to time series and forecasting problems, obtaining satisfactorily results and constructing a robust theoretical base for the K-NN method. The intuitiveness of the approach and the powerful theoretical basis have made the method attractive to forecasters, and the method found successful applications in hydrology (e.g. Galeati, 1990; Kember and Flower, 1993; Todini, 1999).

For each forecast instant t, let $\underline{\mathbf{x}}^{\mathbf{d}}(t) = (x_{t-d+1}, \ldots, x_t)$ be a *feature vector* of past records. The method assumes that the probability distribution of the random variable conditioned on the entire past is the same of the random variable conditioned on the d past observations only $(x_{t+1} / \underline{\mathbf{x}}^{\mathbf{d}}(t))$.

It was proved that the K-NN forecaster is asymptotically optimal among all the forecasters defined on the feature vector $\underline{\mathbf{x}}^{\mathbf{d}}(t)$. That is, under fairly general circumstances, convergence to the optimal forecaster is assured as the historical data set increases (Karlsson and Yakowitz, 1987b). Optimality is preserved for any function relating past and future values, and also when the forecasting error depends on past values. On the contrary, conventional methods, such as ARMA or Kalman filters, are optimal only if the function is linear and the error is white noise (Galeati, 1990).

To estimate $\hat{x}_{t+1}$ the K-NN method requires to impose a metric $\| \cdot \|$, usually the Euclidean norm, on the feature vector $\underline{\mathbf{x}}^{\mathbf{d}}(t)$ and to find the set of K past *nearest neighbours* of $\underline{\mathbf{x}}^{\mathbf{d}}(t)$, i.e. the K d-dimensional vectors of past observations: $\underline{\mathbf{x}}^{\mathbf{d}}(t_j)$, j = 1,…., K, which minimise $\|\underline{\mathbf{x}}^{\mathbf{d}}(t) - \underline{\mathbf{x}}^{\mathbf{d}}(t_j)\|$.

The forecast is obtained by averaging the temporal evolution of the nearest neighbours, assumed to be similar to the evolution of the current situation:

$$\hat{x}_{t+L} = \frac{1}{K} \sum_{j=1}^{K} x_{t_j+L} \ . \tag{2}$$

The nature of the Nearest-Neighbour method makes it not suitable for an adaptive calibration, because the approach is based on the availability of an extended database and it has no extrapolation ability when presented with an unfamiliar input vector. Therefore, only the split-sample calibration was performed. A trial-and-error test was implemented for a number of nearest neighbours, K, ranging from 5 to 100 and a dimension of the feature vector, d (corresponding to the number of past rainfall data considered representative for the forecast), ranging from 2 to 12.

As equation (2) indicates, in no case a value higher than the maximum historical rainfall depth can be predicted. This may be a strong limitation in extreme events forecasting. To circumvent this deficiency the method was applied to forecast:

(a) the change in value, that is the difference between the predicted and the last observed value x_t instead of the forecasting the value itself:

$$\hat{x}_{t+L} = x_t + \frac{1}{K} \sum_{j=1}^{K} \left(x_{t_j+L} - x_{t_j} \right); \tag{3}$$

(b) the *differenced* rainfall depths time series:

$$x'_t = x_t - x_{t-1,} \forall t\,. \qquad (4)$$

These alternative methods, although promising because allowing to forecast values higher than the historically observed, failed to bring any substantial improvement in the performances of our forecasts in comparison with the standard nearest neighbour approach.

6 ANALYSIS OF RAINFALL FORECASTING RESULTS

For each one of the considered time series methodologies (ARMA models, ANN and K-NN method), the performances of all the forecasting schemes tested in the trial-and-error tests were classified according to the mean of the *correlation coefficient* over all the 6 steps ahead for which the forecasts were issued. The *correlation coefficient* is given by the covariance of forecasts and observations divided by the product of the square root of the respective variances. It ranges from –1 to 1, higher values indicating better agreement.

All the ARMA models tested in the split-sample calibration provided analogous results, whereas the performances of ARIMA models were sometimes not satisfactory. The trends of the correlation coefficients of the ARMA and ARIMA model adaptively calibrated were all comparable: the performance was good for lead-time of 1 hour, but there was a strong deterioration for longer lead-times.

When calibrated with the split-sample approach, the ANN performance considering all the lead-times improves as the number of input nodes increases, with modest additional improvement for more than 15 nodes. For a given number of input nodes, the dimension of the hidden layer providing the best results is low, between 2 and 6 hidden nodes. The ANN adaptive calibration proved to be not reliable for short lead-times but it was satisfactorily stable for lead-times longer than three hours, provided that the dimensions of the layers are neither too small nor too large (the best performing architecture has 3 input and 3 hidden nodes).

As far as the Nearest-Neighbour method is concerned, the performance improves with increasing number of nearest neighbours, K, while small values (from 2 to 4) for the feature vector dimension, d, seem the most appropriate.

Figure 2 presents the correlation coefficients of the best performing among all the investigated methods.

The ANN corresponding to the split-sample obtains the overall best results for lead-times longer than 2 hours, even if this kind of structure slightly penalises the one-hour ahead forecast. Considering all the lead-times, this methodology provides the most satisfactory performance among all the considered approaches. Thus, neural networks seem to be the best performing time-series method for rainfall forecasting among those herein considered, in reference to the Sieve River case study. In addition, almost all the computational effort for the implementation of the ANN split-sample application is spent in the training phase, while the issue of the forecasts with the trained network is practically instantaneous, thus making this approach very appealing in a real-time forecasting framework.

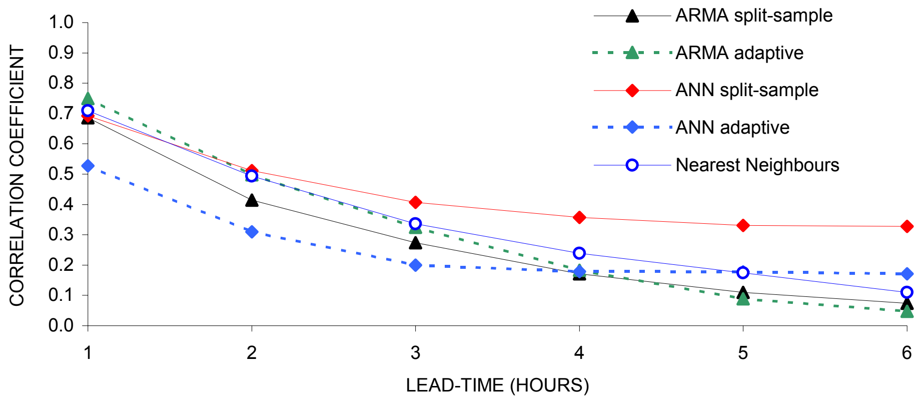

Figure 2: Correlation coefficients of the rainfall forecasting procedures: ARMA(2,2) models with split-sample and adaptive calibration; best ANN with split-sample and adaptive calibration; best performing Nearest-Neighbour implementation.

7 RAINFALL-RUNOFF TRANSFORMATION

7.1 Hydrologic model description

The deterministic model used for simulating the rainfall-runoff transformation is a conceptual continuous simulation model called ADM (Franchini, 1996), which is based on the concept of probability distributed soil moisture storage capacity. The model is divided into two main blocks: the first represents the water balance at soil level and is characterised by 7 parameters, while the second represents the transfer of runoff production at the basin outlet and involves 4 parameters. The soil, in turn, is divided into two zones: the upper zone produces surface and subsurface runoff, while the lower zone produces base runoff. The transfer of these components to the outlet section takes place in two distinct stages: the first representing the flow along the hillslopes towards the channel network, while the second the flow along the channel network towards the basin outlet. The calibration of the conceptual model was performed with a global optimisation algorithm, the SCE-UA proposed by (Duan et al, 1992).

7.2 Standards of reference: heuristic rainfall predictive approaches

In order to evaluate the performances of the analysed time series forecasting methods when used as inputs in the rainfall-runoff transformation model, the results in terms of obtained discharges will be compared with some predictive benchmarks, or standards of reference, consisting in rainfall forecasting approaches of purely heuristic nature.

The probably most widespread approach when modelling rainfall-runoff transformation in real-time is to assume that the future rainfall will be null (*null rainfall approach*). It is an optimistic hypothesis, assuming that the forecast is issued at the end of the event while, especially in basins with short response time, forecasts are needed earlier in the storm progress.

A second term of comparison, widely used in forecasting theory, is the *persistent* method, which equals the future rainfall intensity, over all the investigated lead-times, to the last measured value,

$$\hat{x}_{t+L} = x_t, \forall L . \tag{4}$$

The last investigated heuristic approach, denoted as the *modified persistent* method, consists in extrapolating future values setting the intensity for each given lead-time L equal to the mean intensity measured over the last L observations, that is,

$$\hat{x}_{t+L} = \frac{1}{L}\sum_{i=1}^{L} x_{t-i+1} . \tag{5}$$

7.3 Analysis of flow forecasting performances

The improvement in the discharge forecasts attainable using the QPF provided by the different rainfall predictive models was evaluated computing the correspondent *coefficients of efficiency*, widely recognised as one of the most suitable goodness-of-fit measures for runoff.

For the analysis of discharge performances, the discharge series chosen as a reference was not the series of observed discharges, but the hourly discharges simulated by the conceptual model when using as inputs the observed precipitation (*"true"* discharges). This scenario was considered in order to be able to evaluate the improvement retrievable by the rainfall forecasting alone, independently of the effects of the simulation errors induced by possible inadequacies of the hydrologic model. Accordingly, the *coefficient of efficiency* is given by:

$$E = 1 - \frac{\sum (Q_t - \hat{Q}_t)^2}{\sum (Q_t - \overline{Q})^2} , \tag{6}$$

where $\hat{Q}_t$ is the discharge at time t forecasted with a given lead-time, Q_t is the value of the corresponding "true" discharge and $\overline{Q}$ is the mean of the whole series Q_t.

Figure 3 shows the performances, in terms of efficiency coefficient, of the coupled rainfall-runoff forecasting schemes obtained with all the considered rainfall forecasting procedures.

It may be observed that the rainfall-runoff transformation tends to level out all the rainfall forecasts corresponding to very short lead-times. As a consequence the good performance of ARMA and ARIMA models with adaptive calibration for lead-time of one hour becomes unnoticeable. The ANN adaptive calibration architectures provide by far the worst results, and this is not surprising, considering the limits of ANN when trained on small data sets. As it was expected, the *null rainf*all hypothesis proves to be not realistic, since it may strongly underestimate the rainfall volumes, whereas the *persistent* methods (both in the traditional formulation and *modified*) provide an improvement with respect to the *null rainfall* approach.

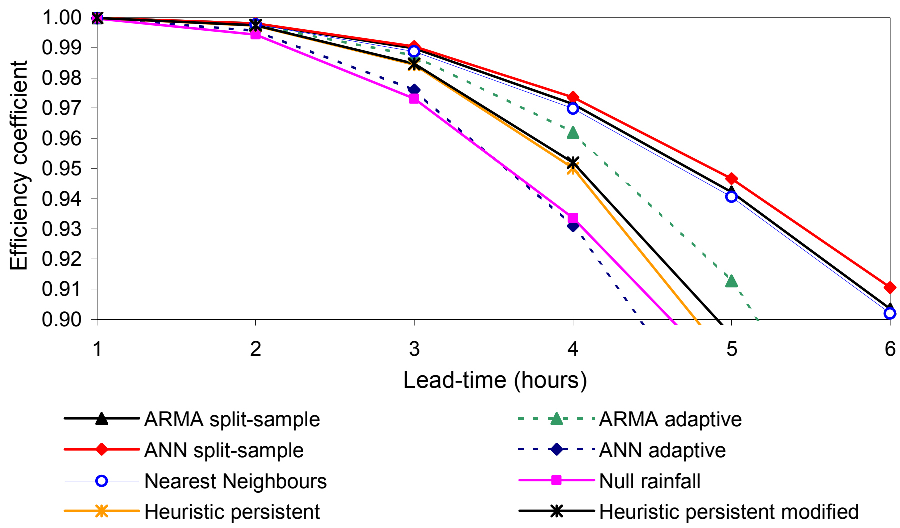

Figure 3: Efficiency coefficients of the river flows corresponding to the rainfall forecasting procedures: ARMA(2,2) models with split-sample and adaptive calibration; best ANN with split-sample and adaptive calibration, best Nearest-Neighbour implementation; null rainfall, *persistent* and *persistent modified* methods.

Overall the split-sample calibration techniques seem to be preferable with respect to the adaptive calibrations. This is probably due to the "experience" they learned from past samples, which allows them to better reproduce the rainfall evolution mechanism for longer lead-times, and the flattening caused by the hydrologic transformation gives more weight to the accuracy of the rainfall forecasts corresponding to longer time horizons. On the other hand the adaptive calibration procedures yielded better results for lead-times of one and two hours.

The split-sample calibrated Artificial Neural Networks produced the highest efficiency values. Therefore, the coupled rainfall-runoff forecasting comparison confirms, with regard to our case study, the superiority of ANN already shown in the analysis of the performances of rainfall forecasts.

8 CONCLUSIONS

The study indicates that the considered time-series analysis techniques provide an improvement in the flood forecasting accuracy with respect to the use of intuitive, heuristic rainfall prediction approaches. The results show that the use of time series analysis techniques for precipitation forecasting may allow an extension of the lead-time up to which a reliable flood forecast may be issued, providing a quick prediction based on past values solely and directly in the format required by the rainfall-runoff transformation model. On the other hand strong limitations to a time-series analysis approach are due to the lack of other meteorological information needed for a reliable prediction. It follows that a more substantial improvement may be pursed through the coupling of time series techniques with Numerical Weather Prediction models, thus providing a physically-based forecasting framework at the temporal and spatial scales required by hydrologic models

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