

Predicting and forecasting flow discharge at sites receiving significant lateral inflow

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Abstract:

Two models, one linear and one non-linear, were employed for the prediction of flow discharge hydrographs at sites receiving significant lateral inflow. The linear model is based on a rating curve and permits a quick estimation of flow at a downstream site. The non-linear model is based on a multilayer feed-forward back propagation (FFBP) artificial neural network (ANN) and uses flow-stage data measured at the upstream and downstream stations. ANN predicted the real-time storm hydrographs satisfactorily and better than did the linear model. The results of sensitivity analysis indicated that when the lateral inflow contribution to the channel reach was insignificant, ANN, using only the flow-stage data at the upstream station, satisfactorily predicted the hydrograph at the downstream station. The prediction error of ANN increases exponentially with the difference between the peak discharge used in training and that used in testing. ANN was also employed for flood forecasting and was compared with the modified Muskingum model (MMM). For a 4-h lead time, MMM forecasts the floods reliably but could not be applied to reaches for lead times greater than the wave travel time. Although ANN and MMM had comparable performances for an 8-h lead time, ANN is capable of forecasting floods with lead times longer than the wave travel time. Copyright © 2007 John Wiley & Sons, Ltd.

KEY WORDS rating curve; ANN; feed-forward back propagation; modified Muskingum method; prediction; forecasting; flood hydrograph; flow stage; lead time

Received 17 March 2005; Accepted 24 February 2006

INTRODUCTION

Determination of flow discharge at a river site is required for water resource management and flood control. Discharge is computed from the measurement of flow depth, channel width, and flow velocity. For these measurements, the river section is equipped with hydro-metric sensors for flow depth measurement, and cableway and current meter for velocity measurement. For channel cross-section, a topographic survey is carried out. Although the measurement of flow depth is simple and relatively inexpensive, velocity and channel cross-section measurements are not. For example, sampling of velocity points by current meter is quite difficult during severe floods, especially in the lower portion of the flow area (Moramarco *et al.*, 2004). Furthermore, velocity measurements and channel cross-section surveys are expensive, especially at sites that are not easily accessible. This is one reason for relating flow discharge to flow depth.

Hydraulic modelling based on the Saint Venant equations is commonly used for translating discharge into flow depth, e.g. Hydrologic Engineering Centers River Analysis System (HEC-RAS) (U.S. Army Corps of Engineers, 1998). However, this requires topographic information on river cross-sections. For many rivers,

topographic surveys neither exist nor are readily available. For this reason, many simplified approaches, such as the Jones formula (Henderson, 1966; Fenton, 1999) or the Muskingum method (Franchini and Lamberti, 1994), have been employed to relate the local stage to the discharge. However, these models involve parameters that are related to flood hydraulic characteristics. When lateral inflow is predominant during the evolution of flood, estimation of these parameters becomes difficult (Moramarco *et al.*, 2005).

Moramarco *et al.* (2005) developed a practical model that can also be applied to cases in which lateral inflow is significant. It is especially useful when the downstream boundary condition is unknown or velocity measurements are available for low flows only. This model was also compared with the Muskingum model. The model of Moramarco *et al.* (2005) assumes a linear relation between the upstream and downstream flow variables and performs satisfactorily when the linearity is not unduly violated. This model, however, remains to be tested for cases in which the non-linearity between upstream and downstream flow variables is significant. Furthermore, it is desirable to have a model to simulate the non-linear flood process, especially when there is significant lateral inflow. Thus, the motivation for this study was to develop a non-linear artificial neural network (ANN) based on feed-forward back propagation (FFBP) for predicting the stage–discharge relationship.

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In addition, this study also deals with flood forecasting in real-time, where conceptual rainfall-runoff models of the semi-distributed type have been most reliable for operational purposes (Boyle *et al.*, 2001; Michaud and Sorooshian, 1994). However, the complexity of the watershed system, the large number of parameters involved, and uncertainty in the determination of spatial resolution of each hydrologic process have led to the implementation of rather simple models (Boyle *et al.*, 2001). One such approach is the Muskingum model (Franchini and Lamberti, 1994; Barbetta *et al.*, 2003), but this model is not suitable where the lateral inflow contribution is significant and the rating curve is unknown (Moramarco *et al.*, 2005). To overcome this difficulty, Barbetta *et al.* (2004) developed a modified Muskingum model (MMM). This is a 5-parameter model and the parameters are estimated by non-linear regression using upstream flow discharge hydrograph and downstream flow-stage data. Furthermore, MMM is limited to forecasting floods for lead times less than or equal to the flow wave travel time. Therefore, this study developed an ANN model to forecast real-time hourly flow hydrographs of individual storms.

Dawson and Wilby (1998) and Laio *et al.* (2003), among others, have also developed ANN models for flood forecasting. The ANN model in this study is different in that (1) it does not require rainfall data in the input vector, (2) it uses only semi-hourly flow-stage data measured at the upstream and downstream stations in the input vector, and (3) it does forecasting for individual storms at sites receiving significant lateral inflows.

Thus, the objective of this study is to (1) investigate the effectiveness of ANN in both predicting and forecasting hourly flow discharge hydrographs of individual storms in real-time at a downstream station using only hourly flow-stage data measured at the upstream and downstream stations of a river reach receiving significant lateral inflow, and (2) to compare the ANN with the linear model of Moramarco *et al.* (2005) and the MMM for predicting and forecasting individual storm hydrographs. The models are evaluated using flood events measured at different gauging stations on the Tiber River in central Italy, which receives significant lateral inflows.

ARTIFICIAL NEURAL NETWORKS FOR FLOOD PREDICTION AND FORECASTING

ANNs have the ability to capture a relationship from given patterns and this makes them suitable for employment in the solution of large-scale complex problems, such as pattern recognition, non-linear modelling, classification, association, and control. ANNs are attractive for discharge prediction and flood forecasting because they can accommodate the non-linearity of the watershed runoff process and uncertainty in the parameter estimation, they have the capability to extract the relationship between input and output of the process without explicitly considering the physics of the process, they

can find the relationships between different input samples, and they can generalize a relationship from small subsets of data while remaining robust in the presence of noisy or missing inputs. Because of these desiderata, they have been widely used in solving a range of hydrologic problems (ASCE Task Committee, 2000b). Tokar and Johnson (1999) developed an ANN to predict daily runoff as a function of daily precipitation, temperature, and snowmelt for a watershed in Maryland, USA. Tokar and Markus (2000) applied an ANN to predict monthly streamflow for the Fraser River Watershed in Colorado, USA. Using daily rainfall data, Rajurkar *et al.*, (2002) applied an ANN for predicting daily flows during monsoon flood events for a large size catchment in India. Cigizoglu (2003) applied an ANN to estimate daily flow data of the rivers in the eastern part of the Mediterranean region of Turkey. Most of the ANNs employed only daily or monthly hydrometric data in the input vector for making long term predictions. ANNs have also been compared with regression using simple conceptual black box or stochastic models (ASCE Task Committee, 2000b; Rajurkar *et al.*, 2002; Cigizoglu, 2003).

ANNs also have found wide application in forecasting studies. French *et al.* (1992) used an ANN to forecast rainfall intensity fields in space and time. Using real hydrometric data, Dawson and Wilby (1998) used an ANN to forecast flow rates for a 6-h lead time in two flood-prone catchments in the United Kingdom. They also carried out forecasting at a gauging station for longer periods (about 6 months) using rainfall and flow discharge data measured at the same station. Imrie *et al.* (2000) developed a cascade-correlation ANN to forecast flow rates for 4-h and 12-h lead times for two rivers in the catchment of river Trent in the United Kingdom using measured flow rates from 1996 to 1998. Similarly, using rainfall data in the input vector, Laio *et al.* (2003) performed a comparative study of forecasting flow stage at a gauging station on the Tanaro river in Alba in northwestern Italy. They compared the performances of ANN and NLP (non-linear prediction) for lead times of 1, 3, 6, 12, and 24 h.

MATHEMATICAL MODELS

Artificial neural networks (ANNs)

In hydrologic applications, a three layer feed-forward type of ANN is commonly considered (Figure 1). In a feed-forward network, the input quantities are fed into input layer neurons, which, in turn, pass them on to the hidden layer neurons after multiplication by a weighted value. A hidden layer neuron adds up the weighted input received from each input neuron, associates it with a bias, and then passes on the result through a non-linear transfer function. The output neurons execute the same operation as performed by a hidden neuron. The back propagation algorithm finds the optimal weights by minimizing a predetermined error function (E) of the following form

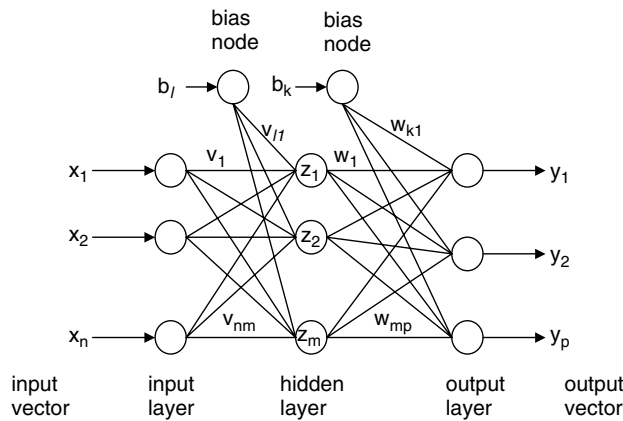


Figure 1. Representation of the three layer feed-forward ANN

(ASCE Task Committee, 2000a):

$$E = \sum_P \sum_p (y_i - t_i)^2 \tag{1}$$

where y_i = component of a network output vector \mathbf{Y} ; t_i = component of a target output vector \mathbf{T} ; p = number of output neurons; and P = number of training patterns.

In the back propagation algorithm, optimal weights would generate an output vector $\mathbf{Y} = (y_1, y_2, \dots, y_p)$ as close as possible to the target values of the output vector $\mathbf{T} = (t_1, t_2, \dots, t_p)$ with a selected accuracy. The back propagation algorithm employs the gradient-descent method, along with the chain rule of differentiation, to modify the network weights as follows (ASCE Task Committee, 2000a):

$$v_{ij}^{new} = v_{ij}^{old} - \delta \frac{\partial E}{\partial v_{ij}} \tag{2}$$

where v_{ij} = weight from the i th neuron in the previous layer to the j th neuron in the current layer; and δ = learning rate.

The network learns by adjusting the biases and weights that link its neurons. Before training begins, a network's weights and biases are set equal to small random values. Also, owing to the nature of the sigmoid function used in the back propagation algorithm, all external input and output values are standardized before passing them into a neural network. Without standardization, input of large values into an ANN would require extremely small weighting factors to be applied, and this could cause a number of problems (Dawson and Wilby, 1998). The details of ANNs are available in the literature (ASCE Task Committee, 2000a).

Rating curve method (RCM)

The model of Moramarco *et al.* (2005), termed as the Rating Curve Method (RCM), is briefly summarized. Discharge at the downstream station is related to the measured flow variables at the upstream station as

$$Q_d(t) = \alpha \frac{A_d(t)}{A_u(t - T_L)} Q_u(t - T_L) + \beta \tag{3}$$

where Q_u = the upstream discharge; Q_d = the downstream discharge; A_d and A_u = the effective downstream and upstream cross sectional flow areas obtained from the observed stages, respectively; T_L = the wave travel time depending on the wave celerity, c ; and α and β = model parameters (Moramarco *et al.*, 2005).

Parameters α and β are estimated from the following equations utilizing the base flow and peak discharge (Moramarco and Singh, 2001):

$$Q_d(t_b) = \alpha \frac{A_d(t_b)}{A_u(t_b - T_L)} Q_u(t_b - T_L) + \beta \tag{4}$$

$$Q_d(t_p) = \alpha \frac{A_d(t_p)}{A_u(t_p - T_L)} Q_u(t_p - T_L) + \beta \tag{5}$$

where $Q_d(t_b)$ = base flow rate at the downstream section; $Q_d(t_p)$ = peak discharge at the downstream section; t_p and t_b = times when the peak stage and base flow occurs at the downstream section, respectively. In particular, t_b is assumed to be the time just before the start of the rising limb of the hydrograph.

Once $Q_d(t_b)$ and $Q_d(t_p)$ are known, parameters α and β are obtained from the solution of Equations (4) and (5) (Moramarco *et al.*, 2005). The base flow at the downstream end, $Q_d(t_b)$, can be estimated through velocity measurements of low flow or it can be assumed that the velocity along the reach is constant when the base flow occurs (Moramarco *et al.*, 2005). The peak discharge, $Q_d(t_p)$, is surmised as the contribution of two main elements: (i) the upstream discharge delayed for the wave travel time T_L , $Q_u(t_p - T_L)$, with its attenuation, Q^* , due to flood routing along the reach of length L ; and (ii) the lateral inflows, $q_p L$, during the time interval $(t_p - T_L, t_p)$:

$$Q_d(t_p) = (Q_u(t_p - T_L) - Q^*) + q_p L \tag{6}$$

In Equation (6), T_L is implicitly assumed as the time required to match the rising limb and the peak region of the upstream and downstream dimensionless hydrographs. The flood attenuation (Q^*) is computed from the Price formula (Raudkivi, 1979). The lateral inflow contribution, $q_p L$, is obtained from the characteristic form of the continuity equation (Moramarco *et al.*, 2005). q_p is estimated by assuming that, along the characteristics corresponding to the downstream peak stage, the following relationship holds (Moramarco and Singh, 2000):

$$\frac{A_d(t_p) - A_u(t_p - T_L)}{T_L} = q_p \tag{7}$$

Modified Muskingum Method (MMM)

A brief summary of the MMM, developed by Barbetta *et al.* (2004), is given here. When significant lateral inflow occurs along a reach, the Muskingum model expresses the discharge at the downstream end as

$$Q_d(t + \Delta t) = k_o Q_u(t + \Delta t) + k_1 Q_u(t) + k_2 Q_d(t) \tag{8}$$

where $k_o = (1 + p_l)c_o$; $k_1 = (1 + p_l)c_1$; $k_2 = c_2$, satisfying $k_o + k_1 + k_2 > 1$; c_o, c_1 , and c_2 are parameters

depending upon the Muskingum coefficients K and x and the time step Δt (Franchini and Lamberti, 1994) ($c_0 + c_1 + c_2 = 1.0$; $c_1 = \frac{Kx + 0.5\Delta t}{K - Kx + 0.5\Delta t}$, and $c_2 = \frac{K - Kx - 0.5\Delta t}{K - Kx + 0.5\Delta t}$; subscripts u and d are for the upstream and downstream sections, respectively; Q is the flow discharge; t is time; and q_l takes account of the lateral inflow contribution.

Assuming that the discharge is known only at the upstream hydrometric section, Equation (8) can be expressed in terms of flow stage at the downstream station (h_d) using the kinematic wave relationship $Q = \lambda h^\delta$ for the downstream rating curve. The MMM can then be formulated in terms of water level, h_d , as

$$h_d(t + \Delta t) = \left\{ \frac{1}{\lambda} [(1 + p_l)c_0 Q_u(t + \Delta t) + (1 + p_l)c_1 Q_u(t) + c_2 \lambda h_d^\delta(t)] \right\}^{1/\delta} \quad (9)$$

Since the aim is to produce a water level forecasting model, the term $Q_u(t + \Delta t)$ on the right-hand side of Equation (9) must be eliminated. To do so, it is sufficient to choose the time interval as $\Delta t = \Delta t^* = 2Kx$ resulting in $c_0 = 0$. Thus, the final version of the MMM is obtained as follows (Barbetta *et al.*, 2004):

$$h_d(t_f + \Delta t^*) = \left\{ \frac{1}{\lambda} [(1 + p_l)c_1^* Q_u(t_f) + c_2^* \lambda h_d^\delta(t_f)] \right\}^{1/\delta} \quad (10)$$

where c_1^* and c_2^* are obtained when $\Delta t = \Delta t^* = 2Kx$.

Parameters λ , δ , c_1^* , c_2^* , and p_l in Equation (10) are estimated by a non-linear regression technique using observations of downstream water level and upstream discharge. An adaptive scheme can be used to take account of the variability of lateral inflow during flood evolution, such as the one proposed in Barbetta *et al.* (2004).

MODEL APPLICATION

Watershed

The upper basin of Tiber river in central Italy, which has river reaches that are equipped, was selected for testing the linear and non-linear models for both prediction and flood forecasting. Figure 2 shows locations of the selected hydrometric sections along with the subtended drainage areas. Table I summarizes the main characteristics of the selected river reaches. Each gauged section is equipped with a remote ultrasonic water level gauge, and the velocity measurements are carried out by current meter.

Hydrologic data

Several accurate flow measurements were available, which allowed the estimation of the rating curve for each section (Moramarco *et al.*, 2005). Of the seven severe storm events that occurred, four events (June 1997, May 1995, January 1997, February 2004) were chosen for

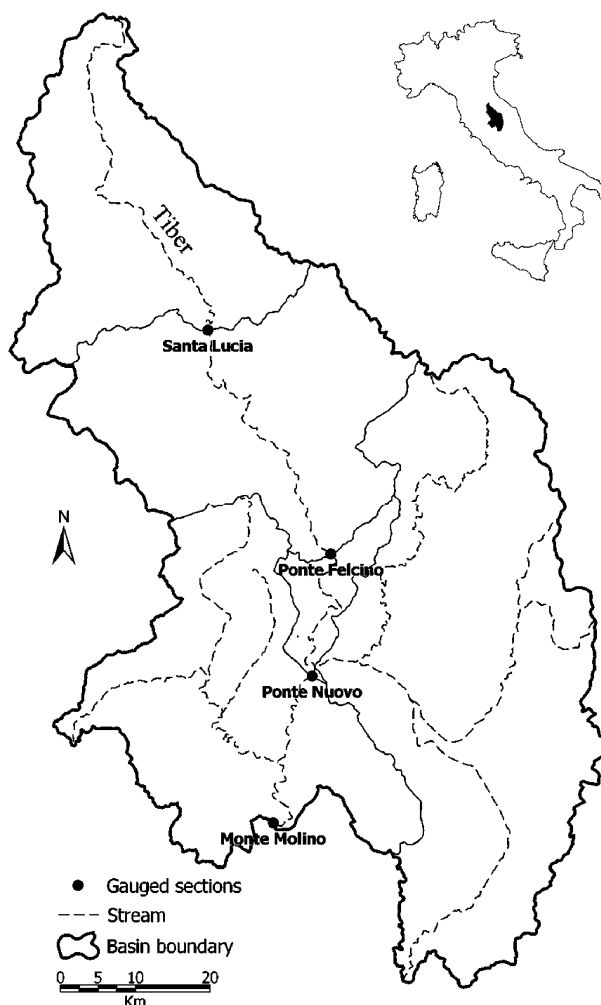


Figure 2. Upper Tiber river basin with the location of the gauging sites and the related subtended drainage areas

Table I. Geomorphologic characteristics of the river reaches

River	Bounded sections	Drainage area (km ²)	Reach length (km)	Mean slope	Mean width (m)
(1)	(2)	(3)	(4)	(5)	(6)
Tiber	Santa Lucia	935	44.6	0.0016	35
Tiber	Ponte Felcino	2035	56.2	0.0009	50
	Monte Molino	5279			

training the FFBP neural network model. The remaining three events were used for testing the model. The main properties of the selected flood events are summarized in Table II. It is seen that the lateral inflow contribution was significant in some of the events. Although the events for the training and testing groups in Table II were randomly chosen, special attention was paid to have testing events with hydrograph characteristics (e.g. base flow rate Q_b ; peak flow rate Q_p ; direct runoff volume V) that are comparable with those in the training set in order to avoid any bias in model predictions (Table II).

The river reach between the Santa Lucia and Ponte Felcino gauging stations (Figure 2) was considered for

Table II. Main characteristics of the observed flood events at stations on Tiber river

Date	Santa Lucia Station			Ponte Felcino Station			T_L (h)
	Q_b ($m^3 s^{-1}$)	Q_p ($m^3 s^{-1}$)	V ($10^6 m^3$)	Q_b ($m^3 s^{-1}$)	Q_p ($m^3 s^{-1}$)	V ($10^6 m^3$)	
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
December 1990	8.2	418	49.5	9.6	404.2	59.5	2.0
January 1994	35.6	108	19	50.8	241	34.7	3.0
May 1995 ^a	4.2	71.0	10.3	8.8	138.7	19.1	4.0
January 1997 ^a	18.2	120.2	24.3	36.2	225.0	51.8	3.5
		146.2			359.0		
June 1997 ^a	5.0	345.6	27.6	10.8	449.6	49.1	5.0
January 2003	24	58	13.5	50	218	40.9	3.5
February 2004 ^a	22	91	7.4	55	276	27.3	3.5

Q_b , base flow; Q_p , peak discharge; V , direct runoff volume; T_L , travel time.
^a Used for ANN model training.

testing the models for flood prediction. The ANN model used the flow-stage data at Santa Lucia station (upstream station) and Ponte Felcino station (downstream station) to predict the flow discharge at Ponte Felcino station. The travel time between the two stations is about 4 h. As pointed out earlier, since flow stage is an easily measurable variable, hydrologists prefer to relate flow rate to flow stage, as in the case of the RCM. This is why this study chose flow stage as an input variable to predict the flow rate in a river cross-section.

Error criteria

The prediction or forecasting error was computed as follows:

$$Error (\%) = \frac{(predicted\ quantity - observed\ quantity)}{observed\ quantity} \times 100$$

Quantity may be the peak discharge or the time to peak. The error was assessed using the persistence coefficient defined as follows (Kitanidis and Bras, 1980):

$$C_p = 1 - \frac{\sum [Q_d^o(t) - Q_d^p(t)]^2}{\sum [Q_d^o(t) - Q_d^o(t - \Delta t)]^2} \quad (11)$$

where C_p = the persistence coefficient; $Q_d^o(t)$ = the observed discharge at the downstream station at time t ; $Q_d^p(t)$ = the predicted discharge at the downstream station at time t ; and Δt = the forecasting lead time. If $C_p = 1$, then the performance of the proposed model for forecasting is perfect. If $C_p = 0$, then there is no need to use the proposed model for forecasting.

Flood hydrograph prediction

ANN model training. ANN was trained with a learning rate of 0.01 and 2000 iterations. The network had 2 neurons in the input layer, 5 neurons in the inner layer, and 1 neuron in the output layer. Input neurons represent flow stage at the upstream and downstream points while output neuron is for the flow rate at the downstream location. Before training was initiated, all the data fed

into the network were standardized and small random values were assigned for the network's weights and biases. Further details are given by Tayfur (2002). The number of neurons in the hidden layer was decided by the commonly employed trial and error procedure. For this purpose, the mean error (ME) and mean relative error (MRE) were used as the error measures. Accordingly, the number of iterations that provided the minimum ME and MRE values was the criteria for terminating the iterations. For example, for this particular problem of flood hydrograph prediction application, the values of the error measures started with $ME = 181.7 m^3 s^{-1}$ and $MRE = 63.4$ at the first iteration and then rapidly decreased to $31.1 m^3 s^{-1}$ and 32.4 , respectively, after the 100th iteration. The errors then gradually decreased and stabilized at $ME = 10.4 m^3 s^{-1}$ and $MRE = 16.5$ after 2000 iterations.

Model testing: hydrograph prediction. The trained ANN and the linear RCM were applied to predict the hydrographs of the three testing events (December 1990, January 1994, January 2003) measured at the Ponte Felcino station (Table II). Figure 3a–c show the predicted hydrographs. It is seen that ANN satisfactorily predicted the hydrographs in terms of the overall trend, time to peak, and peak discharges. Overall, it yielded better results than did the RCM, which generally over-estimated the discharge. For the two-peak hydrograph of January 2003 (Figure 3c), ANN under-predicted the lower peak but closely captured the higher peak, whereas RCM predicted the lower peak better, but over-predicted the higher peak. The percentage error in peak discharge and time to peak was computed for each event and is given in Table III. Note that a negative error value indicates underestimation whereas a positive value indicates overestimation. ANN predicted the peak discharge of each event with less than 5% error whereas RCM had more than 10% error. For the January 2003 event, RCM over-predicted the peak discharge with about 24% error whereas ANN had 5% error. The time to peak was accurately predicted by ANN whereas RCM had about 4% error.

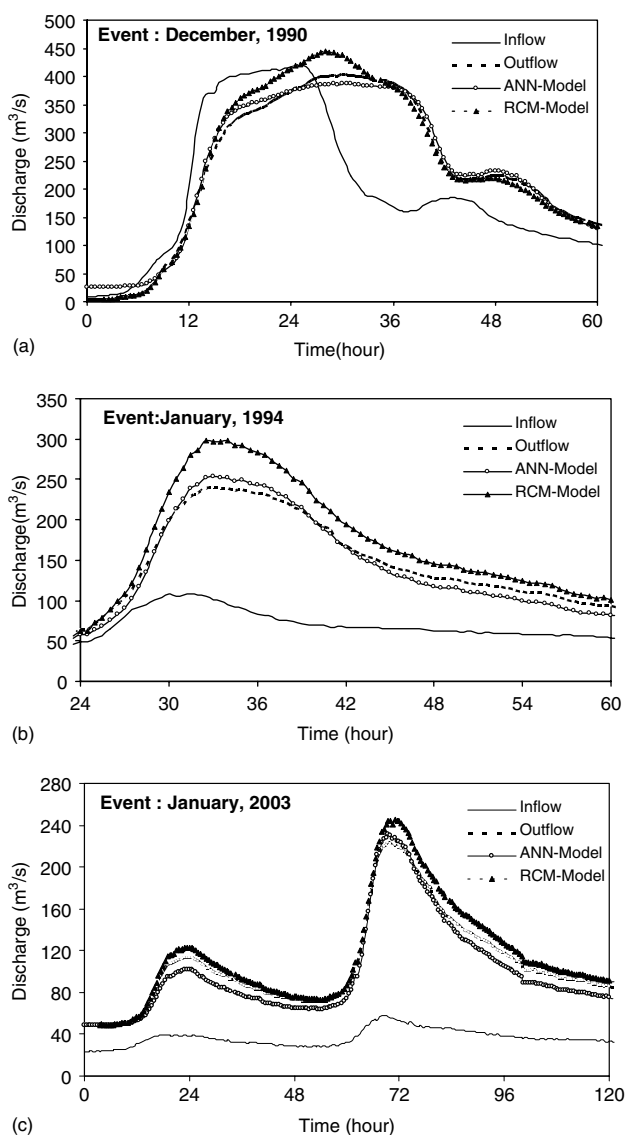


Figure 3. ANN and RCM model simulations of the flood hydrographs measured at the Ponte Felcino gauging station on (a) December 1990, (b) January 1994, and (c) January 2003

Table III. Percentage errors in peak discharge, E_{Qp} , and time to peak, E_{Tp}

Event	E_{Qp} (%)		E_{Tp} (%)	
	ANN	RCM	ANN	RCM
December 1990	-4.2	9.9	0.0	-6.7
January 1994	3.1	9.4	0.0	2.2
January 2003	5.4	23.7	0.0	3.0
Average	4.2	14.3	0.0	4.0

Sensitivity analysis. For sensitivity analysis, ANN was evaluated using only the flow-stage data measured at the upstream station as input and predicting the discharge at the downstream station. For this purpose, the ANN network had 1 neuron in the input layer and 4 neurons in the hidden layer. The network was trained with a 0.01 learning rate and 2000 iterations. The storm events in Table II were used for ANN training and testing. Figure 4a–c

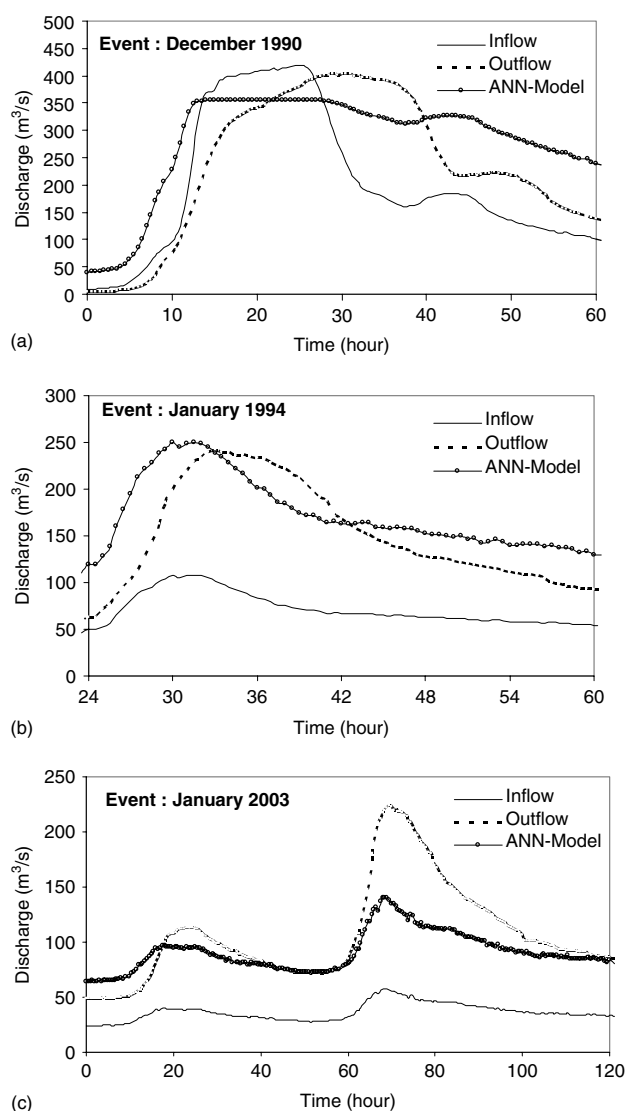


Figure 4. ANN model simulations of the flood hydrographs measured at the Ponte Felcino gauging station on (a) December 1990, (b) January 1994, and (c) January 2003 (The network input is the flow discharge measured at the Santa Lucia station)

show the predicted and measured hydrographs. ANN captures the magnitude of peak discharge with delay in each case in which there is insignificant lateral inflow into the channel reach (Figure 4a and b). On the other hand, the model poorly predicts the hydrograph when there is significant lateral inflow into the channel reach (Figure 4c). The model prediction error for each event is given in Table IV. When lateral inflow is not significant, the model under-predicts the discharge with delay, with an error of about 10%. If lateral inflow is significant, the prediction error in peak discharge reaches 40% (Figure 4c, Table IV). This result indicates that when the contribution of lateral inflow to the channel reach is not significant, the ANN model may be employed using only the flow-stage data at the upstream station for predicting the hydrograph at a downstream station.

Extrapolation. The extrapolation capability of ANN for predicting peak discharge outside the range of values

Table IV. Percentage errors in peak discharge, E_{Q_p} , and time to peak, E_{T_p} (flow stage at the upstream station is the only ANN model input)

Event	E_{Q_p} (%)	E_{T_p} (%)
December 1990	-12.1	-15.0
January 1994	4.1	-4.5
January 2003	-37.5	-2.2
Average	17.9	7.2

employed in network training was investigated. The purpose here was to calculate the error of ANN in predicting hydrographs with higher peaks when a hydrograph with a lower peak was used in training. Table V summarizes three different cases and the events used therein for this purpose, and Table VI presents the main characteristics of these events. In Case-I, a hydrograph with a peak, $Q_{\max} = 230 \text{ m}^3 \text{ s}^{-1}$, was used in network training and the other 11 events were used for prediction. Similarly, in Case-II, a hydrograph with a peak, $Q_{\max} = 322 \text{ m}^3 \text{ s}^{-1}$, was used in training and hydrographs of the other nine events were predicted. Finally, in Case-III, a hydrograph with a peak, $Q_{\max} = 404 \text{ m}^3 \text{ s}^{-1}$, was used in network training and hydrographs of the other six events were predicted. In each case, ANN had 2 neurons in the input layer, 5 neurons in the inner layer, and 1 neuron in the output layer. Input layer neurons stand for flow stage at the upstream and downstream stations while the output neuron is for the outflow rate at the downstream station. The network was trained with a 0.01 learning rate and 2000 iterations. The percent error with regard to peak discharge predictions is presented in Figure 5. The prediction error (percent) in peak discharge in each case varies exponentially with the difference between the peak discharge used in training and the peak discharge used in testing. It is seen from Figure 5 that when an event whose peak discharge is $100 \text{ m}^3 \text{ s}^{-1}$ is used in network training to predict an event whose peak discharge is $200 \text{ m}^3 \text{ s}^{-1}$, peak discharge will be under-predicted with a 50% error.

The prediction error would be about 10, 15, or 25% if the peak discharge to be predicted were 110, 120, or $140 \text{ m}^3 \text{ s}^{-1}$, respectively. Furthermore, using a single event with a low peak in network training would yield better prediction of the events with higher peaks than if more events with lower peaks were used in network training. This is because ANN tends to further underestimate peak discharge if hydrographs with lower peaks are used in training. Imrie *et al.* (2000) developed modified a cascade-correlation training algorithm to improve the extrapolation capability of ANNs.

Flood hydrograph forecasting

ANN training. ANN was trained using six (January 1986, February 1991, December 1995, January 1997, March 2000, February 2004) events for a 4-h lead forecast time. Using flow-stage data at the Santa Lucia upstream station and Ponte Felcino downstream station for network training, flood discharge was forecast at the Ponte Felcino downstream station with a lead time of 4 h. ANN had 2 neurons in the input layer, 5 neurons in the hidden layer, and 1 neuron in the output layer. Input layer neurons stand for flow stage at the upstream and downstream stations while the output layer neuron represents outflow rate at the downstream station. The optimal number of neurons in the inner layer was found by trial and error procedure, as described earlier. The model was trained with a 0.01 learning rate and 2000 iterations.

For 8-h and 12-h lead time flood forecasting, the reach of the Tiber river between Ponte Felcino and Monte Molino (Figure 2) was considered. The wave travel time of the reach is approximately 8 h. Six events (marked with *) in Table VII) were used for model training. The table summarizes the main characteristics of these storm events. Using the flow-stage data measured at the upstream gauging station of Ponte Felcino and downstream gauging station of Monte Molino, 8-h and 12-h lead time flow discharges were forecast at the Monte

Table V. Events used for the ANN peak discharge extrapolation

CASE I		CASE-II		CASE-III	
Training event	Q_{\max}	Training event	Q_{\max}	Training event	Q_{\max}
March 2000	$230 \text{ m}^3 \text{ s}^{-1}$	November 1997	$322 \text{ m}^3 \text{ s}^{-1}$	December 1990	$404 \text{ m}^3 \text{ s}^{-1}$
Testing events	$Q_{\max} (\text{m}^3 \text{ s}^{-1})$	Testing events	$Q_{\max} (\text{m}^3 \text{ s}^{-1})$	Testing events	$Q_{\max} (\text{m}^3 \text{ s}^{-1})$
January 94	240	January 86	548	January 86	548
November 97	322	December 96	373	April 97	437
December 96	373	December 90	404	February 91	593
December 90	404	April 97	437	December 95	424
April 97	437	February 91	593	June 97	450
January 86	548	December 95	424	February 99	429
February 91	593	January 97	359		
December 95	424	June 97	450		
January 97	359	February 99	429		
June 97	450				
February 99	429				

Table VI. Main characteristics of the observed flood events at stations on Tiber river

Date (1)	Santa Lucia section			Ponte Felcino section			T_L (h) (8)
	Q_b ($m^3 s^{-1}$) (2)	Q_p ($m^3 s^{-1}$) (3)	V ($10^6 m^3$) (4)	Q_b ($m^3 s^{-1}$) (5)	Q_p ($m^3 s^{-1}$) (6)	V ($10^6 m^3$) (7)	
January 1986	13.0	412.2	45.2	5.3	548.3	76.2	4.0
December 1990	8.2	418	49.6	9.6	404	59.5	2.0
February 1991	27.7	276	27.8	22.9	600	58.5	4.0
January 1994	35.6	103	19	47.8	271	34.7	3.0
December 1995	4.2	71.0	10.3	8.8	138.7	19.1	4.0
December 1996	14.0	282.7	18.8	12.5	373.5	29.7	4.0
January 1997	18.2	120.2	24.3	36.2	225.0	51.8	3.5
		146.2			359.0		
April 1997	3.7	366.0	32.8	11.7	437.7	57.7	4.0
June 1997	5.0	345.6	27.6	10.8	449.6	49.1	5.0
November 1997	7.8	108.6	6.6	45.7	322.5	24.3	3.5
February 1999	19.0	229.0	15.2	25.4	429.2	39.4	4.0
March 2000	19.4	53.3	4.6	31.8	230.3	20.9	4.0

Q_b , base flow; Q_p , peak discharge; V , direct runoff volume; T_L , travel.

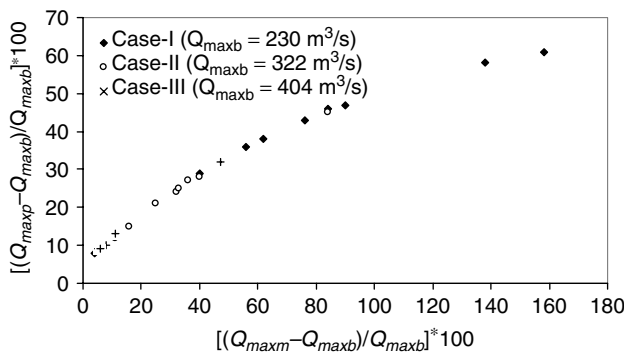


Figure 5. ANN peak discharge extrapolation error results (Q_{maxb} = peak discharge of the hydrograph used for network training, Q_{maxp} = peak discharge of a hydrograph that is predicted by ANN model during the testing stage, and Q_{maxm} = measured peak discharge of the hydrograph predicted by ANN during the testing stage)

neurons in the input layer, 12 neurons in the inner layer, and 1 neuron in the output layer. Input layer neurons stand for flow stage at the upstream and downstream stations while the output layer neuron represents the outflow rate at the downstream station. The optimal number of neurons in the hidden layer was found by trial and error, as described earlier. The network was trained with a 0.005 learning rate and 10 000 iterations. Note that the applicability of ANN for forecasting in actual practice might be somewhat limited as the input data consists of only river stage at the upstream and downstream stations. However, when hydrologists are provided with such easily measurable data, it would be easier to perform the forecasting by ANN and thereby forewarn the responsible authorities for taking precautionary measures for mitigating possible flood damages.

Molino downstream station. The constructed ANN had 2

Table VII. Main characteristics of the observed flood events at stations on Tiber river

Date (1)	Ponte Felcino			Monte Molino			T_L (h) (8)
	Q_b ($m^3 s^{-1}$) (2)	Q_p ($m^3 s^{-1}$) (3)	V ($10^6 m^3$) (4)	Q_b ($m^3 s^{-1}$) (5)	Q_p ($m^3 s^{-1}$) (6)	V ($10^6 m^3$) (7)	
December 1998 ^a	18	120	8.2	90	837	61.2	6.5
February 1999	25.4	430	39.4	45	814	66.2	8
April 1999	21	171	31.4	68	350	117.7	8
November 1999 ^a	48	120	31.8	94	400	85.3	6.5
		239			450		
December 1999 ^a	25	165	21.1	73	984	125.6	4.5
March 2000	22	162	39.1	39	450	82.2	8.5
December 2000	5	525	114	28	927	224.7	7
January 2001 ^a	45	279	36.1	123	409	65.9	8
		169			372		
March 2001 ^a	26	191	17.2	80	399	37	6.5
April 2001 ^a	22	224	16.3	68	288	26.2	8

Q_b , base flow; Q_p , peak discharge; V , direct runoff volume; T_L , travel.

^a Used for model training.

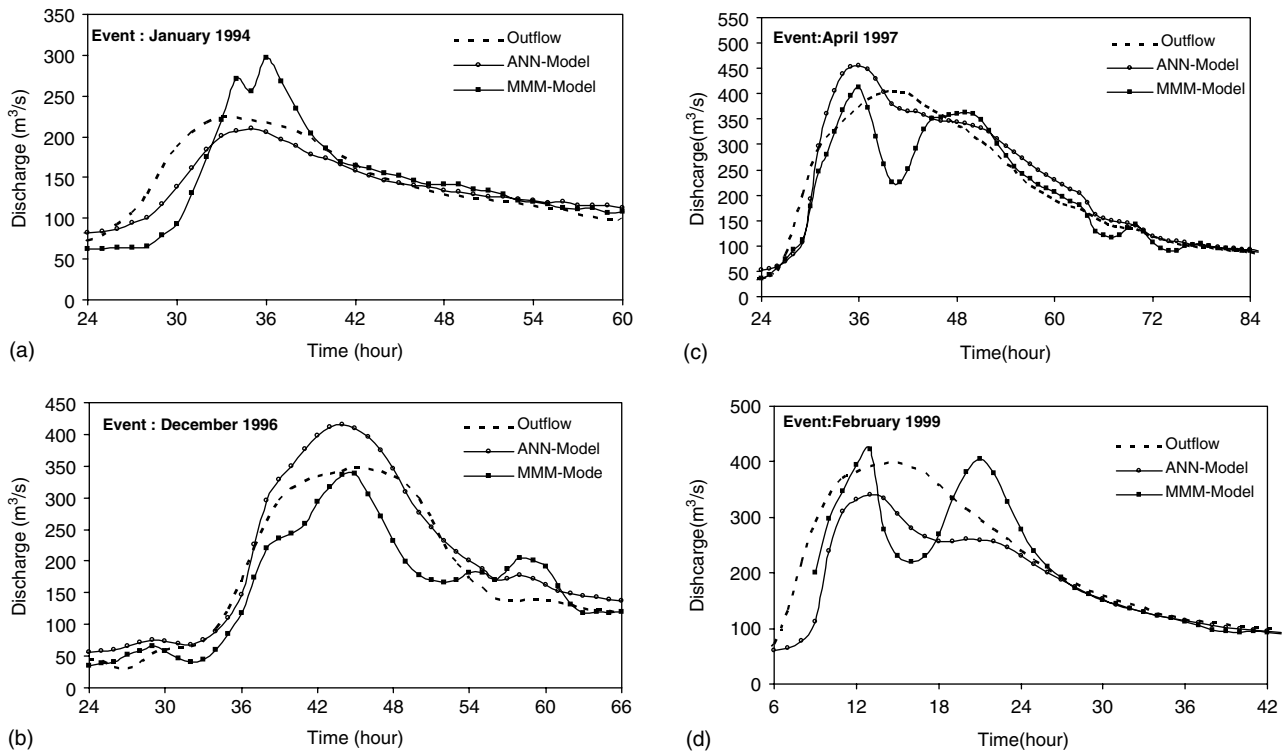


Figure 6. Forecasting storm hydrographs of (a) January 1994, (b) December 1996, (c) April 1997, and (d) February 1999 by ANN and MMM models with a 4-h lead time (Santa Lucia–Ponte Felcino Reach)

Model testing: forecasting. The ANN and MMM developed here were applied to forecast flood hydrographs with different lead times. It was noted that RCM cannot be employed for flood forecasting because information on the time to peak and peak discharge of a hydrograph measured at a downstream station is needed for estimation of its parameters α and β . Four events (January 1994, December 1996, April 1997, February 1999) were used for model testing. Figure 6a–d show the model forecasting results for a 4-h lead time. It is seen that ANN, in general, made satisfactory forecasts of storm hydrographs. In general, it outperformed the MMM, whose discharge forecasts were irregular and sometimes fluctuating, and otherwise provided smooth hydrographs. For example, for the storm events of April 1997 and February 1999, fluctuations in the hydrograph forecast by MMM were pronounced, as shown in Figure 6c and d. The forecast errors of ANN and MMM for a 4-h lead time are given in Table VIII. It is seen that both models, on average, produced comparable errors that hovered around 10% in the time to peak and peak discharge. However, ANN has a higher value of the persistence coefficient than does MMM. Although the error produced by MMM were comparable to that produced by ANN, it could not capture the hydrograph trends, especially for the hydrographs of April 1997 and February 1999 (Figure 6c and d). The results presented in Figure 6a–d and Table VIII indicate that ANN can be employed for flood forecasting for a 4-h lead time.

Four flood events measured at the Ponte Felcino and Monte Molino gauging stations were used for testing the ANN. These events are summarized in Table VII.

Table VIII. Percentage errors in peak discharge, E_{Qp} , time to peak, E_{Tp} , and persistence coefficient (C_p) for 4-h lead time flood forecasts (Santa Lucia–Ponte Felcino Reach)

Event	E_{Qp} (%)		E_{Tp} (%)		C_p	
	ANN	MMM	ANN	MMM	ANN	MMM
January 1994	-6.7	31.6	6.1	9.1	0.46	0.23
December 1996	19.6	-2.6	-2.2	0.0	0.76	0.53
April 1997	12.1	1.2	-10.0	-10.0	0.60	0.34
February 1999	-14.3	6.0	-13.3	-40.0	0.63	0.44
Average	13.2	10.4	7.9	14.8	0.61	0.39

Figure 7a–d present the results of the 8-h lead time flood forecasting. Both ANN and MMM performed satisfactorily. ANN captured the peak of each hydrograph but overestimated the lower peak of the two-peak hydrograph (Figure 7d), whereas in two cases MMM underestimated the peaks (Figure 7a and d). ANN captured the peak of the storm hydrograph of February 1999 while overestimating the recession limb, and MMM underestimated the entire hydrograph (Figure 7a). Both models captured the peaks of the storm event of April 1999 while ANN closely forecast the entire hydrograph (Figure 7b). Both the models captured the peak of the March 2000 hydrograph, whereas ANN over-predicted the rising limb and MMM underestimated it (Figure 7c). Table IX presents the error for each 8-h lead time flood forecast. It is seen that both models have comparable errors (less than 5%) with respect to the time to peak and peak discharge forecasts. On the other hand, MMM has a higher value of persistence coefficient (C_p) than ANN for each storm

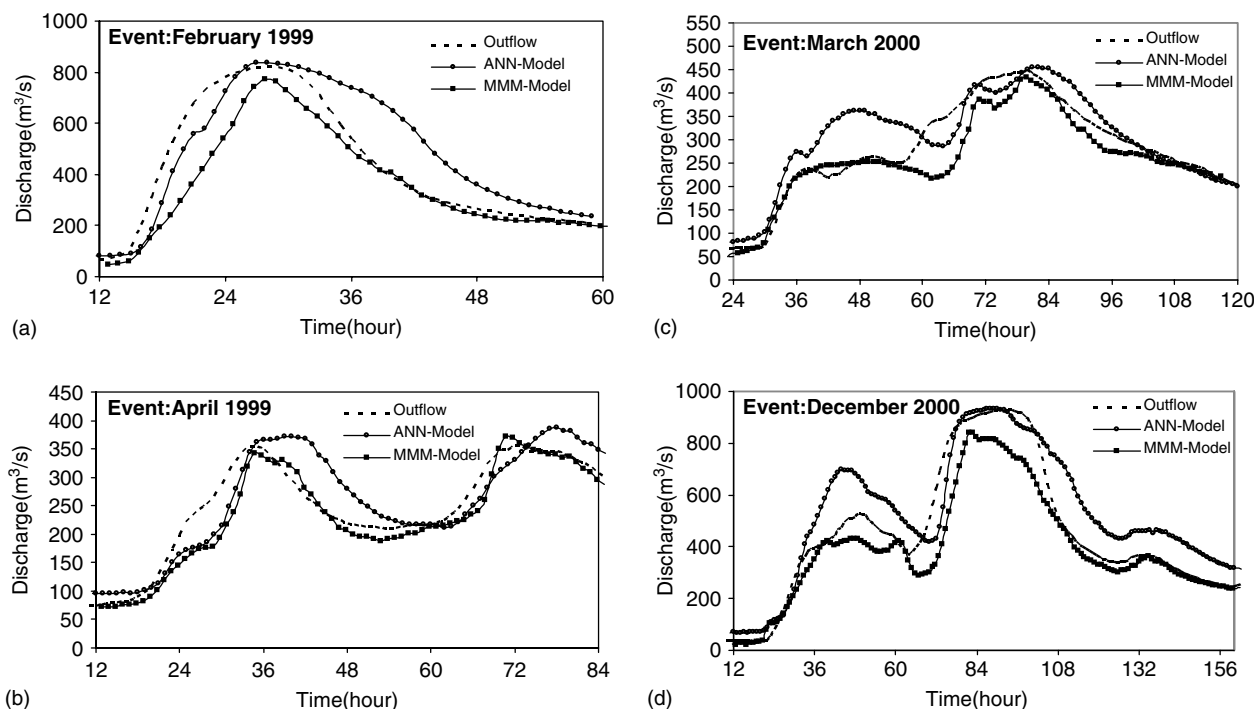


Figure 7. Forecasting storm hydrographs of (a) February 1999, (b) April 1999, (c) March 2000, and (d) December 2000 by ANN and MMM models with an 8-h lead time (Ponte Felcino–Monte Molino Reach)

event. The results in Figure 7a–d and Table IX indicate that both models can be confidently employed for flood forecasting for the 8-h lead time.

Figure 8a–d shows the 12-h lead time flood forecasts for storms observed at the Monte Molino downstream station (Figure 2). The travel time between the two stations is about 8 h. MMM cannot be applied for forecasting here because the lead time is longer than the wave travel time. Thus, for the 12-h lead time forecasting, only ANN was employed. It is seen from Figure 8a–d that the model, in general, predicted each peak with a delay (Figure 8a, b and c). It over-predicted the first lower peak of the hydrograph, but slightly underestimated the higher peak (Figure 8c and d). Table X gives the percentage of error for the cases shown in Figure 8a–d. On average, it had less than 10% error in forecasting the time to peak and also less error in the peak discharge. Its persistence coefficient in three cases is more than 60%. These results indicate that the ANN can satisfactorily forecast floods with a lead time longer than the wave

travel time. This has important implications in that hydrologists will have sufficient time to warn authorities for minimizing flood damages long before the flood peak arrives at a downstream station.

CONCLUSIONS

The following conclusions are drawn from this study: (1) ANN outperformed RCM in predicting individual storm hydrographs observed in the Tiber river basin in Italy. When the flow-stage data is sufficient to train ANN, it can be confidently employed for individual storm predictions. (2) The results of sensitivity analysis indicate that when only flow-stage data measured at an upstream station is used as input, ANN can be cautiously employed for flood prediction at the downstream station if the lateral inflow to the river each is not significant. (3) The extrapolation error of ANN increases with the difference between the peak discharge used in training and that used in testing. (4) MMM cannot be employed for forecasting

Table IX. Percentage errors in peak discharge, E_{Qp} , time to peak, E_{Tp} , and persistence coefficient (C_p) for the 8-h lead time flood forecasts (Ponte Felcino–Monte Molino Reach)

Event	E_{Qp} (%)		E_{Tp} (%)		C_p	
	ANN	MMM	ANN	MMM	ANN	MMM
February 1999	1.7	-6.6	0.0	0.0	0.81	0.85
April 1999	8.7	4.2	8.3	-1.4	0.66	0.70
March 2000	1.8	-3.4	1.3	0.0	0.34	0.55
December 2000	0.4	-9.3	-3.2	-10.8	0.37	0.51
Average	3.2	5.9	3.2	3.1	0.55	0.65

Table X. Percentage errors in peak discharge, E_{Qp} , time to peak, E_{Tp} , and persistence coefficient (C_p) for the 12-h lead time flood forecasts by the ANN Model (Ponte Felcino–Monte Molino Reach)

Event	E_{Qp} (%)	E_{Tp} (%)	C_p
February 1999	-9.7	10.7	0.81
April 1999	5.6	12.5	0.63
March 2000	-6.7	6.3	0.41
December 2000	-6.9	-1.1	0.61
Average	7.2	7.7	0.62

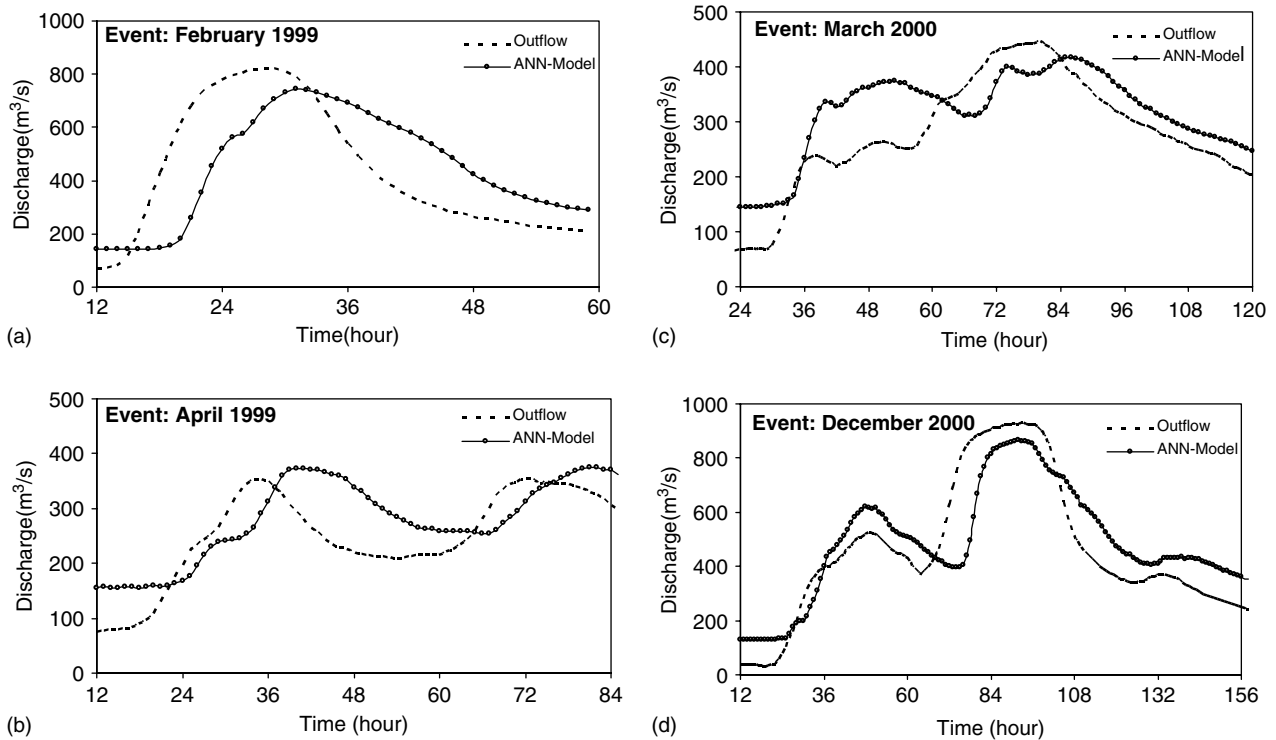


Figure 8. Forecasting storm hydrographs of (a) February 1999, (b) April 1999, (c) March 2000, and (d) December 2000 by ANN model with a 12-h lead time (Ponte Felcino–Monte Molino Reach)

if the lead time is greater than the wave travel time. (5) ANN can be employed for forecasting individual storm hydrographs for different lead times, such as 4-, 8- or 12-h periods. (6) Although ANN outperformed MMM in forecasting with shorter lead times, the performances of both are comparable for longer lead times. Unlike MMM, ANN can be employed for forecasting individual storm hydrographs with lead times greater than the wave travel time.

It should be noted that the data used in this study for ANN prediction and forecasting are obtained from the upper Tiber river basin in Italy. Therefore, the conclusions of this study are specific to the data used and, consequently, to the upper Tiber river basin. This implies that before directly applying the ANN model developed in this study to a different basin, the model should be retrained with the data for that particular basin.

ACKNOWLEDGMENTS

The authors are thankful to the Department of Soil Conservation of the Umbria Region for providing part of the data; they are also grateful to Dr. Silvia Barbetta for her contribution in data processing.

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- L = river reach length;
- p_1 = parameter in the lateral inflow component;
- p = number of output neurons;
- P = number of training patterns.
- q = lateral inflow per unit length;
- q_p = lateral inflow per unit length during the time interval $(t_p - T_L, t_p)$
- Q = discharge;
- Q_u, Q_d = upstream and downstream discharge;
- Q_u^p = upstream peak discharge;
- Q^* = upstream peak discharge attenuation;
- t = time;
- t_b, t_p = time when base flow and peak stage occurred at the downstream section;
- t_i = component of a target output vector T ;
- T_L = wave travel time;
- v_{ij} = weight from the i th neuron in the previous layer to the j th neuron in the current layer;
- x = distance along the river reach;
- y_i = component of a network output vector Y ;
- α, β = RCM model parameters;
- Δt^* = time interval equal to one fifth of the time to peak of the inflow hydrograph;
- Δt = Muskingum time step simulation;
- ε_{Q_p} = percentage error in peak discharge;
- ε_{t_p} = percentage error in time to peak;
- δ = learning rate.

APPENDIX NOTATION

The following symbols are used in this paper:

- A = flow area;
- A_u, A_d = upstream and downstream effective flow area;
- c = wave celerity;
- c_0, c_1, c_2 = Muskingum model coefficients;
- h = water level;
- h_d = water level recorded at the downstream section;
- K = attenuation parameter for the peak discharge;