FLASH FLOOD FORECASTING USING REMOTELY SENSED INFORMATION AND NEURAL NETWORKS PART I : MODEL DEVELOPMENT

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Abstract: Accurate quantitative forecasting of rainfall for basins with a short response time is essential to predict flash floods. In this study, a Quantitative Flood Forecasting (QFF) model was developed by incorporating the evolving structure and frequency of intense weather systems and by using neural network approach. Besides using radiosonde and rainfall data, the model also used the satellite-derived characteristics of storm systems such as tropical cyclones, mesoscale convective complex systems and convective cloud clusters as input. The convective classification and tracking system (CCATS) was used to identify and quantify storm properties such as lifetime, area, eccentricity, and track. As in standard expert prediction systems, the fundamental structure of the neural network model was learned from the hydroclimatology of the relationships between weather system, rainfall production and streamflow response in the study area. All these processes stretched leadtime up to 18 hours. The QFF model will be applied to the mid-Atlantic region of United States in a forthcoming paper.

Key Words: Neural networks, Convective weather systems, Weather classifier, Flash flood forecasting, Hydroclimatology

1. INTRODUCTION

Floods are the most frequent natural hazard in the United States: between 1989 and 1999, floods took 988 lives and caused $4.5 billion worth of damage (US Army Corps of Engineers, 1999). Despite many advances in weather forecasting over the last decades, the need for accurate flood forecasting remains as one of the most elusive challenges in operational hydrology. In this paper, we focus on this problem, and present a Quantitative Flood Forecasting (QFF) model which was designed to forecast peak streamflow in small size watersheds up to 18 hours in advance.

The methodology adopted to develop a QFF (Quantitative Flood Forecasting) model consists of using neural networks as a data transforming tool combining information from the state of the atmosphere and its recent evolution along with standard hydrometeorological data to issue streamflow forecasts. The structure of the model is dictated by our understanding of the regional hydrometeorology, flood hydrology and by an empirically derived classification that establishes relationships among data from different types of sensors: streamflow and rain gauges, radiosondes, and satellite imagery.

Neural networks have been applied to a wide variety of hydrologic problems such as precipitation forecasting (Kuligowski and Barros, 1998a,b; Hall et al., 1999); streamflow prediction (Imrie et al., 2000); tornado prediction (Marzban and Stumpf, 1996); cloud classification (Bankert, 1994); sunspot prediction (Koons and Gorney, 1990); and prediction of water quality parameters (Maier and Dandy, 1996) among others. Previous work has demonstrated that neural networks are appropriate to capture the complex nonlinear rainfall-runoff relationships (Hsu et al., 1995; Minns and Hall, 1996; Shamseldin, 1997; Campolo et al., 1999). Most previous neural network applications of the rainfall and runoff processes were restricted to short lead-time for accurate forecasts: 1-5 hours (Campolo et al., 1999), 30-75 minutes (Michaud and Sorooshian, 1994), 2.5 hours (Amburn and Fortin, 1993); 1-5 minutes (Jinno et al., 1993). Typically, these studies are based on conceptual rainfall-runoff models and require that raingauges need to be distributed within and, or near the forecast watersheds. Also, the forecasts are issued after the arrival of rainfall events. Because the rainfall-runoff response times are in the range of a few hours, this constitutes a natural upper bound on forecast lead-times.

Here, our goal is to focus on operational Quantitative Flood Forecasting (QFF) for basins where raingauges are not necessarily available, and to extend the forecast lead-times up to 18 hours in advance, which should provide disaster management agencies with enough time to implement flood control and mitigation measures. The driving hypothesis is that such long lead-times can be attained if the synoptic evolution of atmospheric conditions is taken into consideration. This includes the classification of weather systems as they begin to arrive at the region of interest, and the detection and monitoring of convective weaher systems which may or may not be embedded in large-scale storms. Figure 1 shows the schematic diagram of the new approach, which indicates the difference between the new approach and the typical approach. Next, a description of the QFF model is in Section 2. The QFF model was applied to the mid- tlantic region of United States in a forthcoming paper.

2. DESCRIPTION OF THE QUANTITATIVE FLOOD FORECASTING MODEL

The overall approach to develop the QFF model consisted in developing a multisensor data-driven model using an expert system of neural networks, the configuration of which is determined by regional hydroclimatology, operational data availability, and forecast criteria. Hourly streamflow and rainfall data are used to describe rainfall-runoff response, while radiosonde and satellite data are used to describe the evolving structure of regional weather. This approach evolved from an existing Quantitative Precipitation Forecasting (QPF) model, which was used to forecast point rainfall 6 to 12 hours in advance at more than one location using only raingauge data and output from Numerical Weather Prediction (NWP) models (Kuligowski and Barros, 1998a,b). The existing QPF model was greatly modified to handle multisensor data at large spatial scales, and to issue streamflow forecasts with long lead-times. The synoptic evolution of atmospheric conditions was taken into consideration using satellite data in the weather classifier module. Specifically, the foremost forecast criterion is to capture the timing and magnitude of peak flood discharge at least 18 hours in advance. Table 1 shows the comparison between the previous approach and new approach.

The QFF model consists of three different modules as illustrated schematically in Fig. 2(a). In the first module, the raingauges are surveyed to look for rainfall occurrences. If no rainfall is detected in the study area, a no-rain forecast is used. Next, the classification and decision module is used to describe and classify current weather conditions using radiosonde and satellite data. A second rain/no rain forecast is issued based on the likelihood that rain may, or may not occur at the forecast locations within the prescribed lead-time (i.e.

Table 1. Comparison between the previous approach and the new approach.

New Approach	Previous Approach
• Use convective weather system information	• Do not use convective weather system information
• Wide range raingauge and radiosonde network	• Raingauge network within or near watershed
• Forecast before rainfall arrival	• Forecast after rainfall arrival
• Long lead time (up to 18 hours)	• Short lead time

Table 2. Definitions and basic characteristics of convective weather systems from satellite cloud imagery (Evans and Shemo, 1996)

Tropical Cyclones (CYC)	
Published storm tracks are used to validate storm tracks analyzed by CCATS.	
A tracking algorithm is used to follow the trajectory of tropical cyclones.	
Systems are matched with MCC or CCC tracks as defined below.	
Mesoscale Convective Complexes (MCC)	
Size	<-54°C region has area >50,000 km^2
Duration	>6 hours (2 frames in the case of ISCCP-B3)
Shape	Eccentricity (minor axis/major axis) > 0.7
Convective Cloud Clusters (CCC)	
Size	<-54°C region has area >4,000 km^2
Duration	> 6 hours (2 frames in the case of ISCCP-B3)
Shape	No shape criterion
Disorganized, Short-Lived Convection (DSL)	
Size	Temperature <-54°C for at least one pixel (i.e. Minimum size determined only by satellite resolution)
Duration	3 hours or less (1 frame in the case of ISCCP-B3)
Shape	No shape criterion

Table 3. Basic statistics of convective weather systems in our study region during 1989 - 1993

	CYC	MCC	CCC	DSL
Number	7	50	1,470	7,018
Average Life	-	14	6	< 3
Area (km^2)	42,690	239,920	132,850	15,654
Temperature	212	214	214	216
Eccentricity	0.75	0.70	0.53	0.61

Table 4. Summary of the different neural network configurations used in the QFF model

C4	· Convective weather systems are present, and all predictor raingauges are wet.
C3	· Convective weather systems are present, and more than 75% of predictor raingauges are wet.
R4	· Convective weather systems have not been detected, and all predictor raingauges are wet.
R3	· Convective weather systems have not been detected, and more than 75% of predictor raingauges are wet.
Combined	· Various combinations of C4, C3, R4 and R3 based on data availability.

the next 18 hours). If a positive rain forecast is issued by the second module, then the configuration of the neural network model will be selected according to the weather conditions (e.g. weather class) and as a function of input data available. CCATS (Convection Classification and Automated Tracking System), an algorithm developed by Evans and Shemo (1996) was used to analyze infrared satellite data. The classification criteria and the basic characteristics of each convective class are presented in Table 2. For this work, only five years of data between 1989 and 1993 were available, and Table 3 provides a summary of the basic statistics of the convective systems identified in this five-year period in our region of study. Finally, the forecast module consists of a system of neural network models with at least four different configurations for each weather class. Hourly rainfall at four locations (i.e. predictor raingauges) and streamflow at the predicted gauge are respectively the inputs and outputs to the selected neural network model. The neural network output is an hourly streamflow forecast at the desired location at the desired time (desired time = current time + forecast lead-time). Detailed descriptions of the classification and forecast modules are presented in the following sections.

2.1 Weather Classifier

Appropriate selection of the neural network model configurations depends on the effectiveness of the weather classification module in relating streamflow at a specific location, rainfall at four raingauges, and regional atmospheric conditions. Indeed, a key element of the QFF model is the selection of the four predictor raingauges among the available

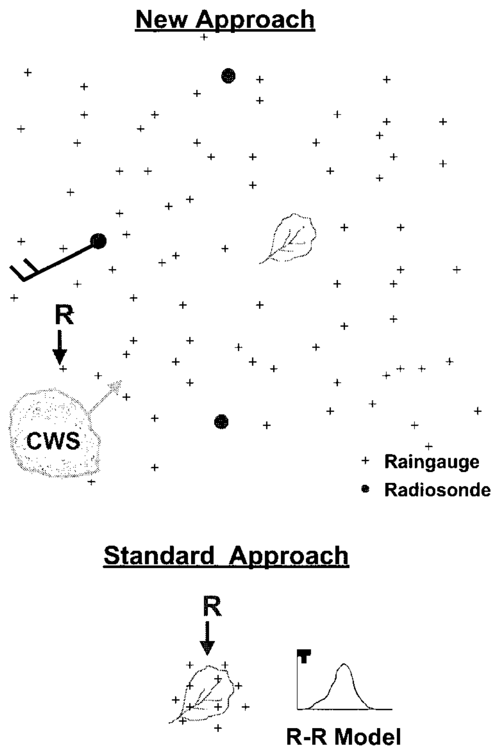
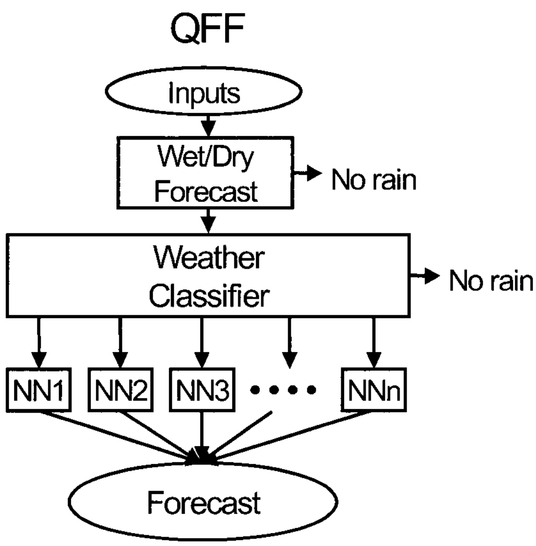


Fig. 1. The schematic diagram of the new approach



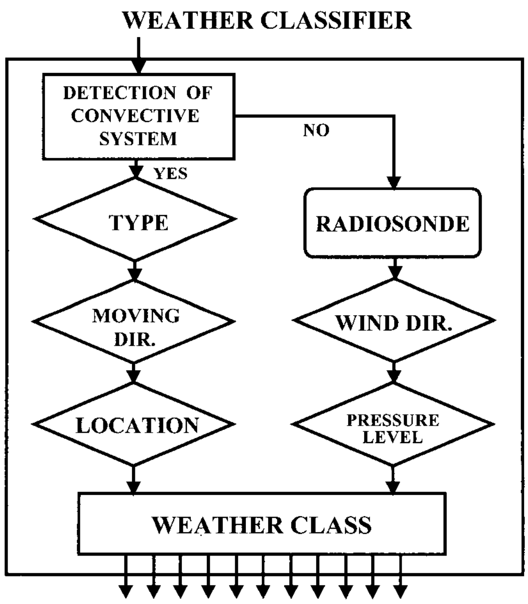


Fig. 2. (a) Flowchart of the quantitative flood forecasting model; (b) Flowchart of the weather classifier

meteorologist. This combines advantages of automated and manual classification methods. Kohonen self-organizing feature maps are now beginning to be applied for classification problems in hydrology (Hall and Minns, 1999; Barros and Kuligowski, 1996). In this study, we used a more physical classification method using expert knowledge of convective weather system with conditional correlation analysis. Analysis of model performance according to the different weather classification methods remains a challenging topic.

The schematic of the weather classifier is illustrated in Fig. 2(b). The optimal combination of predictor raingauges for each weather class was selected based on statistical analysis between the streamflow gauges and the available raingauges. Correlation analysis between streamflow and rainfall was conducted for each forecast location as a function of the weather class type (e.g. MCC or CCC), origin and moving direction of the weather system, and also as a function of the distance between its current location of the weather system and its location at the time for which the forecast is issued. Two zones of influence were considered: zone1 and zone 2, respectively for distances less than and greater than 300 km, the characteristic spatial scale of synoptic weather systems in the mid-Atlantic region. When more than one type of weather system was identified, the priority was given to MCCs over CCCs, and when several convective systems of the same type were identified, the priority was given to the weather system nearest to the streamflow gauge for which location the forecast is desired (i.e. the predicted location). For each weather class, the four raingauges that exhibit the highest correlation with the streamflow gage were selected as predictor gauges. For each weather class, a suite of neural network models was subsequently trained using the data from the corresponding four predictor raingauges as input.

When no convective systems are detected in the satellite imagery, the weather classification is made according to the radiosonde wind data. The predictor raingauges are selected in this case as a function of the wind direction at the radiosonde location, and at the pressure level for which the highest correlation between streamflow and rainfall occurs when southwesterly storm systems approach the area of interest. This criterion is based on the regional hydroclimatology of floods that relates southwesterly rainstorms with heavy precipitation and extended flooding as mentioned earlier in the manuscript. In fact, about 70% of all weather systems approach the lee side of the Appalachian mountains from the W-SW-S, which is consistent with the predominant trajectories of convective systems. Table 4 provides a description of the four neural network model configurations used to issue four different types of forecasts in this study.

2.2 Neural Networks

Artificial neural networks are data-processing systems that can learn the relationships between a pair of one- or multi- dimensional data sets by tuning a set of model parameters. These parameters (weights) form a mapping from a set of given values (inputs) to an associated set of values (outputs). The process of tuning the weights to the correct value (i.e. training) is carried out by passing a large number of input-output pairs through the model and adjusting the weights to minimize the error between the observed and predicted data. The practical advantages and limitations of neural networks in forecast applications have been discussed by Maier and Dandy (1996) and Kuligowski and Barros (1998a,b) among others, while Hassibi et. al. (1994, 1995) demonstrated theoretically why neural networks are robust estimators of nonlinear phenomena. In principle, the self- learning nature of a neural network allows it to forecast without extensive prior knowledge of all the processes involved. However, because data analysis techniques are unable to evaluate the generality of the relationships that they find, the data sets used for training must be representative of the physically-based dynamical range of the forecasts. That is why the application of neural networks in environmental problems cannot be successful without a good understanding of the physics involved, and without a hypothesis as to how different processes (and their state variables) interact with each other.

A schematic diagram of the basic architecture of multi-layer artificial neural networks is shown in Fig. 3. In this study, the neural networks are composed of three layers including input layer, hidden middle layer, and output layer. Each node of the hidden layer receives a signal from every node in the input layer. Besides the data at the four predictor raingauges, the current streamflow is also used as input to the neural network model. The number of nodes in the hidden layer is an important parameter with respect to the computational efficiency of the neural network model. Fletcher and Goss (1993) proposed a number ranging from $(2n+1)$ to $(2n^{0.5}+m)$, where n is the number of input nodes and m is the number of output nodes. Although this formula provides an useful guideline, the best results are obtained by trial- and-error experiments (Kuligowski and Barros 1998a,b; Swingler, 1996). In the case of our applications, best results were obtained using only three hidden layer nodes. The effective incoming signal to node j is the weighted sum of all input signals:

$$h_j = \sum_{i=1}^{m} w_{ji} r_i \qquad (j = 1, \ldots\ldots, n) \tag{1}$$

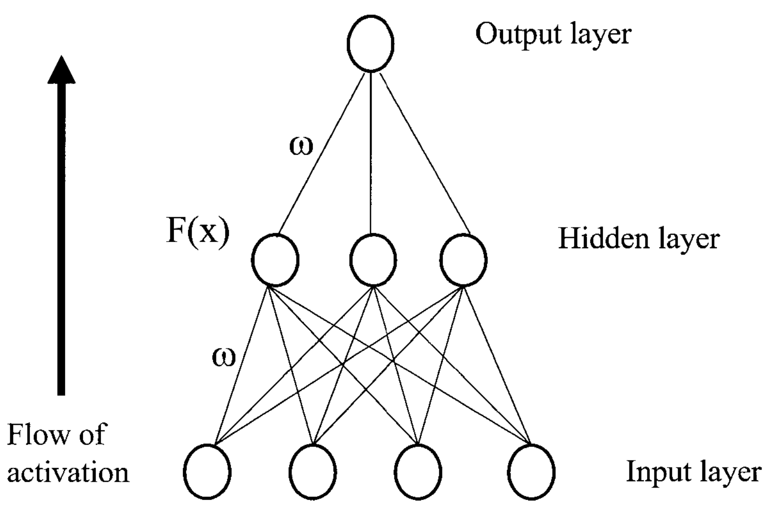


Fig. 3. Schematic of the artificial neural network configuration

where m is the total number of neurons in the input layer, n is the total number of neurons in the hidden layer, w is the weight assigned to the path from i to j, r_i is input from unit i and h_j is value at unit j of hidden layer. Subsequently, the combined signal is modified by the so-called transfer function to produce the output signal:

$$o_k = \sum_{j=1}^{n} w_{kj} f(h_j) = \sum_{j=1}^{n} w_{kj} f\left(\sum_{i=1}^{m} w_{ji} r_i\right) \quad (k=1, \ldots\ldots, l) \tag{2}$$

where f denotes the selected transfer function, w is the weight assigned to the path from j to k, o_k is network output and l denotes total number of nodes in the output layer.

A nonlinear transfer function (the sigmoidal function) allows the neural networks to consider nonlinear relationships between input and output data:

$$f(h) = \frac{2}{1 + \alpha\, e^{-h}} - 1 \tag{3}$$

where h is input to the node, $f(h)$ is the node output, α is the gain which is introduced to consider nonlinear behavior of input data.

The training process consists in determining a new set of weights that minimizes the mean squared error E of the output:

$$E = \sum_{k=1}^{l} (t_k - o_k)^2 \tag{4}$$

where t_k is the desired output at the output node k.

Because the transfer function is nonlinear, the error E will be a nonlinear function of the weights w. The steepest descent method was the nonlinear minimization technique adopted. Accordingly, the weights are adjusted as follows:

$$\Delta w = -\eta' \frac{\partial E}{\partial w} = -(1-\beta)\eta' \frac{\partial E}{\partial w} + \beta(\Delta w)_{old} = \eta \frac{\partial E}{\partial w_{ji}} + \beta(\Delta w)_{old} \tag{5}$$

where η is learning rate which tells the network how quickly the weights must be changed and β is the fraction of average change in the weights. The momentum term $\beta(\Delta w)_{old}$ is added to the weight adjustment to avoid local minima. Both η and β are typically between zero and one, and are estimated by trial and error method (Maier and Dandy, 1996). Values of 0.001 for the learning rate η, 0.01 for the fraction of average change in weights β, and 2.0 for the gain parameter α gave satisfactory results for the applications reported here.

The QFF model will be tested in 2 small watersheds along the leeward side of the Appalachian mountains in the mid-Atlantic region where the hydroclimatology of floods is characterized by the recurrence of floods in small to medium watersheds. Such watersheds have a short response time for flooding, and are typically located in regions of complex orography, with narrow valleys and relatively strong relief. Often these watersheds are instrumented with streamflow gauges, but not with raingauges. At these locations, orographic effects on storm duration and intensity lead to the occurrence of heavy rainfall and leads to extreme floods (Barros and Kuligowski, 1998). Results will be presented in a forthcoming paper.

3. CONCLUSION

This study proposes an operational flood forecasting model for ungauged watersheds in the mid-Atlantic region using a data-driven approach. While physically-based numerical weather prediction and river routing models cannot accurately depict complex natural non-linear processes, based on scientific understanding of regional hydrometeorology with multisensor data and expert information system such as neural networks, the developed model can lead to significant gains in the forecast skill of extreme rainfall and associated floods. Therefore, the proposed model should be viewed as a strong alternative in operational hydrology.

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