Journal of Hydrology 390 (2010) 85–91

Contents lists available at ScienceDirect

Journal of Hydrology

journal homepage: www.elsevier.com/locate/jhydrol

Development of a coupled wavelet transform and neural network method for flow forecasting of non-perennial rivers in semi-arid watersheds

Jan Adamowski [a,*], Karen Sun [b]

[a] Department of Bioresource Engineering, McGill University, 21 111 Lakeshore Road, Ste. Anne de Bellevue, QC, Canada H9X 3V9
[b] Department of Mathematics, Massachusetts Institute of Technology, 183 Memorial Drive, Cambridge, MA 02139, USA

ARTICLE INFO

Article history:
Received 7 March 2010
Received in revised form 19 June 2010
Accepted 24 June 2010

This manuscript was handled by A. Bardossy, Editor-in-Chief, with the assistance of Sheng Yue, Associate Editor

Keywords:
Artificial neural networks
Forecasting
River flow
Time series analysis
Wavelet

SUMMARY

In this study, a method based on coupling discrete wavelet transforms (WA) and artificial neural networks (ANN) for flow forecasting applications in non-perennial rivers in semi-arid watersheds is proposed. The discrete à trous wavelet transform is used to decompose flow time series data into wavelet coefficients. The wavelet coefficients are then used as inputs into Levenberg Marquardt artificial neural network models to forecast flow. The relative performance of the coupled wavelet-neural network models (WA–ANN) was compared to regular artificial neural network (ANN) models for flow forecasting at lead times of 1 and 3 days for two different rivers in Cyprus (Kargotis at Evrychou and Xeros at Lazarides). In both cases, the coupled wavelet-neural network models were found to provide more accurate flow forecasts than the artificial neural network models. The results indicate that coupled wavelet-neural network models are a promising new method of short-term flow forecasting in non-perennial rivers in semi-arid watersheds such as those found in Cyprus.

1. Introduction

Short-term and long-term forecasts of river flows are an important component of water resources management for a variety of reasons such as helping optimize water resources systems as well as planning for future expansion or reduction in a sustainable manner. Highly accurate and reliable flow forecasts are particularly important in semi-arid watersheds due to the intermittent nature of river flows and frequent scarcity of water. Based on highly accurate and reliable flow forecasts, water managers in semi-arid watersheds can optimally allocate water to different sectors such as agriculture, municipalities, hydropower generation, while ensuring that environmental flows are maintained.

Intermittent river flows in semi-arid watersheds can be defined as river flow series that have zero values for some intervals, and non-zero values for the remaining intervals. All the rivers in Cyprus have periods of no flow (i.e. they are intermittent or non-perennial). Despite this, such rivers are an important component in meeting increasing water demands in semi-arid and arid watersheds such as those found in Cyprus. However, very few studies have explored the forecasting of intermittent flows in semi-arid or arid watersheds.

In river flow forecasting applications, data-based hydrological methods are becoming increasingly popular due to their rapid development times and minimum information requirements. Although they may lack the ability to provide physical interpretation and insight into catchment processes, they are nevertheless able to provide relatively accurate flow forecasts. In data-based flow forecasting, statistical models have traditionally been used. Multiple linear regression (MLR) and autoregressive moving average (ARMA) models are probably the most common methods for forecasting flows. More recently, artificial neural networks (ANN) have been introduced for flow forecasting applications.

In one of the first applications of ANNs to river flow forecasting, Kang et al. (1993) used ANNs and ARMA models to predict daily and hourly river flows. They found that ANNs could be used for forecasting river flows. Since then, a number of studies have confirmed the usefulness of ANN models in river flow forecasting, with the most popular type of ANN being the multi-layer perceptron (MLP) model optimized with a backpropagation (BP) algorithm. Hsu et al. (1995) showed that a non-linear ANN model provided a better representation of the rainfall–runoff relationship of a medium sized basin, just less than 2000 km^2, than the linear ARMAX (with the X referring to an exogenous input) time series approach or the Sacramento model. Markus (1997) made monthly streamflow forecasts with MLP ANN models for several rivers, and compared the performance of ANN models with other models.

* Corresponding author. Tel.: +1 514 398 7786.
E-mail address: jan.adamowski@mcgill.ca (J. Adamowski).

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doi:10.1016/j.jhydrol.2010.06.033

Nomenclature

CWT	continuous wavelet transform
N	number of data points used
s	scale parameter
$x(t)$	signal
$\bar{y}_i$	mean value taken over N
y_i	observed peak weekly water demand
$\hat{y}_i$	forecasted peak weekly water demand
τ	translation parameter
$*$	complex conjugate
$\Psi(t)$	mother wavelet

See and Openshaw (1999) combined ANNs with other soft computing methods, such as fuzzy logic and genetic algorithms, to forecast river levels. Jain et al., 1999 used MLP ANN models for monthly flow forecasting. Abrahart and See (1998) compared the use of ANN and ARMA models, and found that the ANN models outperformed the ARMA models. Zealand et al. (1999) used MLP ANN models for 1–4 week ahead streamflow forecasting. Sajikumar and Thandaveswara (1999) demonstrated the use of a special type of MLP ANN model, a temporal back propagation neural network, for monthly rainfall–runoff modeling. Birikundavyi et al. (2002) investigated the performance of ANN models for 7-day-ahead daily streamflow forecasting and showed that the ANNs outperformed a conceptual rainfall–runoff model for up to 5-day-ahead forecasts. Tawfik (2003) applied ANN models to predict the Nile River inflows into the Aswan reservoir for the months of July, August, and September. Kisi (2004) used MLP ANN models for monthly flow forecasts. Chen et al. (2005) and Corani and Guariso (2005) independently developed flood forecasting models based on neuro-fuzzy networks.

Other types of ANNs have also been applied to streamflow forecasting problems, but less frequently. Radial basis function (RBF) ANN models have been investigated for river flow forecasting (Fernando and Jayawardena, 1998; Dibike and Solomatine, 2001; Dawson et al., 2002; Piotrowski et al., 2006). Moradkhani et al. (2004) investigated the use of a Self Organizing Radial Basis (SORB) function to one-step ahead forecasting of daily river flow. Modular neural networks (MNN), hybrid neural networks, Elman networks, and threshold neural networks have also been investigated (Elman, 1988; Zhang and Govindaraju, 2000; Hu et al., 2001).

There are several studies in the literature that explored the use of ANNs to forecast river flows where the flow was intermittent. Cigizoglu (2005) explored the use of MLP ANNs and generalized regression neural networks (GRNN) for intermittent flow forecasting, and Kisi and Cigizoglu (2007) explored the use of MLP ANNs, radial basis ANNs, and GRNNs for forecasting intermittent flow series.

However, a problem with artificial neural network and other linear and non-linear methods is that they have limitations with non-stationary data. Many methods such as neural networks may not be able to handle non-stationary data if pre-processing of the input data is not done. The methods for dealing with non-stationary data are not as advanced as those for stationary data. In the last decade, wavelet analysis has been investigated in a number of disciplines outside of water resources engineering and hydrology, and it has been found to be very effective with non-stationary data. Wavelet transforms provide useful decompositions of original time series, and the wavelet-transformed data improves the ability of a forecasting model by capturing useful information on various resolution levels.

Wavelet transforms have become a tool for analyzing local variation in time series (Torrence and Compo, 1998), and hybrid models have been proposed for forecasting a time-series based on a wavelet transform pre-processing (Aussem and Murtagh, 1997; Aussem et al., 1998; Zheng et al., 2000; Zhang and Dong, 2001). Wavelet transforms provide useful decompositions of original time series, so that wavelet-transformed data improve the ability of a forecasting model by capturing useful information on various resolution levels. In the field of water resources, wavelet analysis has been very recently applied to examine the rainfall–runoff relationship in a Karstic watershed (Labat et al., 1999), to characterize daily streamflow (Smith et al., 1998; Saco and Kumar, 2000) and monthly reservoir inflow (Coulibaly et al., 2000), to evaluate rainfall–runoff models (Lane, 2007), to analyze streamflow trends (Adamowski et al., 2009), and to forecast river flow (Adamowski, 2007, 2008a,b).

Over the last couple of years, several studies have been published that developed hybrid wavelet transform and ANN (WA–ANN) models for river flow forecasting. Anctil and Tape (2004) developed WA–ANN models for 1 day ahead flow forecasting in the US and France. Cannas et al. (2006) developed a hybrid model for monthly rainfall–runoff forecasting in Italy, Kisi (2008) developed a hybrid model for monthly flow forecasting in Turkey, Partal (2009) developed WA–ANN models for monthly flow forecasting in Turkey, Kisi (2009) explored the use of WA–ANN models for daily flow forecasting of intermittent rivers, and Wu et al. (2009) developed WA–ANN models for 1–3 days ahead forecasting. Apart from the Wu et al. (2009) study, all the studies found that the WA–ANN models outperformed the ANN models for flow forecasting. Of these, however, only one study has explored the use of WA–ANN models for flow forecasting in semi-arid watersheds with intermittent flow (Kisi, 2009).

Based on a review of the literature, it appears that a number of important issues need to be explored in greater detail: (1) lead times greater than 1 day but less than 1 month need to be explored in greater detail since the only study (Wu et al., 2009) that explored lead times greater than 1 day but less than 1 month found that the WA–ANN models did not perform as well as other models; (2) the use of all wavelet decomposed sub-series as inputs to the ANN models needs to be explored since averaging or optimizing the selection of only certain sub-series (as has been done in most of the studies to date in the literature) can be viewed as a potentially diminutive approach since all sub-series coefficients are equally important and contain information about the original time series; (3) the use of WA–ANN models in semi-arid watersheds with intermittent flows needs to be explored further since only one published study to date has explored this issue.

This study explored each of these issues. In this research, coupled discrete wavelet transform and artificial neural network models (WA–ANN) were developed and compared with regular artificial neural network (ANN) models for 1 and 3 days ahead forecasting of flow for two non-perennial rivers in Cyprus.

2. Methods

2.1. Wavelet analysis

Wavelets are mathematical functions that give a time-scale representation of the time series and their relationships to analyze time series that contain non-stationarities. Wavelet analysis allows the use of long time intervals for low frequency information and shorter intervals for high frequency information and is capable of revealing aspects of data like trends, breakdown points, and discontinuities that other signal analysis techniques might miss. Another advantage of wavelet analysis is the flexible choice of the mother wavelet according to the characteristics of the investigated time series.

The continuous wavelet transform (CWT) of a signal $x(t)$ is defined as follows:

$$\mathrm{CWT}_x^{\Psi}(\tau, s) = \frac{1}{\sqrt{|s|}} \int_{-\infty}^{+\infty} x(t)\Psi^*\left(\frac{t-\tau}{s}\right)dt \tag{1}$$

where s is the scale parameter, τ is the translation parameter and '$*$' denotes the complex conjugate (Cannas et al., 2006). The mother wavelet $\Psi(t)$ is the transforming function. The CWT calculation necessitates a large amount of computation time and resources. The discrete wavelet transform (DWT) requires less computation time and is simpler to implement than the CWT. DWT scales and positions are usually based on powers of two (dyadic scales and positions). This is achieved by modifying the wavelet representation to:

$$\Psi_{j,k}(t) = \frac{1}{\sqrt{|s_0^j|}} \Psi\left(\frac{t - k\tau_0 s_0^j}{s_0^j}\right) \tag{2}$$

where j and k are integers and $s_0 > 1$ is a fixed dilation step (Cannas et al., 2006). The effect of discretizing the wavelet is that the time–space scale is now sampled at discrete levels. The DWT operates two sets of functions: high-pass and low-pass filters. The original time series is passed through high-pass and low-pass filters, and detailed coefficients and approximation series are obtained. In this study, the à trous DWT was used.

2.2. Artificial neural networks

An artificial neural network (ANN) is a data-driven method with a flexible mathematical structure that is capable of identifying complex non-linear relationships between input and output data sets without the necessity of understanding the nature of the phenomena. ANNs have become popular for hydrological forecasting in the last decade.

ANNs belong to a class of data-driven approaches, like transfer function models, as opposed to process-driven approaches, such as conceptual and physically-based models. A neural network can be used to predict future values of possibly noisy multivariate time-series based on past histories. An ANN is a computational model, whose architecture basis, as reported by many authors (Hsu et al., 1995; See and Openshaw, 1999; Imrie and Durucan, 1999; amongst others), was inspired by the current understanding of the functioning of the human brain. This comparison however, can be inaccurate. A more accurate representation is when a neural network is described as a network of simple processing nodes or neurons, interconnected to each other in a specific order, performing simple numerical manipulations (See and Openshaw, 1999).

The most widely used neural network is the MLP. In the MLP, the neurons are organized in layers, and each neuron is connected only with neurons in contiguous layers. Each neuron j receives a weighted input, that is the output from every neuron i in the previous layer. The effective incoming signal then propagates forward through a non-linear activation function, towards the neurons in the next layer. In other words, the task of each individual neuron consists of two parts. Initially, integration of the information from an external source or from other neurons takes place. The integration is often through a linear function. Next, it produces an output in accordance with a predetermined activation function (also called a transfer function or threshold function) such as the sigmoid, the linear, or the cubic polynomial (See and Openshaw, 1999). This transformation of the inputs to output within a single neuron is relatively simple; the complexity and the power of ANNs is ultimately achieved by the interaction of several neurons (Shamseldin, 1997).

2.3. Model performance comparison

The performance of developed models can be evaluated using several statistical tests that describe the errors associated with the model. After each of the model structures is calibrated using the calibration/testing data set, the performance can then be evaluated in terms of statistical measures of goodness of fit. In order to provide an indication of goodness of fit between the observed and forecasted values the coefficient of determination (R^2) and the root mean squared error (RMSE) can be used.

The coefficient of determination (R^2) measures the degree of correlation among the observed and predicted values. It is a measure of the strength of the model in developing a relationship among input and output variables. The higher the R^2 value (with 1 being the maximum value), the better is the performance of the model. R^2 is given by:

$$R^2 = \frac{\sum_{j-1}^{N}(\hat{y}_i - \bar{y}_i)^2}{\sum_{j-1}^{N}(y_i - \bar{y}_i)^2} \tag{3}$$

with

$$\bar{y}_i = \frac{1}{N}\sum_{i-1}^{N} y_i \tag{4}$$

where $\bar{y}_i$ is the mean value taken over N, N is the number of data points used, y_i is the observed peak weekly water demand, and $\hat{y}_i$ is the forecasted peak weekly water demand from the model.

The root mean square error (RMSE) evaluates the variance of errors independently of the sample size, and is given by:

$$\mathrm{RMSE} = \sqrt{\frac{SEE}{N}} \tag{5}$$

where SEE is the sum of squared errors, and N is the number of data points used. SEE is given by:

$$SEE = \sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \tag{6}$$

with the variables having already been defined. The smaller the RMSE, the better is the performance of the model.

3. Study areas and data

3.1. Study rivers

For the last several years Cyprus has been facing an unprecedented water crisis. There has been minimal rainfall since 2003, reservoirs in the country are at less than 10% of their capacity, and its two newly built desalination plants have been unable to supply sufficient quantities of water (Gabriel, 2008). Rainfall on the island averages 460 mm, a 15% drop from 1970. Over-abstraction from aquifers has been estimated to be between 29 and 40 MCM (Million Cubic Meters) per year, and due to water scarcity and multiyear droughts, this has led to a near exhaustion of the 'cushioning' effects of the aquifers as well as sea water intrusion (Socratous, 2005). The overall average aridity index of Cyprus is 0.295, which makes the entire island a semi-arid island.

It is anticipated that climate change will have a number of impacts in Cyprus: a mean summer temperature increase of 5 °C by 2070–2100, a mean summer precipitation change of −4 mm/month by 2070–2100, and an increase in the duration and intensity of droughts (Lange, 2007). Intense precipitation events could result in excess surface run-off rather than infiltration to groundwater, and rising seawater levels could increase flooding and seawater ingress, resulting in the contamination of surface and groundwater bodies.

One of the major sources of water in Cyprus is rivers, none of which are perennial in nature. All the rivers of Cyprus are fed by the melting snow of the Troodos mountain range. Two rivers in Cyprus with different characteristics were selected for this study:

(1) *The Xeros River at Lazarides.* This is a river in the western part of the island. It has a drainage area of 67 km^2. The Lazarides station is located in the Paphos Forest and the site is considered pristine. Between 1965 and 2007, the mean flow was 0.3522 m^3/s, the max flow was 29.0 m^3/s, and the minimum flow was 0.02 m^3/s.
(2) *The Kargotis River at Evryvhou.* This is a river located in the northern part of the island. It has a drainage are of 63 km^2. The Kargotis station is located in an urbanized valley. Between 1965 and 2007, the mean flow was 0.3626 m^3/s, the max flow was 17.0 m^3/s, and the minimum flow was 0 m^3/s.

Additional detail on the mean flows, maximum flows, minimum flows, and standard deviations for each of the two stations can be found in Table 1.

3.2. Data

This study used river flow (mean daily streamflow in m^3/s) from the two different rivers mentioned above. River flow data from 1965 to 2007 was available for each of the two rivers. Flow data for the two rivers was provided by the Water Development Department of Cyprus.

For both the WA–ANN and the ANN models, the data series were divided into a training/calibration set (80% of the data) and a testing set (the remaining 20% of the data).

4. Model development

4.1. Artificial neural network models

Multi-layer perceptrons (MLPs) are the simplest and most commonly used neural network architectures. MLPs can be trained using many different learning algorithms. In this research, MLPs were trained using the Levenberg–Marquardt (LM) algorithm. The Levenberg–Marquardt algorithm, like the quasi-Newton methods, was developed to approach second-order training speed without having to compute the Hessian matrix. The LM algorithm has been found to be the fastest method for training moderate-sized feed-forward neural networks, although it requires a greater amount of memory than other algorithms (Karul et al., 2000).

When developing an ANN model, the primary objective is to arrive at the optimum architecture of the ANN that captures the relationship between the input and output variables. The task of identifying the number of neurons in the input and output layers is normally simple as it is dictated by the input and output variables considered to model the physical process. The number of neurons in the hidden layer has to be optimized using the available data through the use of a trial and error procedure. In addition, optimal values for the learning coefficients have to be determined for certain types of ANNs.

For the regular ANNs used in this study (i.e. those not using wavelet decomposed input flow data) ANN models consisting of an input layer with 1–21 input neurons, one single hidden layer composed of 22 neurons, and one output layer consisting of one neuron denoting the predicted mean daily flow, were developed. Each ANN model was tested on a trial and error basis for the optimum number of neurons in the hidden layer (found to be between 22). This is shown in Table 2.

For the regular ANNs used in this study, 400 ANN models were developed for each of the two different rivers. The ANN models were developed using a combination of the following variables: mean flow from 1 day before up to and including mean flow from 15 days before.

For both rivers, all of the regular ANN models were first trained using the data in the training sets (using 80% of the data) to obtain the optimized set of connection strengths, and then tested (using the remaining 20% of the data). The models were then compared using two statistical measures of goodness of fit (coefficient of determination and root mean square error).

4.2. Coupled wavelet and artificial neural network models

The coupled wavelet and neural network models are ANN models which use, as inputs, sub-series components (DWs) which are derived from the use of the DWT on the original flow time series data. The coupled wavelet and neural network models are referred to as WA–ANN models in this research (with WA referring to wavelet analysis and ANN referring to artificial neural networks). Each sub-series component plays a different role in the original time series and the behavior of each sub-series is distinct. The ANN models are built such that the DWs of the original flow time series are the inputs to the ANN and the original un-decomposed flow time series are the outputs of the ANN.

In this study, the flow data for each of the two rivers was decomposed into sub-series of decomposition and details (DWs). The process consists of a number of successive filtering steps. The original flow time series is first decomposed into an approxi-

Table 1
Mean, maximum, minimum and standard deviation of flows.

Station	x_{mean}	x_{max}	x_{min}	s_x
Kargotis at Evrychou				
Training data	.4005	17.00	0	.6184
Testing data	.2740	10.50	0	.4698
Whole data	.3626	17.00	0	.5808
Xeros at Lazarides				
Training data	.3614	19.70	.0200	.8629
Testing data	.3308	29.00	.0200	1.069
Whole data	.3522	29.00	.0200	.9295

Note: x_{mean} = mean daily mean flow; x_{max} = maximum daily mean flow; x_{min} = minimum daily mean flow; s_x = standard deviation.

Table 2
ANN model information for both $t-1$ and $t-3$ forecasting.

Station	# Neurons	Window length
Kargotis at Evrychou		
$t-1$	22	5
$t-3$	22	17
Xeros at Lazarides		
$t-1$	22	21
$t-3$	22	9

Note: # neurons refers to the optimum number of neurons in the hidden layer.

mation and accompanying detail signal. The decomposition process is then iterated, with successive approximation signals being decomposed in turn, so that the original flow time series is broken down into many lower resolution components.

Eight wavelet decomposition levels (2–4–8–16–32–64–128–256) were selected for this study. All sub-series were used as inputs to the ANN models because an averaging or optimizing selection of only certain sub-series would have been a diminutive approach – all sub-series coefficients are equally important and contain information about the original time series. In addition, using each sub-series coefficient for each data point resulted in eight times the normal number of data points, therefore rendering it possible to use less number of days to forecast accurately.

For both rivers, different sub-series input combinations into the ANN models were tested (which were chosen based on the correlation coefficients between each sub-series and the original flow data). As well, different combinations of the number of neurons in the hidden layer as well as different window lengths (1–15 days) were tested.

For the WA–ANN models, ANN networks consisting of an input layer with 1–160 input neurons, one single hidden layer composed of 22 neurons, and one output layer consisting of one neuron denoting the predicted mean daily flow, were developed. Each ANN model was tested on a trial and error basis for the optimum number of neurons in the hidden layer (found to be 22).

For the coupled WA–ANN models, 400 ANN models were developed for each of the two different rivers. The ANN models were developed using a combination of the following variables: mean flow from 1 day before up to and including mean flow from 15 days before.

For both rivers, all of the ANN models were first trained using the data in the training sets (using 80% of the data) to obtain the optimized set of connection strengths, and then tested (using the remaining 20% of the data). The models were then compared using two statistical measures of goodness of fit (coefficient of determination and root mean square error).

5. Results

5.1. ANN and coupled wavelet-neural network models for 1 day lead time forecasting

Tables 2 and 3 show the number of neurons and window lengths for the best ANN and WA–ANN models for 1 and 3 days ahead flow forecasting, respectively. Tables 4 and 5 show the ANN and WA–ANN model performance statistics (R^2 and RMSE) for the best ANN and WA–ANN models for both rivers for both 1 and 3 days ahead flow forecasting.

For the Kargotis River, it can be seen that the best model overall for 1 day lead time forecasting was the best WA–ANN model, which had a testing R^2 of 0.9706, and a testing RMSE of 0.1315. This WA–ANN model had 22 neurons in the hidden layer and a window length of 5 days. The best ANN model had a testing R^2 of 0.9357, and a testing RMSE of 0.1448. This ANN model had 22 neurons in the hidden layer and a window length of 5 days. Fig. 1 compares the observed flow for the Kargotis River at Evrychou station with the flow forecasted using the best WA–ANN model for 1 day lead time forecasting (for the test period). Fig. 2 is a close up of test years 1 and 2 of the test period (i.e. a close up of part of Fig. 1). From the figures, it can be seen that the WA–ANN model slightly under-forecasts low flows and peak flows. Despite this, it can be seen that the WA–ANN model provides highly accurate forecasts.

For the Xeros River, it can be seen that the best model overall for 1 day lead time forecasting was the best WA–ANN model, which had a testing R^2 of 0.7823, and a testing RMSE of 0.2718. This WA–ANN model had 22 neurons in the hidden layer and a window length of 5 days. The best ANN model had a testing R^2 of 0.6233, and a testing RMSE of 0.4992. This ANN model had 22 neurons in the hidden layer and a window length of 21 days. It can be seen that in the case of the Xeros River, neither the WA–ANN nor the ANN models provided very accurate forecasts, although the WA–ANN model did provide more accurate forecasts than the ANN model.

Overall, it can be seen that for 1 day ahead forecasting the coupled wavelet-neural network models provided more accurate forecasting results than the regular artificial neural network models.

5.2. ANN and coupled wavelet-neural network models for 3 days lead time forecasting

Tables 2 and 3 show the number of neurons and window lengths for the best ANN and WA–ANN models for 3 days ahead flow forecasting, respectively. Tables 4 and 5 show the ANN and WA–ANN model performance statistics for the best ANN and WA–ANN models for both rivers for 3 days ahead flow forecasting.

For the Kargotis River, it can be seen that the best model overall for 3 days lead time forecasting was the best WA–ANN model, which had a testing R^2 of 0.8597, and a testing RMSE of 0.1258. This WA–ANN model had 22 neurons in the hidden layer and a window length of 11 days. The best ANN model had a testing R^2 of 0.7919, and a testing RMSE of 0.1945. This ANN model had 22 neurons in the hidden layer and a window length of 17 days.

For the Xeros River, it can be seen that the best model overall for 3 days lead time forecasting was the best WA–ANN model, which had a testing R^2 of 0.4197, and a testing RMSE of 0.3980.

Table 3
WA–ANN model information for both $t-1$ and $t-3$ forecasting.

Station	# Neurons	Window length
Kargotis at Evrychou		
$t-1$	22	5
$t-3$	22	11
Xeros at Lazarides		
$t-1$	22	5
$t-3$	22	12

Note: # neurons refers to the optimum number of neurons in the hidden layer.

Table 4
R^2 and RMSE values for ANN models for both rivers for both training and testing periods (use of original time shifted F-series).

Station	R^2 $(t-1)$	R^2 $(t-3)$	RMSE $(t-1)$	RMSE $(t-3)$
Kargotis at Evrychou				
Training period	.9215	.7228	.9413	1.597
Testing period	.9357	.7919	.1448	.1945
Xeros at Lazarides				
Training period	.8025	.4159	.9402	2.220
Testing period	.6233	.4045	.4992	.6519

Table 5
R^2 and RMSE values for WA–ANN models for both rivers for both training and testing periods (use of wavelet time shifted F-series).

Station	R^2 $(t-1)$	R^2 $(t-3)$	RMSE $(t-1)$	RMSE $(t-3)$
Kargotis at Evrychou				
Training period	.9512	.9109	.8660	2.939
Testing period	.9706	.8597	.1315	.1258
Xeros at Lazarides				
Training period	.9026	.4578	4.848	1.652
Testing period	.7823	.4197	.2718	.3980

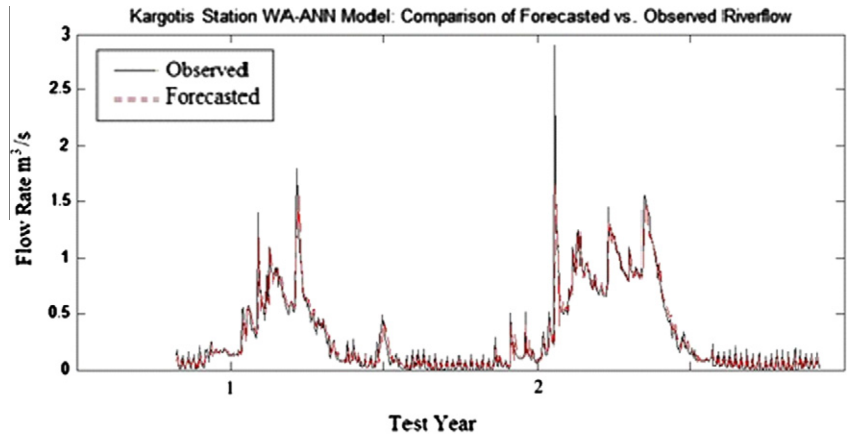

Fig. 1. Comparison of forecasted versus observed flow using the best WA–ANN model for 1 day ahead forecasting for the Kargotis River at Evrychou station (test period).

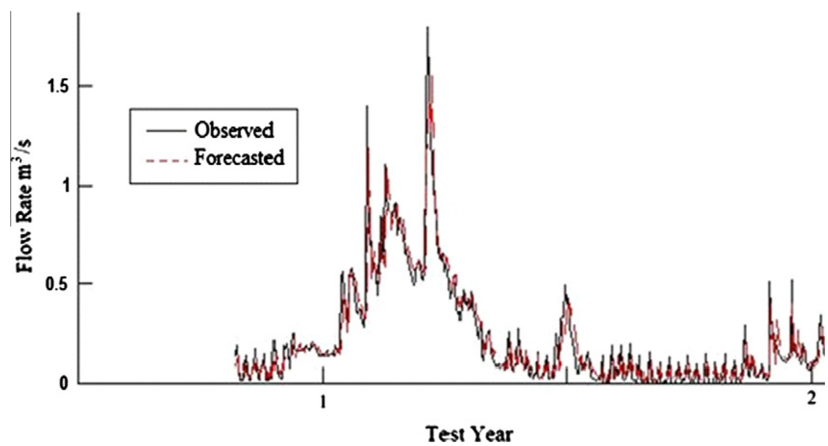

Fig. 2. Close up of comparison of forecasted versus observed flow using the best WA–ANN model for 1 day ahead forecasting for the Kargotis River at Evrychou station.

This WA–ANN model had 22 neurons in the hidden layer and a window length of 12 days. The best ANN model had a testing R^2 of 0.4045, and a testing RMSE of 0.6519. This ANN model had 22 neurons in the hidden layer and a window length of 9 days.

Overall, it can be seen that for 3 days ahead forecasting the coupled wavelet-neural network models provided more accurate forecasting results than the regular artificial neural network models.

6. Conclusions

The potential of coupled wavelet-neural network models (WA–ANN) for 1 and 3 days ahead flow forecasting was investigated in this study for non-perennial rivers in semi-arid watersheds. The coupled wavelet-neural network models were developed by combining two methods, namely the discrete wavelet transform and artificial neural networks. The coupled wavelet-neural network models were compared to regular artificial neural network models for 1 and 3 days ahead flow forecasting using data from two non-perennial rivers in Cyprus. It was determined that for both 1 and 3 days lead time forecasting, the WA–ANN models provided more accurate results than the regular ANN models. It is thought that the WA–ANN models are more accurate since wavelet transforms provide useful decompositions of the original time series, and the wavelet-transformed data improves the ability of the ANN forecasting model by capturing useful information on various resolution levels.

In reference to the original aims of this study, it was determined that: (1) the WA–ANN method can be used with high accuracy for 1 day ahead flow forecasting, and with some accuracy for 3 days ahead flow forecasting, in semi-arid watersheds with intermittent flows; and (2) the use of all wavelet decomposed sub-series as inputs to the ANN models helps provide very accurate forecasts of flow. The results indicate that coupled wavelet-neural network models are a promising new method of short-term flow forecasting in non-perennial rivers in semi-arid watersheds such as in Cyprus.

The present study focused on the forecasting of daily mean flow using only flow data. It is hypothesized that the forecasts could be improved if other variables which affect flow were to be included. Examples of climatic variables not used in this research that could be investigated in future studies include: maximum and minimum temperature as well as total rainfall. It is likely that different combinations of flow and climatic variables would improve the forecasting ability of the models explored in this study. Other recommendations for future studies include: exploring the application of coupled wavelet-neural network models for forecasting flows in different semi-arid and arid areas; exploring lead times of 1 week and 2 weeks; comparing the use of the continuous wavelet transform with the use of the discrete wavelet transform for data pre-processing; and comparing the use of different types of artificial neural networks in the coupled wavelet-neural network models.

Acknowledgement

Flow data was provided by Mr. Gerald Dorflinger of the Water Development Department of Cyprus. His help is greatly appreciated.

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