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Heuristic Modelling of the Water Resources Management in the Guadalquivir River Basin, Southern Spain

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Abstract A model comprising blocks of artificial neural networks (ANNs) combined in sequence was used to simulate the inflow and outflow in a water resources system under a shortage of water. We assessed the selection of appropriate input data using linear and non-linear cross-correlation functions and sensitivity analysis. The potential model inputs were flow, precipitation and temperature data from various gauging stations throughout the upper watershed of the 'Guadiana Menor' River (southern Spain), and the model considered various input time lags. The ANNs based on the selected inputs were effective relative to those with no relevant inputs, and produced more parsimonious models. We also investigated conceptual analogies inherent in the ANN models by analyzing the response profiles of the modelled variables (inflow and outflow) in relation to each of the selected input data. The results demonstrate that the neural approach approximated the behaviour of various components of the water resources system in terms of various hydrologic cycle processes and management rules. Our findings suggest that in dry periods a mean temperature increase of 1°C in low altitude locations of the region will result in a mean decrease of approximately 2% in the inflow to the water resources system, and a mean increase of approximately 12% in the outflow requirements for irrigation purposes.

Keywords Artificial neural networks · Input selection · Response patterns · Cluster analysis · 'Guadiana Menor' River

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1 Introduction

Water is an essential resource for life, progress and environmental conservation. Its effective management is therefore one of the basic requirements for sustainable economic development and social welfare in any country. Water policies and reforms have too often been guided by assumptions about the need to increase supplies through investment in physical infrastructure. Reform of the water sector, particularly in developing countries, has increasingly aimed at balancing infrastructure with aspects of governance and management, such as water resources assessment (understanding resources and needs) and improving knowledge of demand management at the level of each river basin (Omedas et al. 2008).

In this context, a program for the establishment of an Automatic Hydrological Information System (SAIH; *Sistema Automático de Información Hidrológica*) has been created in each of the nine main river basins in Spain. SAIH is a real-time information system that captures hydrological, hydraulic and other basic meteorological data. These data are transmitted to the corresponding control centre, where they are analyzed and applied to the management of the water resources in both normal (exploitation) and emergency (droughts and floods) situations. The transmission of data from control stations of the SAIH project in the Guadalquivir River basin (SAIH Guadalquivir) commenced in 1999.

The Guadalquivir River extends in a westerly direction across southern Spain. Use of water in the Guadalquivir River basin is dominated by irrigated agriculture, which accounts for approximately 80% of water consumption. Municipal and industrial uses account for approximately 12%, and the remaining 8% is used for environmental and other water needs. The Guadalquivir River basin is considered to be in 'water deficit' because the estimated relationship between available water resources and the total water demand is negative (Bhat and Blomquist 2004). This situation may worsen because the latest climate change predictions for Spain suggest a 17% reduction in available water resources (Iglesias et al. 2005). Rodríguez-Díaz et al. (2007) modelled the impacts of climate change on the current irrigation water demand in the Guadalquivir River basin, and showed an expected increase of 15−20% in seasonal irrigation requirements by the 2050s, depending on the location and cropping pattern.

To conserve water supplies in the Guadalquivir River basin, the water authority has reduced the volume of water assigned to each irrigation district. Major infrastructural investments have been made to improve irrigation efficiency, including the adoption of high technology micro-irrigation systems. In this water shortage context, the present basin management plan is based on an equilibrium situation among all water uses. However, expansion of the irrigated area in recent decades and the existing irrigation water deficit makes the present situation difficult to sustain (Camacho 2005; Rodríguez-Díaz et al. 2007). Thus, it is essential to assess the water resources management policies that are being implemented in the basin. To this end we used a simulation model based on the SAIH Guadalquivir data. The main objective in using this model was to evaluate the hydrological consequences of various climatic situations in terms of the probability of demand failure in the water resources system. Such information will assist river basin managers in their decision-making process, and to plan response measures in advance.

A simulation model of water resource systems usually requires analysis of various hydrological components (including precipitation, evaporation and air temperature) and management components (including inflow to and outflow from reservoirs), which represent demands for irrigation, hydropower, and municipal and industrial water uses. Such an analysis involves sequences of variables whose values change over time (multivariate time series) (Raman and Sunilkumar 1995). Various models have been proposed as a consequence of the random characteristics of these time series (Bras and Rodríguez-Iturbe 1985). The more popular and extensive ones include simple and multiple linear regressions, autoregressive models AR, ARMA and ARIMA, and the artificial neural network (ANN) models (Ochoa-Rivera et al. 2007). Comparisons between the linear and neural network models (which are non-linear) have generally indicated that the latter perform best (Hsu et al. 1995; Ochoa-Rivera et al. 2002, 2007; Pulido-Calvo et al. 2003). Therefore, in this study we adopted the ANN approach to simulate the management of the water resources system in the upper watershed of the 'Guadiana Menor' River, which is a sub-watershed of the Guadalquivir River basin. The performance of the ANN model was compared with the IHACRES model, which has been extensively used in surface water applications (Jakeman et al. 1990; Dye and Croke 2003).

Most reported uses of ANNs to simulate water resources systems have been limited to independent analysis of many of the hydrological and management components involved in these systems, including: (a) modelling of monthly, daily and hourly rainfall — runoff processes (Hsu et al. 1995; Lorrai and Sechi 1995; Mason et al. 1996; Abrahart et al. 1999; Tokar and Johnson 1999; Thirumalaiah and Deo 2000; Tokar and Markus 2000; Chiang et al. 2004; Moradkhani et al. 2004; Anctil and Rat 2005); (b) generation of synthetic inflows to reservoirs (Raman and Sunilkumar 1995; Ochoa-Rivera et al. 2002, 2007); (c) short term river stage forecasting (Thirumalaiah and Deo 1998; Abrahart and See 2000, 2002; See and Openshaw 2000; Cameron et al. 2002; Pulido-Calvo and Portela 2007; Makkeasorn et al. 2008); (d) rainfall forecasting (French et al. 1992; Zhang et al. 1997; Kuligowski and Barros 1998); (e) groundwater modelling (Roger and Dowla 1994; Yang et al. 1997); and (f) water demand prediction in urban and irrigation delivery systems (Jain et al. 2001; Bougadis et al. 2005; Pulido-Calvo et al. 2007; Pulido-Calvo and Gutiérrez-Estrada 2009; Firat et al. 2008; Adamowski and Karapataki 2010).

The research described here extends these previous studies by providing a method for simulating integrated management of a water resources system. It included two modules: (a) the first modelled the synthetic inflow series for a reservoir or set of reservoirs comprising the water resources system, and (b) the second modelled the various uses (irrigation, municipal, industrial, hydropower) of the water resources system. Various decision support systems have been designed for water resources planning and operational management (Andreu et al. 1996; Jamieson and Fedra 1996a, b; Ochoa-Rivera et al. 2007; Gastélum et al. 2009), but these require diverse calibration parameters to simulate phenomena including infiltration through aquifers, reservoir evaporation and hydraulic losses from channels, which can complicate the decision-making processes in those watersheds where these data are not available or are not easy to obtain. It is important to emphasize that the main goal in developing the method was to improve the management and administration of water at the sub-watershed level, using the SAIH Guadalquivir information system.

We evaluated the performance of neural approaches to simulation of the management of a water resources system in southern Spain. This Mediterranean region was selected because it is an area of 'water-deficit'. The analysis involved the use of sequential ANN blocks (Shrestha et al. 2005; Elgaali and García 2007). The first ANN block simulated the inflow series to a reservoir or set of reservoirs, and the second block simulated the water demands on the water resources system. As the performance of data driven techniques (such as ANNs) is highly sensitive to the selected input variables (Fernando et al. 2009), this study explored procedures for selecting an optimal model input vector from a set of candidate parameters (flow, temperature and precipitation data scattered throughout of the study watershed at various time lags).

2 Material and Methods

2.1 Study Area

The water resources system in this study is the upper watershed of the 'Guadiana Menor' River, which is located in the Guadalquivir basin (southern Spain). This sub-watershed is one of 15 areas covering the basin; these form the basis for promotion and management of basin water resources by the Guadalquivir River Basin Agency (*Confederación Hidrográfica del Guadalquivir*) (Bhat and Blomquist 2004). The water resources system comprises three reservoirs: (a) the Negratín reservoir in the main course of the 'Guadiana Menor' River; (b) the 'La Bolera' reservoir, which regulates the Guadalentín River; and (c) the 'San Clemente' reservoir, which regulates the Guardal River. The Guadalentín and Guardal rivers are both tributaries of the 'Guadiana Menor' River. Table 1 shows the general characteristics of these three reservoirs. The Castril, Cúllar, Orce and Baza rivers are other tributaries of the 'Guadiana Menor' River, in its upper watershed (Fig. 1).

Water use in the watershed is dominated by irrigated agriculture (total area approximately 32,600 ha), which accounts for approximately 91% of water consumption. Municipal and industrial uses account for approximately 6% of use, and the remaining 3% provides for environmental requirements and other water needs (Confederación Hidrográfica del Guadalquivir 1995; AQUAVIR 2005).

The catchment area of the upper watershed of the 'Guadiana Menor' River (approximately 3,500 km^2) is almost entirely within the Andalusia region, but includes small areas in the 'Castilla-La Mancha' and Murcia regions. Mean annual precipitation is 535 mm, but rainfall varies significantly over space and time. Annual precipitation ranges from 160 to 780 mm in the low altitude areas of the region (climate area 'Hoyas Guadix-Baza'), and from 370 to 1,300 mm in the high altitude areas (climate area 'Sierra de María y los Filabres'). At high altitudes much of the precipitation falls as snow. Most precipitation occurs in the winter months, with peak rainfall occurring from November to March. The summers are dry, with virtually no precipitation. Seasonal and interannual variability of temperature and reference evapotranspiration are very large. The mean annual temperature is 14.4°C, with extremes of −10°C and 40°C in winter and summer, respectively. The mean annual reference evapotranspiration is 250 mm, with extremes of 10 mm and 500 mm in winter and summer, respectively (The values indicated are over the period from October 2000 to September 2008).

Table 1 General information on the reservoirs in the study water resources system

Parameter	Negratín reservoir (E06)	'La Bolera' reservoir (E05)	'San Clemente' reservoir (E03)
Capacity (hm^3)	567	53	118
Elevation above sea level (m)	625	971	1032
Latitude	37°33′	37°45′	37°51′
Longitude	2°57′	2°54′	2°39′
Water uses	. Irrigation . Hydropower . Urban uses . Flow control	. Irrigation	. Irrigation . Flow control

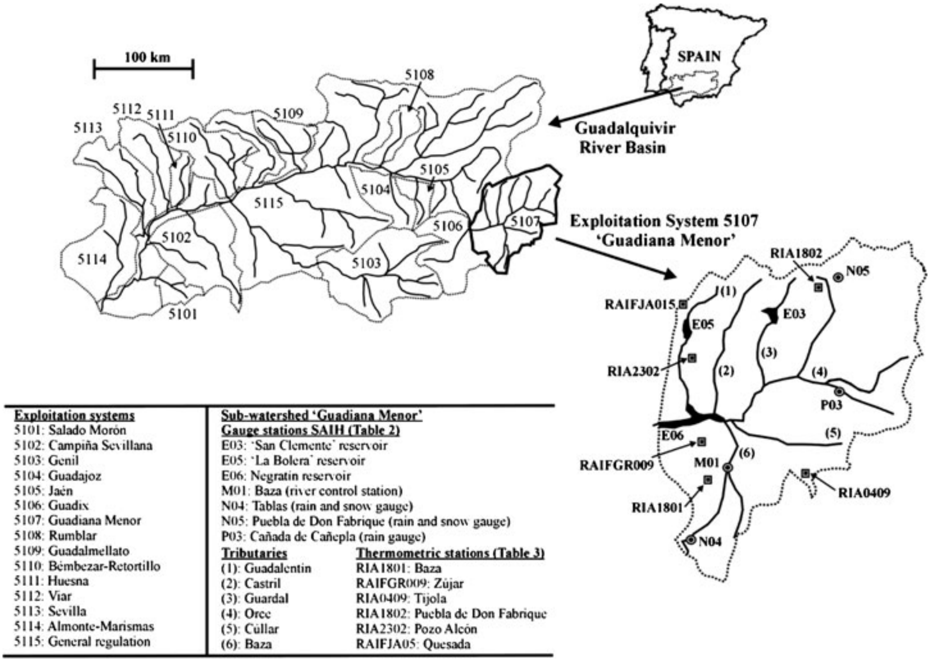

Fig. 1 Location of the Guadalquivir River basin and associated exploitation systems. Gauging stations of the upper watershed of the 'Guadiana Menor' River (exploitation system 5107)

Seasonal variability of water supplies is also great. During the 8-year period of this study (October 2000 to September 2008) the mean annual inflows were 2.69±3.74 m^3/s (mean value ± standard deviation) to the Negratín reservoir, 1.03±3.84 m^3/s to the 'La Bolera' reservoir, and 0.36±0.85 m^3/s to the 'San Clemente' reservoir. The maximum inflows in this period were 58.20 m^3/s (Negratín reservoir), 83.64 m^3/s ('La Bolera' reservoir), and 14.29 m^3/s ('San Clemente' reservoir).

2.2 Automatic Hydrologic Information System

The Guadalquivir SAIH consists of a branching network distributed throughout the Guadalquivir basin. Its main objective is to provide precipitation and stream flow data, including reservoir and river levels. The main components of the SAIH are: (a) remote stations that capture the signals from the rain and snow gauges, and the water flow and level meters; (b) the concentration stations, which receive and store the field signals sent from the remote or gauging stations; and (c) the central control site, which stores, displays, processes and disseminates the data recorded at the concentration stations (Fig. 2).

The Guadalquivir SAIH has 140 remote stations and 4 concentration stations, and provides (www.juntadeandalucia.es/agenciadelagua/) information (hourly, daily and monthly data) recorded since 1999. In the 'Guadiana Menor' River sub-watershed (exploitation system 5107 in the Guadalquivir basin) there are 7 gauging stations (Fig. 1), the characteristics of which are shown in Table 2.

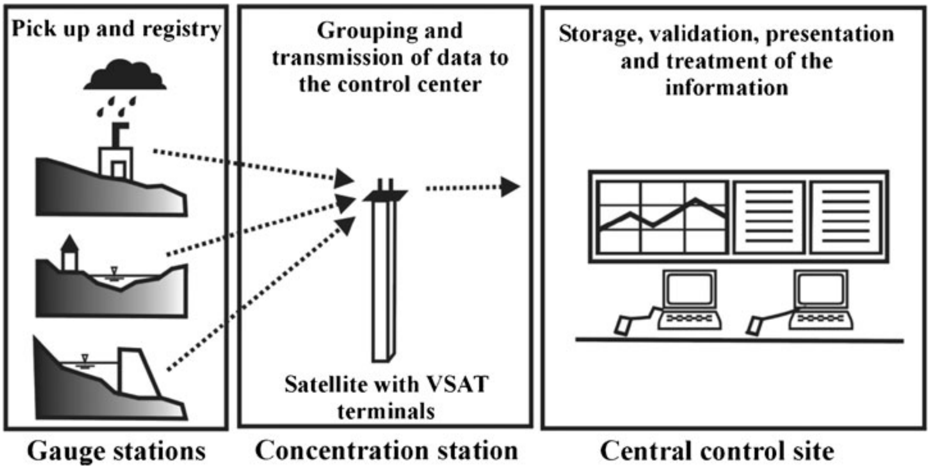

Fig. 2 Scheme of operation of the Guadalquivir SAIH network

2.3 Data Synthesis

The variables used in this study include historic inflow and outflow data for the Negratín reservoir, precipitation recorded by the Guadalquivir SAIH (Table 2), and air temperature recorded at 6 thermometric stations in the study watershed. Air temperature data were provided by two real-time data acquisition networks, the Agro-climatic Information Network (RIA) and the Phytosanitary Alert and Information Network (RAIF); these information networks are available at www.juntadeandalucia.es/medioambiente/. The characteristics of these thermometric stations are shown in Table 3.

Figure 1 shows the locations of the Guadalquivir SAIH gauging stations and the thermometric stations in the watershed. All the datasets were collected and used on a weekly basis for the period 1 October 2000 and 30 September 2008. The inflow/outflow and air temperature data were mean weekly values, and the precipitation data was accumulated values.

2.4 Neural Approaches — General Procedure

The simulation of the water resources management of the 'Guadiana Menor' River sub-watershed was based on ANNs, which are mathematical models inspired by the neural architecture of the biological nervous system. The most widely studied and used ANN models involve multilayer feed-forward networks, or multilayer perceptrons (Rumelhart et al. 1986). These models 'learn' in an iterative way, whereby the data are introduced a number of times to the neural network until a pre-determined error level (calculated as the sum of the squared errors) is reached; the iteration where all the data are introduced to the ANN is termed the 'epoch'. These supervised ANNs allow the analysis of complex datasets and the assessment of non-linear relationships between dependent and independent variables. Detailed descriptions of the performance of multilayer perceptron ANNs have been reported by Hsu et al. (1995), Tsoukalas and Uhrig (1997), ASCE (2000a, b), Shrestha et al. (2005), Gutiérrez-Estrada et al. (2007), and Pulido-Calvo and Portela (2007). There are many ANN calibration or learning methods; in this study the standard back-propagation algorithm was used.

Table 2 Characteristics of the data acquisition stations in the Guadalquivir SAIH for the study sub-watershed

Parameter	Negratín reservoir	'La Bolera' reservoir	'San Clemente' reservoir	Baza	Puebla de Don Fabrique	Tablas	Cañada de Cañepla
Station type	Reservoir control point	Reservoir control point	Reservoir control point	River control point	Rain and snow gauge	Rain and snow gauge	Rain gauge
Denomination*	E06	E05	E03	M01	N05	N04	P03
Elevation above sea level (m)	642	973	1064	740	1038	1909	1075
Latitude	37°33′33″	37°45′45″	37°51′42″	37°31′16″	37°55′14″	37°16′53″	37°47′57″
Longitude	2°57′4″	2°54′10″	2°39′7″	2°42′33″	2°28′36″	2°46′44″	2°17′8″
Measured data	. Water level . Water volume . Precipitation . Inflow . Partial and total outflows	. Water level . Water volume . Precipitation . Inflow . Partial and total outflows	. Water level . Water volume . Precipitation . Inflow . Partial and total outflows	. Water level . Precipitation	. Precipitation	. Precipitation	. Precipitation

*Denomination according Guadalquivir SAIH

Table 3 Characteristics of thermometric stations in the upper watershed of the ‘Guadiana Menor’ River

Parameter	Baza	Zújar	Tíjola	Puebla de Don Fabrique	Pozo Alcón	Quesada
Denomination*	RIA1801	RAIFGR009	RIA0409	RIA1802	RIA2302	RAIFJA015
Elevation above sea level (m)	814	860	796	1110	893	700
Latitude	37°33′56″	37°32′28″	37°22′47″	37°52′38″	37°40′23″	37°49′37″
Longitude	2°45′59″	2°50′23″	2°27′30″	2°22′49″	2°55′44″	2°56′12″

*Denomination according RIA and RAIF information networks

Prior to the calibration of any ANN the dataset was divided in two subsets: (i) the CSS, which equates to the calibration subset (CS) + the select subset (SS), comprised data from 1 October 2000 to 30 September 2006 (6 years of weekly data); (ii) the TS (test subset) comprised data from the 2 remaining years, from 1 October 2006 to 30 September 2008. The TS was not used for model calibration or training, but was involved in verification or validation of the simulation models. In the CSS, the 25% data (randomly selected) composed the select subset (SS) and these ones were used to avoid the ANN overtraining or overcalibration.

The best method of ensuring that overtraining does not occur is to periodically (at the end of each epoch) monitor the sum square error for both the CS and the SS (internal validation). The sum square error for the CS normally decreases continuously with training. However, this may force the neural network to fit the noise in the CS. To avoid this problem, training is stopped at the end of each epoch, and the sum square error of the SS is calculated. Training ceases when the sum square error of the SS begins to increase, and at this point the weight of the epoch, which provides a minimum error for the SS, is tested with the TS. This last phase is also called the generalization phase, or external validation. Iyer and Rhinehart (1999) recommend repeating this process at least 30 times for each model, and this recommendation was followed here.

The procedure described above was carried out for each neural configuration tested. ANNs with one and two hidden layers were assessed in this study; in each case 5−50 neurons were tested (Gutiérrez-Estrada et al. 2008).

All of the CSS data that were used for model training were standardized by subtracting the mean and dividing by the standard deviation. The TS data that were used for model generalization or verification were also transformed using the mean and standard deviation of those variables in the CSS. This procedure was implemented to avoid the masking of features of interest (Ochoa-Rivera et al. 2007; Makkeasorn et al. 2008).

Four accuracy measures were calculated in the calibration and validation phases for each ANN: the coefficient of determination or the square of the Pearson’s product-moment correlation coefficient (r^2), the square root of the mean square error (RMSE), the Nash-Sutcliffe efficiency coefficient (E_2), and the persistence index (PI with a lead-time = 1) (Nash and Sutcliffe 1970; Kitanidis and Bras 1980; Legates and McCabe 1999; Pulido-Calvo and Portela 2007).

Two blocks of ANNs, the first to model inflow to the Negratín reservoir and the second to model outflow from the reservoir to the various water uses, were combined in sequence. The first block comprised one ANN, and the second block comprised three ANNs (one for each of the various uses of the reservoir water) (Fig. 3). The outflow ANNs (1) and (2) related to irrigation uses and hydropower, respectively. The outflow ANN (3) related to

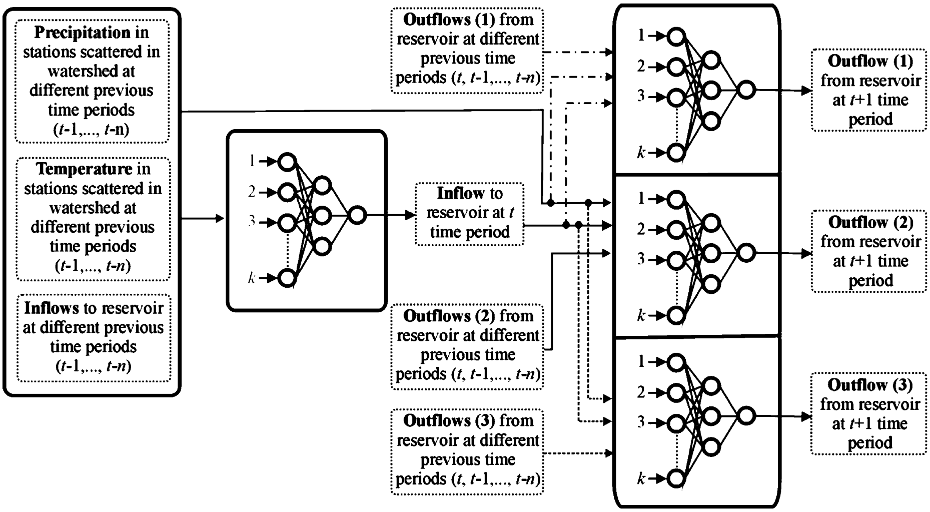

Fig. 3 ANN model for the management simulation of the water resources system

other needs including: (a) municipal and industrial uses; (b) environmental requirements; (c) flow regulation for the entire Guadalquivir basin; and (d) distribution to other reservoir (water transfer 'Negratín — Almanzora'). While the latter services irrigation and urban uses it is not part of the exploitation system in this study, but the demand involved accounts for the majority of water involved in outflow ANN (3).

To test the coherency of results obtained with the ANNs, the behaviour of the inflow ANN model was compared with the IHACRES model (Jakeman et al. 1990; Dye and Croke 2003). The core of this model is a non-linear loss module that converts precipitation and temperature into effective rainfall, and a linear routing module that converts effective precipitation into stream flow. The IHACRES model was applied in the same way as the inflow ANN, to describe climate — inflow relationships. Nevertheless, as a consequence of that the inputs to the IHACRES model are time series of 'catchment average' precipitation and temperature and therefore it cannot use inflow inputs, it only was compared with those ANNs that had only precipitation and temperature as input variables. On the other hand, with the intention of doing a comparison as accurate as possible, the IHACRES models were calibrated using the relationships between elevation and climate proposed by Croke et al. (2006) in order to calculate the time series of 'catchment average' precipitation and temperature.

2.5 Selection of Input Data

The selection of appropriate input variables from among the available parameters is an important consideration in ANN modelling (Bowden et al. 2005; Shrestha et al. 2005; May et al. 2008; Fernando et al. 2009). For application in the calibration and validation phases, the objective is to select input variables (including time lags) that explain the greatest variance with the least error. Selection of inappropriate input variables may cause undesirable effects including the naïve effect (where forecasts provided by the model for each time period are systematically very close to values observed for the previous time periods), the increased presence of local optima, or extreme difficulty in extracting physical meaning from the calibrated models. To overcome these problems many neural approaches have adopted methodologies including autocorrelation and partial autocorrelation function analysis, linear cross-correlation analysis, or spectral analysis (Jain et al. 2004; Shrestha et al. 2005; Elgaali and García 2007; Pulido-Calvo and Portela 2007; Gutiérrez-Estrada et al. 2007). However, it appears that these methods are designed to capture linear dependence measures between potential model inputs and outputs, which could mask the strength of non-linear relationships and favour the omission of relevant inputs (i.e. the model will be under-specified).

To mitigate this problem in the present study, the selection of model inputs was made through analysis of linear and non-linear cross-correlation functions calculated between the model outputs (inflow to and outflows from the Negratín reservoir) and the potential model inputs (flow, temperature and precipitation data from throughout the watershed and at various time lags). Using this approach, 22 models (Table 4) were fitted to extract the linear and non-linear cross-correlations for each possible two-dimensional relationship. The fitting for each pair of variables accounted for the influence of the potential input variable lagged in time t. Thus, lags from $t=1$ (time lag of 1 week) to $t=12$ (time lag of 12 weeks) were analyzed. The maximum lag ($t=12$) was selected because it corresponded to seasonal periods (spring, summer, autumn, winter).

Table 4 Models used for the determination of linear and non-linear cross-correlation. The constant term is designated by β_0. β_1 and β_2 are parameters of the model and Y and X are the dependent and independent variables, respectively

Model	Equation
(1) Linear	$Y = \beta_0 + \beta_1 X$
(2) Reciprocal Linear	$Y = 1/(\beta_0 + \beta_1 X)$
(3) Rectangular Hyperbola I	$Y = (\beta_0 + \beta_1 X)/(1 + \beta_1 X)$
(4) Reciprocal Rectangular Hyperbola I	$Y = (1 + \beta_1 X)/(\beta_0 + \beta_1 X)$
(5) Rectangular Hyperbola II	$Y = X/(\beta_0 X + \beta_1)$
(6) Reciprocal Rectangular Hyperbola II	$Y = (\beta_0 X + \beta_1)/X$
(7) Parabola	$Y = \beta_0 + \beta_1 X + \beta_2 X^2$
(8) Power	$Y = \beta_0 X_1^{\beta}$
(9) Modified Power	$Y = \beta_0 \beta_1^X$
(10) Root	$Y = \beta_0^{(1/X)}$
(11) Geometric	$Y = \beta_0 X^{\beta_1 X}$
(12) Modified Geometric	$Y = \beta_0 X^{(\beta_1/X)}$
(13) Exponential	$Y = \beta_0 \exp(\beta_1 X)$
(14) Modified Exponential	$Y = \beta_0 \exp(\beta_1/X)$
(15) Logarithm	$Y = \beta_0 + \beta_1 \log(X)$
(16) Reciprocal Logarithm	$Y = 1/[\beta_0 + \beta_1 \log(X)]$
(17) Hoerl	$Y = \beta_0 \beta_1^X X_2^{\beta}$
(18) Modified Hoerl	$Y = \beta_0 \beta_1^{(1/X)} X_2^{\beta}$
(19) Normal	$Y = \beta_0 \exp\left[-(X-\beta_1)^2/(2\beta_2^2)\right]$
(20) Normal Logarithm	$Y = \beta_0 \exp\left[-(\log(X)-\beta_1)^2/(2\beta_2^2)\right]$
(21) Cauchy	$Y = \beta_0/\left[1 + ((X - X_0)/\beta_1)^2\right]$
(22) Beta	$Y = \beta_0 X_1^{\beta}(1-X)_2^{\beta}$

To facilitate comparison of the fits of the 22 models shown in Table 4 we used the CORN 1.0 program (Gutiérrez-Estrada et al. 2009). For each pair of input — output variables and for each lag, the program fits all non-linear functions using the mean minimum least square method to obtain the total explained variance (TEV). The absolute cross-correlation index (r_n) was obtained as $TEV^{1/2}$. The selected non-linear function maximized the summation of r_n for all lags considered. Following selection of the non-linear function, the lags for each potential input variable were chosen using the following criteria: (a) if the selected non-linear fit and linear fit had similar trends, lags with higher r_n were chosen; (b) if different trends were found between the linear and non-linear fits, the lags associated to lack of trend between both functions were selected.

An alternative form of sensitivity analysis, based on the approach of the missing value problem, was used for each evaluated ANN model. The analysis was carried out by replacing each selected input variable with missing values and assessing the effect of this on the output error. The newly calculated error was compared with the original error to obtain a ratio (error of the model with an input variable with missing values/error of the model with all selected input variables). Thus, for any input variable x, a ratio equal or very close to 1 indicated that this variable had a very low weight in the general structure of the model (Hunter et al. 2000).

2.6 Patterns of Behaviour in the Water Resources System

The contribution profiles or impacts of each climate variable (temperature and precipitation) were obtained in relation to inflow to and outflow from the Negratín reservoir by following and extending the method proposed by Laë et al. (1999). For each climate variable and each ANN, the model response for each weekly time period t was determined by applying arbitrary values from within the variation range of the selected input variable v (25 values equally spaced between the minimum and maximum values of v), while retaining the real values of the remaining climate variables (Gutiérrez-Estrada and Bilton 2010).

To identify response patterns with similar behaviour, the contribution profiles obtained from each ANN model were subsequently subjected to a non-hierarchical cluster analysis using the K-means algorithm. This method was selected as it uses an analysis of variance approach to evaluate the distances between clusters or groups. Thus, this method attempts to minimize the sum of squares of any two (hypothetical) clusters that can be formed at each step. To evaluate the appropriateness of the classification, the Euclidean distances between clusters were examined (Hair et al. 1998), and the centroid of each identified cluster was also determined and analyzed.

3 Results

3.1 Linear and Non-linear Cross-Correlation Analysis

Analysis of the cross-correlation functions allowed *a priori* detection of the lags for each potential input variable having significant correlation with an output variable in each proposed ANN model in the study (Table 5). The absolute values of the cross-correlation indices were (a) the indices (r_n) of the best non-linear fits, and (b) the indices (r) of the linear fits. For all cases it was observed that the best non-linear fit explained more of the variance in the output variable than the linear fit. The cross-correlation index is equivalent to the Pearson's correlation index (r), in the case of linear functions.

Table 5 High values of the absolute cross-correlation index r_n of the best non-linear fits between the output variable and the potential input variables. Comparison with the linear cross-correlation index r (P = precipitation; T = temperature; I = inflow; O = outflow)

Input variable**	Inflow ANN model [output variable I(E06)]			Outflow (1) ANN model [output variable $O(\text{E06})_1$]			Outflow (2) ANN model [output variable $O(\text{E06})_2$]			Outflow (3) ANN model [output variable $O(\text{E06})_3$]		
	Lag (week)	r_n	r	Lag (week)	r_n	r	Lag (week)	r_n	r	Lag (week)	r_n	r
P(E03)	1,2,10*	0.15,0.10,0.05	0.09,0.04,0.06	1,2	0.16,0.14	0.04,0.03	1,2	0.14,0.13	0.02,0.02	1,2	0.16,0.15	0.01,0.01
P(E05)	1,2,10*	0.24,0.15,0.14	0.20,0.10,0.12	1,2	0.20,0.20	0.06,0.05	1,2	0.16,0.16	0.04,0.04	1,2	0.19,0.18	0.02,0.02
P(E06)	1,2,10*	0.14,0.10,0.04	0.07,0.03,0.03	1,2	0.19,0.17	0.05,0.04	1,2	0.14,0.13	0.02,0.02	1,2	0.16,0.16	0.01,0.01
P(M01)	1,2,10*	0.13,0.09,0.03	0.06,0.02,0.03	1,2	0.17,0.16	0.04,0.03	1,2,11*	0.14,0.13,0.12	0.02,0.01,0.004	1,2	0.16,0.15	0.02,0.02
P(N04)	1,2,10*	0.17,0.10,0.08	0.16,0.05,0.11	1,6*	0.18,0.14	0.04,0.01	1,2,11*	0.14,0.13,0.13	0.01,0.01,0.001	1,2,3*	0.15,0.14,0.14	0.01,0.01,0.01
P(N05)	1,2,10*	0.11,0.07,0.03	0.05,0.02,0.03	1,6*	0.15,0.14	0.03,0.01	10,11*	0.12,0.14	0.006,0.007	1,2,3*	0.17,0.17,0.16	0.01,0.01,0.01
P(P03)	1,2,10*	0.09,0.06,0.01	0.03,0.01,0.01	1,6*	0.15,0.14	0.02,0.01	1,2,11*	0.14,0.13,0.12	0.01,0.005,0.01	1*,3,4	0.16,0.17,0.17	0.02,0.01,0.01
T(RIA1801)	5,6,7	0.30,0.29,0.29	0.13,0.13,0.14	1,2	0.44,0.42	0.42,0.41	1,2	0.23,0.20	0.22,0.19	1,2	0.37,0.34	0.21,0.20
T(RAIFGR009)	5,6,7	0.33,0.32,0.32	0.15,0.15,0.16	1,2	0.44,0.42	0.43,0.41	1,2	0.24,0.21	0.23,0.20	1,2	0.36,0.32	0.20,0.19
T(RIA0409)	5,6,7	0.30,0.29,0.29	0.13,0.15,0.15	1,2	0.42,0.40	0.40,0.38	1,2	0.21,0.18	0.20,0.17	1,2	0.38,0.33	0.22,0.20
T(RIA1802)	5,6,7	0.31,0.31,0.31	0.14,0.14,0.15	1,2	0.43,0.42	0.42,0.41	1,2	0.23,0.20	0.22,0.19	1,2	0.37,0.34	0.21,0.20
T(RIA2302)	5,6,7	0.32,0.31,0.31	0.15,0.14,0.15	1,2	0.43,0.41	0.42,0.40	1,2	0.23,0.20	0.23,0.20	1,2	0.37,0.34	0.21,0.20
T(RAIFJA05)	5,6,7	0.33,0.33,0.32	0.15,0.15,0.16	1,2	0.45,0.43	0.43,0.42	1,2	0.24,0.21	0.23,0.20	1,2	0.36,0.33	0.20,0.19
I(E06)	1,5*	0.77,0.44	0.53,0.40	1,2	0.24,0.19	0.08,0.06	1,2	0.15,0.13	0.04,0.04	5*,12	0.11,0.17	0.005,0.01
$O(\text{E06})_1$	–	–	–	1,2	0.79,0.64	0.78,0.62	–	–	–	–	–	–
$O(\text{E06})_2$	–	–	–	–	–	–	1,2	0.90,0.74	0.90,0.74	–	–	–
$O(\text{E06})_3$	–	–	–	–	–	–	–	–	–	1,2	0.90,0.75	0.90,0.75

*Lag that causes different trend between non–linear and linear fits; **see Fig. 1

Figure 4 shows four of these cross-correlation analyses for the ANN modelling of the inflow to the Negratín reservoir [*I*(E06)]. The trends of all the temperature (*T*) variables were similar in the linear and non-linear fits (Fig. 4c). However, different partial trends were found for the cross-correlation analysis between the variable inflow [*I*(E06)] and its past values (Fig. 4d). From the 6-week lag to the 12-week lag the hyperbolic and linear fits had a similar trend. However, among the 1-week to 5-week lags the hyperbolic fit exhibited a different behaviour than the linear function. Therefore, the 5-week lag was selected as the inflexion point for the differing trends between the non-linear and linear fits. The same occurred with the precipitation (*P*) variables in the 10-week lag (Fig. 4a,b) (Table 5).

The cross-correlation analyses for the ANNs used to model the outflows (1−3) from the Negratín reservoir are shown in Table 5. The outflows appeared to have a more rapid response to temperature than did inflow. Therefore, the lags selected for all the temperature variables were 1 and 2 weeks for the outflows, and 5, 6 and 7 weeks for the inflow. For the *P* variables, short (1 and 2 weeks) and long (10 weeks) lags were found for the inflow at all gauging stations. For the outflows, significant long lags were only found for gauging stations N04, N05 and P03, which are the furthest from the Negratín reservoir. This could explain the significant correlation of precipitation that occurred 6 and 11 weeks earlier for outflows (1) and (2), respectively.

Lags of 1 and 2 weeks were selected for the inflow variables for outflows (1) and (2), and lags of 5 and 12 weeks were selected for outflow (3) (Table 5). This could be a consequence of long-term planning related to outflow (3), which is principally directed to areas that are not included in the exploitation system in the present study (water transfer

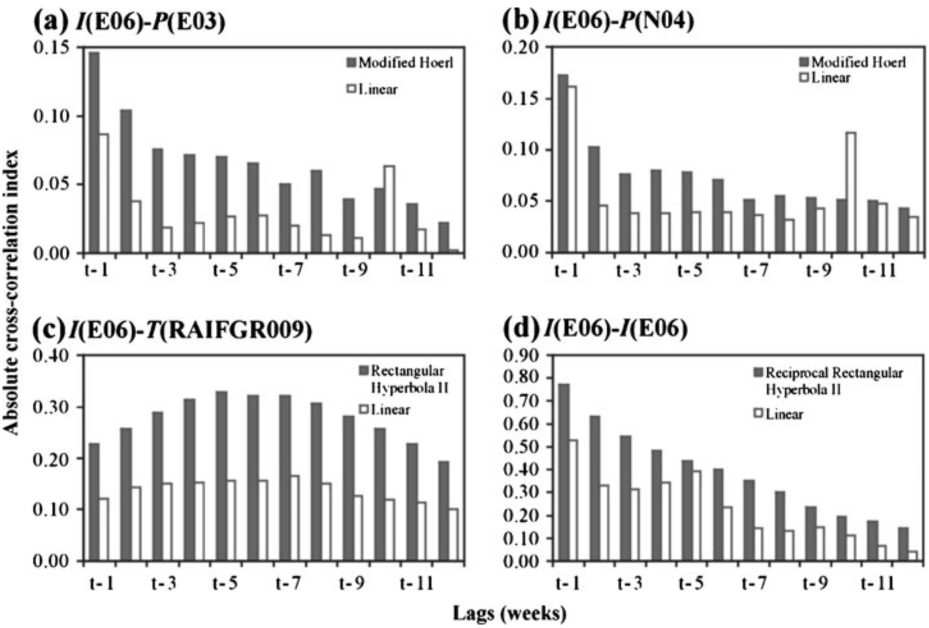

Fig. 4 Linear and non-linear cross-correlation functions for the relationships of inflow to the Negratín reservoir [*I*(E06)] with previous values of the potential input variables: (**a**) precipitation at the 'San Clemente' reservoir gauging station [*P*(E03)]; (**b**) precipitation at the Tablas gauging station [*P*(N04)]; (**c**) temperature at the Zújar gauging station [*T*(RAIFGR009)]; and (**c**) inflow to the Negratín reservoir [*I*(E06)]

'Negratín-Almanzora'), but represent an increasing water demand for greenhouses (intensive agriculture).

3.2 Selection of the Inflow and Outflow ANN Models

In modelling the inflow to the Negratín reservoir, the first neural approaches evaluated had two input configurations: (a) the precipitation and temperature variables (climate data) of all gauging stations, based on the lags determined in the previous sub-section [CONF(a)]; and (b) climate data of all gauging stations and past values of inflow to the reservoir, based on the lags determined in the previous sub-section [CONF(b)]. Using these input configurations the best models reached levels of explained variance of 15% and 22%, and Nash-Sutcliffe efficiency coefficients of 0.33 and 0.37, respectively, during the external validation phase (Table 6). These results indicated the necessity to reduce the input variables, as they may have included redundant information or contributed noise to the fits. It was observed that the inclusion of the past inflow values slightly improved the model accuracy.

Table 6 Accuracy measures for the best inflow ANN and IHACRES models for each input configuration in the external validation phase

Input configuration	Input variables	Number input variables	Architecture ANN*	r^2	RMSE (m^3/s)	E_2	PI
CONF(a)	All climatic data–see lags in Table 5	39	(39,40,40,1)	0.15	0.69	0.33	0.08
IHACRES(a)	Average catchment precipitation and temperature using all climatic stations[†]	2[†]	–	0.44	1.93	−0.22	−0.65
CONF(b)	$[\text{CONF(a)}] + [I(\text{E06})_{t-1}; I(\text{E06})_{t-5}]$	41	(41,22,22,1)	0.22	1.02	0.37	0.36
CONF(c)	$P(\text{E03})_{t-1}$; $P(\text{E03})_{t-2}$; $P(\text{E03})_{t-10}$; $P(\text{E05})_{t-1}$; $P(\text{E05})_{t-2}$; $P(\text{E05})_{t-10}$; $P(\text{N04})_{t-1}$; $P(\text{N04})_{t-2}$; $P(\text{N04})_{t-10}$; $T(\text{RAIFGR009})_{t-5}$; $T(\text{RAIFGR009})_{t-6}$; $T(\text{RAIFGR009})_{t-7}$; $T(\text{RIA1802})_{t-5}$; $T(\text{RIA1802})_{t-6}$; $T(\text{RIA1802})_{t-7}$	15	(15,12,9,1)	0.66	0.72	0.58	0.45
IHACRES(c)	Average catchment precipitation and temperature using the following climatic stations: P(E03); P(E05); P(N04); T(RAIFGR009) and T(RIA1802) [†]	2[†]	–	0.43	1.63	0.13	−0.17
CONF(d)	$[\text{CONF(c)}] + [I(\text{E06})_{t-1}; I(\text{E06})_{t-5}]$	17	(17,15,10,1)	0.48	0.53	0.39	0.60
CONF(e)	$P(\text{E03})_{t-1}$; $P(\text{E03})_{t-2}$; $P(\text{E05})_{t-1}$; $T(\text{RAIFGR009})_{t-5}$; $T(\text{RAIFGR009})_{t-7}$; $T(\text{RIA1802})_{t-6}$; $T(\text{RIA1802})_{t-7}$	7	(7,10,10,1)	0.68	0.74	0.67	0.37
IHACRES(e)	Average catchment precipitation and temperature using the following climatic stations: P(E03); P(E05); T(RAIFGR009) and T(RIA1802) [†]	2[†]	–	0.53	1.26	0.48	0.30
CONF(f)	$P(\text{E03})_{t-10}$; $P(\text{E05})_{t-1}$; $P(\text{E05})_{t-10}$; $T(\text{RAIFGR009})_{t-6}$; $T(\text{RAIFGR009})_{t-7}$; $T(\text{RIA1802})_{t-5}$; $T(\text{RIA1802})_{t-6}$; $I(\text{E06})_{t-1}$	8	(8,10,6,1)	0.83	0.64	0.77	0.64

*An ANN with k, n, m and s nodes or neurons in the input, first hidden, second hidden and output layers, respectively, has the notation (k,n,m,s)

[†] To calculate time series of 'catchment average' precipitation and temperature, relationships between elevation and climate were used (Croke et al. 2006)

It was also obvious that the CONF(a) and CONF(b) approaches lacked the parsimony condition, which is generally a recommended characteristic for utilization, evaluation and application of any model. Therefore, ANNs with independent climate variables, selected on the basis of the developed cross-correlation analyses, were also evaluated. Thus, the input configuration CONF(c) was selected with the following input variables: three precipitation variables with high cross-correlation indices *P*(E03), *P*(E05) and *P*(N04); and two temperature variables representative of different climate areas, *T*(RAIFGR009) for the climate area 'Hoyas de Guadix-Baza', and *T*(RIA1802) for climate area 'Sierra de María y los Filabres'. This selection of input variables was because all the precipitation and temperature variables had the same trend in the cross-correlation analyses (Fig. 4). Input configuration CONF(d) added the inflows to the reservoir in the previous 1 and 5 weeks as input variables.

The best models with the input configurations CONF(c) and CONF(d) reached a level of explained variance of 66% and 48%, and Nash-Sutcliffe efficiency coefficients of 0.58 and 0.39, respectively, in the external validation phase (Table 6). Therefore, improved fits occurred when the input climate data were reduced. However, the addition of past inflow values reduced the model accuracy.

Table 7 shows the sensitivity analysis developed for the best models for the input configurations CONF(c) and CONF(d). Seven and 8 variables, respectively, exhibited a ratio greater than the mean model ratio, and greater than 1. Therefore, these variables were used as input variables for the configurations CONF(e) and CONF(f). In both cases precipitation at the Tablas gauging station *P*(N04) was removed as an input variable because of the low weight

Table 7 Sensitivity analysis for the best inflow ANN models for the input configurations CONF(c) and CONF(d). Ratio, ranking and mean ratio for each model are shown. Bold indicates a variable with a ratio higher than the mean ratio

CONF(c)			CONF(d)		
Variable	Ratio	Ranking	Variable	Ratio	Ranking
$P(E03)_{t-2}$	**1.74**	**1**	**$T(RAIFGR009)_{t-6}$**	**1.67**	**1**
$T(RAIFGR009)_{t-5}$	**1.68**	**2**	**$T(RIA1802)_{t-6}$**	**1.66**	**2**
$P(E03)_{t-1}$	**1.55**	**3**	**$T(RAIFGR009)_{t-7}$**	**1.64**	**3**
$T(RIA1802)_{t-6}$	**1.54**	**4**	**$P(E05)_{t-1}$**	**1.51**	**4**
$P(E05)_{t-1}$	**1.42**	**5**	**$P(E05)_{t-10}$**	**1.47**	**5**
$T(RIA1802)_{t-7}$	**1.35**	**6**	**$I(E06)_{t-1}$**	**1.42**	**6**
$T(RAIFGR009)_{t-7}$	**1.32**	**7**	**$T(RIA1802)_{t-5}$**	**1.40**	**7**
$P(E05)_{t-2}$	1.30	8	**$P(E03)_{t-10}$**	**1.35**	**8**
$T(RAIFGR009)_{t-6}$	1.20	9	$T(RAIFGR009)_{t-5}$	1.15	9
$T(RIA1802)_{t-5}$	1.17	10	$P(N04)_{t-1}$	1.13	10
$P(E03)_{t-10}$	1.15	11	$I(E06)_{t-5}$	1.10	11
$P(N04)_{t-10}$	1.10	12	$P(E03)_{t-1}$	1.06	12
$P(N04)_{t-2}$	1.10	13	$T(RIA1802)_{t-7}$	1.05	13
$P(E05)_{t-10}$	1.09	14	$P(E05)_{t-2}$	1.04	14
$P(N04)_{t-1}$	1	15	$P(E03)_{t-2}$	1.02	15
Mean ratio	*1.31*		$P(N04)_{t-2}$	0.99	16
			$P(N04)_{t-10}$	0.98	17
			Mean ratio	*1.28*	

evident in the sensitivity analyses. CONF(e) had precipitation variables with short-term lags (1 and 2 weeks) as inputs, and CONF(f) had precipitation variables with short- and long-term lags (1 and 10 weeks) as inputs (Table 6). The estimation capacity of CONF(e) was similar to CONF(c), while the estimation capacity of CONF(f) was superior to the previous models, with accuracy measures very statistically acceptable.

When the IHACRES model was used to simulate inflow to the Negratín reservoir, three configurations of model inputs were calibrated: (i) averaging all the gauging stations of precipitation and temperature [IHACRES(a)]; (ii) averaging the gauging stations selected for the neural model CONF(c) [IHACRES(c)]; and (iii) averaging the gauging stations selected for the neural model CONF(e) [IHACRES(e)]. For each IHACRES configuration, the 'catchment average' precipitation and temperature time series were calculated using the parameters in the relationship between precipitation and elevation ρ_0=0.9273 and σ_0=0.00007, and the parameter in the relationship between temperature and elevation λ=−0.00731.These parameters were calculated using the gauging stations available in the study area following the methodology proposed by Croke et al. (2006).

In all cases, the highest levels of explained variance and Nash-Sutcliffe efficiency coefficient were obtained considering in the calibration of the non-linear module, the instrumental variable '2 Exponential Stores in Parallel (2,1)'. The configuration IHACRES(a) provided r^2=0.44 and E_2=−0.22, which supposed 29% of explained variance more than the ANN CONF(a). Globally, these results were improved by the configuration IHACRES(c) (r^2=0.43 and E_2=0.13). The best performance was obtained with the configuration IHACRES(e) (r^2=0.53 and E_2=0.48). In relation to RMSE and PI, the best results were also obtained by IHACRES(e). In the case of IHACRES(a) and IHACRES(c) negative values of the persistence index (PI) indicated a naïve behaviour of these models (Table 6). These results indicated that the proposed method to the selection of input variables in ANN modelling (non-linear cross-correlation functions plus sensitivity analysis) was adequate because the selected input variables for the best ANN without inflow inputs [CONF(e)] also provided the best results with the IHACRES model [IHACRES(e)].

The same procedure for selection of input variables was used for the ANNs modelling the three outflows from the Negratín reservoir. The best ANN models with their evaluation measures are shown in Table 8. In these models only temperature data were significant input variables besides with the past outflows at the one and/or two previous weeks. In the sensitivity analyses, precipitation data and inflow to the Negratín reservoir in previous time periods had very low weight as input variables in the modelling of water demands. The

Table 8 Accuracy measures for the best outflow ANN models in the external validation phase

Outflow	Input variables	Number input variables	Architecture ANN*	r^2	RMSE (m^3/s)	E_2	PI
Outflow (1)	$T(\mathrm{RAIFGR009})_{t\text{-}1}$; $T(\mathrm{RIA1802})_{t\text{-}1}$; $T(\mathrm{RIA1802})_{t\text{-}2}$; $[O(\mathrm{E06})_1]_{t\text{-}1}$; $[O(\mathrm{E06})_1]_{t\text{-}2}$	5	(5,8,8,1)	0.80	0.39	0.80	0.69
Outflow (2)	$T(\mathrm{RAIFGR009})_{t\text{-}1}$; $T(\mathrm{RAIFGR009})_{t\text{-}2}$; $[O(\mathrm{E06})_2]_{t\text{-}1}$	3	(3,6,6,1)	0.90	0.37	0.86	0.68
Outflow (3)	$T(\mathrm{RAIFGR009})_{t\text{-}2}$; $T(\mathrm{RIA1802})_{t\text{-}1}$; $[O(\mathrm{E06})_3]_{t\text{-}1}$	3	(3,8,8,1)	0.84	0.42	0.84	0.64

*An ANN with k, n, m and s nodes or neurons in the input, first hidden, second hidden and output layers, respectively, has the notation (k,n,m,s)

ANN models without past outflow as an input variable were very inaccurate, with coefficients of determination and efficiency coefficients less than 0.5.

3.3 Response Patterns of the Inflow

Using non-hierarchical cluster analysis, the responses of the ANN (8,10,6,1) selected for each input climatic variable versus the inflow to the Negratín reservoir, i.e. CONF(f) (Table 6), were classified according their behaviour in each weekly time period. Analysis of the Euclidean distances between clusters indicated that two groups should be selected for the temperature variable *T*(RAIFGR009) with time lags of 6 and 7 weeks, while only one group should be selected for the remaining temperature [*T*(RIA1802) with time lags of 5 and 6 weeks] and precipitation [*P*(E05) with time lags of 1 and 10 weeks, and *P*(E03) with a time lag of 10 weeks] variables. The contribution profiles of these input variables versus the inflow to the Negratín reservoir are shown in Fig. 5. The contribution profiles of variables $T(\mathrm{RAIFGR009})_{t\text{-}7}$ and $T(\mathrm{RIA1802})_{t\text{-}5}$ were similar to the contribution profiles of variables $T(\mathrm{RAIFGR009})_{t\text{-}6}$ and $T(\mathrm{RIA1802})_{t\text{-}6}$, respectively.

In the case of the temperature variables $T(\mathrm{RAIFGR009})_{t\text{-}6}$ and $T(\mathrm{RAIFGR009})_{t\text{-}7}$ (which are derived from the 'Hoyas Guadix-Baza' climate area, where the main irrigation districts are located), cluster 1 included more dry periods than cluster 2. A *t*-test analysis showed significant differences between precipitation (registered at gauging station E06) in each cluster (*t*-test: weekly mean precipitation of cluster 1=1.6±5.45 mm; weekly mean precipitation of cluster 2=6.3±11.01 mm; *t*-value = −1.62; $p<0.05$; *F* ratio=4.08) (Fig. 5a).

This grouping suggests that an increase of temperature in the 'Hoyas Guadix-Baza' climate area in months with a mean temperature between 0 and 14°C (from October to April) results in a smaller decrease of inflow to the reservoir in dry periods than in normal periods. Thus, in dry periods the flow to the Negratín reservoir from reservoirs upstream ('La Bolera' and 'San Clemente') is less than in normal periods. This result suggests that the ANN identified that the variability associated with the precipitation variable *P*(E06) (variable not selected as input data) was contained in the temperature variable *T* (RAIFGR009), which was finally selected as input data.

The patterns associated with the remaining climate variables showed a lower response level for inflow to the reservoir. The mean values of inflow ranged from 1.5 to 3.8 m^3/s for the temperature variables $T(\mathrm{RIA1802})_{t\text{-}5}$ and $T(\mathrm{RIA1802})_{t\text{-}6}$, from 2.2 to 5.3 m^3/s for the precipitation variable $P(\mathrm{E05})_{t\text{-}1}$, from 2.4 to 4.4 m^3/s for the precipitation variable $P(\mathrm{E05})_{t\text{-}10}$, and from 2.7 to 2.2 m^3/s for the precipitation variable $P(\mathrm{E03})_{t\text{-}10}$ (Fig. 5).

The response pattern for the temperature variables $T(\mathrm{RIA1802})_{t\text{-}5}$ and $T(\mathrm{RIA1802})_{t\text{-}6}$ (Fig. 5b), which are derived from the 'Sierra de María y los Filabres' climate area, showed a clear parabolic increase of inflow associated with thawing of snow in the mountain areas as the temperature increased. This relationship suggests that these flows are not influenced by regulation of water in the watershed.

The precipitation variable in the 'La Bolera' reservoir [*P*(E05)] had slightly different patterns for short and long time lags. Thus, the profile $P(\mathrm{E05})_{t\text{-}1}$–$\mathrm{I(E06)}_t$ showed a linear increase (Fig. 5c), while $P(\mathrm{E05})_{t\text{-}10}$–$\mathrm{I(E06)}_t$ showed an exponential increase (Fig. 5d). Thus, precipitation in the 'La Bolera' reservoir had a direct effect one week later on the inflow to the Negratín reservoir. An effect on inflow to the Negratín reservoir of precipitation recorded 10 weeks previously in the 'La Bolera' reservoir was only observed for a mean weekly precipitation of 30 mm, i.e. high levels of precipitation. Because the 'La Bolera' reservoir functions mainly as a diversion dam for the 'Iturralde' irrigation channel (and not

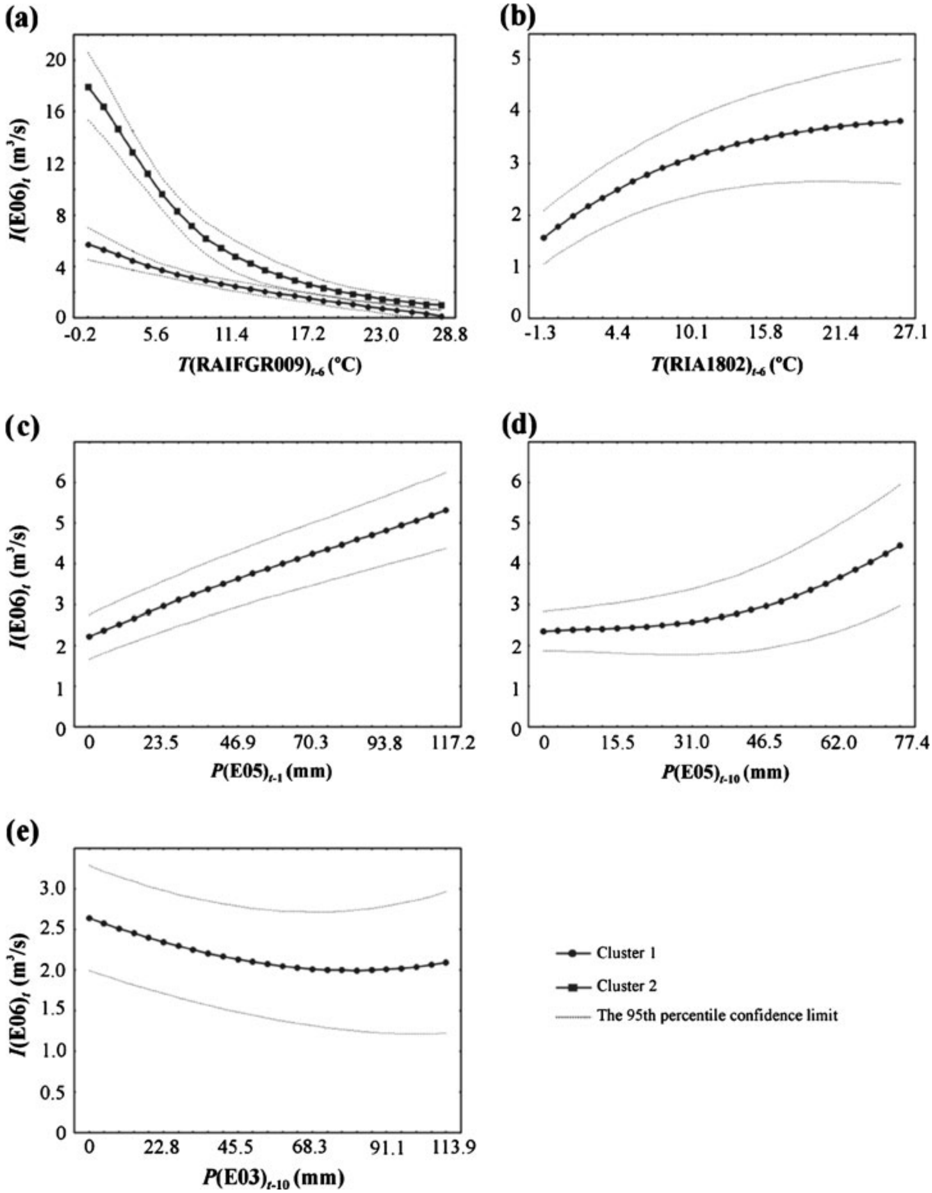

Fig. 5 Response patterns of the selected input variables for the best inflow ANN model

for flow control), this situation could be a consequence of the watershed runoff that sustains a constant level about 2.5 m^3/s (value of the mean inflow to the Negratín reservoir) until the weekly precipitations of 2–3 months previous are higher to 30 mm.

In comparison, the response pattern for the precipitation variable recorded in the 'San Clemente' reservoir [$P(E03)_{t\text{-}10}$] (the main function of which is flow regulation in the watershed) showed slightly variations next to the value of the mean inflow to the Negratín reservoir (Fig. 5e).

3.4 Patterns of Management of the Outflows

Using non-hierarchical cluster analysis, the responses of the neural approaches (Table 8) for each selected input climate variable were classified over weekly time periods in relation to the outflows from the Negratín reservoir. The analysis of the Euclidean distances between clusters indicated that for simulation of outflow (1), two groups should be selected for all temperature variables, with the exception of $T(\mathrm{RIA1802})_{t\text{-}1}$ and $T(\mathrm{RIA1802})_{t\text{-}2}$. The contribution profiles of these input variables versus the outflows from the Negratín reservoir are shown in Figure 6. In the simulation of outflow (1) the response patterns of variables $T(\mathrm{RIA1802})_{t\text{-}1}$ and $T(\mathrm{RIA1802})_{t\text{-}2}$ were similar. In the simulation of outflow (2), the response patterns of variables $T(\mathrm{RAIFGR009})_{t\text{-}1}$ and $T(\mathrm{RAIFGR009})_{t\text{-}2}$ were also similar.

As occurred with the temperature variable $T(\mathrm{RAIFGR009})_{t\text{-}6}$ in relation to inflow, in all cases cluster 1 included drier periods than cluster 2. The t-test showed significant differences between precipitation (registered at all gauging stations) in each cluster. Significant differences were also found between the clusters with respect to inflows to the reservoir (t-test: mean inflow of cluster 1=0.78±0.54 m^3/s; mean inflow of cluster 2= 3.50±3.13 m^3/s; t-value=−2.85; $p<0.05$; F ratio=34.23). These results indicate that the neural models identified the variability associated with the precipitation and inflow variables (data not selected as input data) contained in the temperature variables that were finally selected as input data for modelling of the outflows.

In the case of outflow (1), which is associated with irrigation use, the water demand in dry periods was higher than in normal periods, which was evident in the grouping for the temperature variable $T(\mathrm{RAIFGR009})_{t\text{-}1}$. The maximum requirements of the irrigation districts in the watershed is 6,000 m^3/ha in dry years and 4,000 m^3/ha in normal years (AQUAVIR 2005). An increase in water demand was observed at the Zújar thermometric station (RAIFGR009) as the weekly mean temperature increased from approximately 18 to 30°C (from May to September), which corresponds to the period when the irrigation districts have maximum water requirements. The pattern for the temperature variables $T(\mathrm{RIA1802})_{t\text{-}1}$ and $T(\mathrm{RIA1802})_{t\text{-}2}$ indicated a slight decrease in irrigation water demand with the thawing of snow in the mountain areas (Fig. 6a).

Outflow (2), which corresponds to hydropower use, also showed response patterns that increased with the temperature variables $T(\mathrm{RAIFGR009})_{t\text{-}1}$ and $T(\mathrm{RAIFGR009})_{t\text{-}2}$. In this case the response occurred at approximately 16°C, because hydropower generation takes advantage of the pumping of irrigation water to the crops. As for other outflows, greater water demand for hydropower occurs in dry years (Fig. 6b).

The patterns associated with outflow (3) for the temperature variables $T(\mathrm{RAIFGR009})_{t\text{-}2}$ and $T(\mathrm{RIA1802})_{t\text{-}1}$ were opposite to those associated with outflow (1). Outflow (3) is principally distributed to other reservoirs not included in the exploitation system in the present study, primarily for irrigation and urban water uses (water transfer 'Negratín-Almanzora') and for overall water regulation in the Guadalquivir River basin. This outflow occurs when the requirements of the 'Guadiana Menor' River sub-watershed are low, especially in those periods when the weekly mean temperature ranges from 2.6 to 12°C (from October to April) in the 'Hoyas Guadix-Baza' climate area. Lower flows are supplied for these uses in dry periods. On the other hand, the outflow responses for the temperatures of mountain climatic area ('Sierra de María y los Filabres') were growing with lower values for dry years which had lower events of snow and precipitation (Fig. 6c).

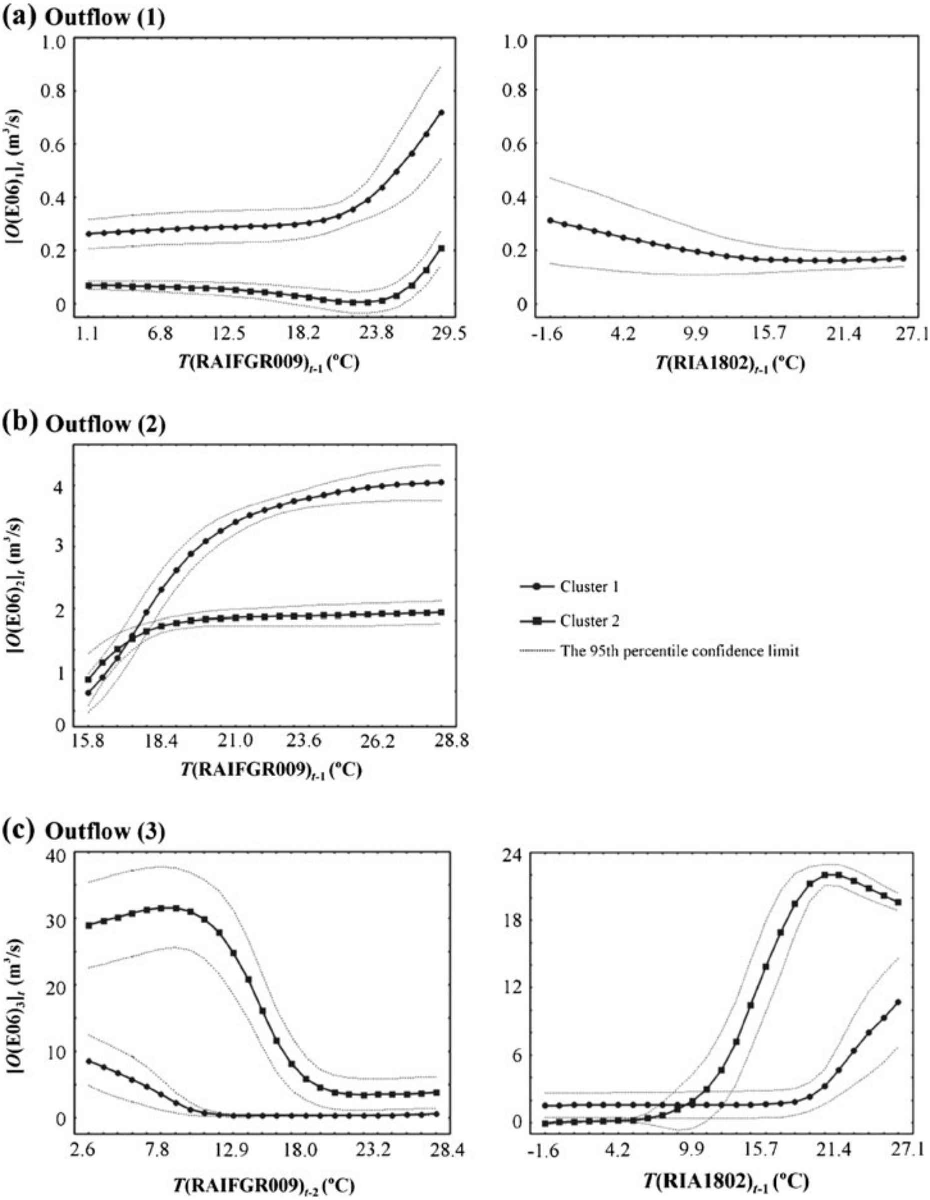

Fig. 6 Response patterns of the selected input variables for the best outflow ANN models

4 Discussion

There is no water resources management regime that is universally applicable. Rather, water resources planning needs to occur at the level of individual river basins to identify the management alternatives and to evaluate the hydrological consequences over various climatic conditions. This study used neural networks to model the inflow to and outflow from a water resources system in a water shortage context. Conceptual analogies were identified in terms of the management rules and the physics of the problem by analyzing the responses of the simulated variables (inflow and outflow) to a number of independent or input variables. Stream flow, precipitation and temperature data from various gauging stations throughout the upper watershed of the 'Guadiana Menor' River (southern Spain) were used to develop the ANN models.

An important step in the development of ANN models is the selection of an appropriate set of input variables from the available parameters. The strengths of the relationships between potential model inputs and outputs were examined using linear and non-linear cross-correlation functions and sensitivity analysis. The results indicated that those ANN models developed with the selected input variables performed very well, and were the most parsimonious. The inclusion of additional variables as inputs did not generally increase the capabilities of the trained ANN models, as Fernando et al. (2009) also found when using the modified PMI algorithm (Partial Mutual Information algorithm) to forecast water salinity in the Murray River (South Australia). Similar conclusions can be obtained from the results of the IHACRES model calibrated in our work. That is, both types of models (ANN and IHACRES) were highly sensitive to the climatic stations from which the inputs to the models were selected.

The input selection procedure identified only 8 variables (from among 492 candidates) as being significant for the inflow ANN model. The climate variables were precipitation data (stations E03 and E05) at short (1 week) and long (10 weeks) time lags, and temperature data (stations RAIFGR009 and RIA1802) at long (5, 6 and 7 weeks) time lags. Among the inputs not selected, the low weight of two precipitation variables at gauging stations E06 (Negratín reservoir, 'Hoyas Guadix-Baza' climate area) and N05 ('Sierra de María y los Filabres' climate area) is remarkable. However, examination of the two response patterns for inflow versus the temperature variable *T*(RAIFGR009) revealed that the differences between the groupings could be explained by inter-annual precipitation differences in the 'Hoyas Guadix-Baza' climate area. Hence the ANN model captured the variability associated with the precipitation variable *P*(E06) contained in the temperature variable *T*(RAIFGR009). The same occurred with the precipitation variable *P*(N05) as significance is a main underlie to explain the response patterns of the temperature variable *T* (RIA1802). Thus, the effect of snow thaw in the 'Sierra de María y los Filabres' climate area is fundamental to understanding the increase of inflow with increasing temperature.

For the outflow ANN models 5 significant variables were identified for outflow (1) from among the 516 candidates, and 3 were identified for each of outflows (2) and (3). The selected climate variables were temperature at short time lags (1 and 2 weeks). The proxy effects indicated previously were also found in these cases, as the ANN models captured the variability associated with the precipitation and inflow variables included in the temperature variables that were finally selected as the input data. Proxy effects in ANNs have been reported previously in ecological modelling and fishery resources management studies (Czerwinski et al. 2007; Velo-Suárez and Gutiérrez-Estrada 2007; Gutiérrez-Estrada et al. 2007, 2008; Watts and Worner 2008). These have shown that candidate model inputs having a strong relationship with the model output are redundant because the same information is already provided by another input variable.

The results suggest that an explicit meaning can be attributed in the form of different physical processes and management rules that are involved in the planning of the water resources system involved in the study. Thus, the response patterns of the selected neural approaches reasonably represented components of the complex physical processes of the water resources system including: (a) the snow thaw in the 'Sierra de María y los Filabres' climate area; and (b) the relationship of precipitation in the 'Hoyas de Guadix-Baza' climatic area over various previous time periods to inflow into the Negratín reservoir. Thus, the inflow showed an almost linear increase of 2.7% with precipitation in the previous week, but precipitation 2−3 months earlier was only evident if mean precipitation reached 30 mm per week, with a 4% of medium increase. Certain components of the water management system or control rules for the water resources were also represented, including: (a) the different operation of the inflow to and outflows from the Negratín reservoir during dry and wet periods; (b) the differing behaviour of the three outflows; and (c) the effect of flow regulation in the upstream reservoirs.

Examination of these relationships (or response patterns) suggested that the T (RAIFGR009) temperature and P(E05) precipitation variables associated with 'Hoyas de Guadix-Baza' climate area be selected as indicator parameters to assess potential water demand failures. In dry periods during the coldest months (from October to April), a mean temperature increase of 1°C at the RAIFGR009 gauging station would result in a mean decrease of approximately 2% in inflow to the Negratín reservoir, and a mean decrease of approximately 9% in outflow to the 'Negratín-Almanzora' water transfer. In the warmest months (from May to September) a mean temperature increase of 1°C would result in a mean increase of approximately 12% in the irrigation water requirements from the Negratín reservoir. The need to use climate driven models to evaluate the possible climate scenarios in the study area is evident, and the models developed in this study enable assessment of potential water demand failures based on these scenarios; this will aid strategic planning in the decision-making processes of the river basin water resources agency.

The modelling outcomes of this study are very promising, and contribute to the debate (Wilby et al. 2003; Jain et al. 2004; Sudheer and Jain 2004; Sudheer 2005, and Jain and Kumar 2009) on whether neural approaches should be considered as purely black-box models, or whether they can explain the underlying processes in a water resources system. Our results suggest that the ANN models are able to capture the behaviour of various components of the hydrologic system. However, as the conclusions are based on investigation of a single exploitation system in the Guadalquivir River basin, the models need to be tested in other sub-watersheds, to assess their value in providing important information on the characteristics of the hydrologic system and general water regulation throughout the basin.

The ability of the neural approaches to provide accurate generalizations is partially a consequence of the method of selection of an appropriate set of input variables from the available parameters (Bowden et al. 2005; May et al. 2008). Therefore, this method will remain rudimentary and highly dependent on the input of experts until it is further developed and perfected. Thus, future studies on the application of non-linear dependence measures, such as mutual information (Sharma 2000; Fernando et al. 2009), and/or soft-computing technologies, such as evolutionary computing (Doglioni et al. 2008; Chen and Chang 2009), should be tested in relation to the inputs identified as being significant and the accuracy of the resulting models.

5 Conclusions

The capacity of the ANN blocks in this study to explain more than 80% of the data variance suggests that realistic simulation of inflow and outflow from the water resources system is possible at the level of sub-watersheds, using the information system of the Guadalquivir SAIH. In this study we used stream flow, precipitation and temperature data from various gauging stations throughout the upper watershed of the 'Guadiana Menor' River (southern Spain) to develop the ANN models.

An understanding of the casual mechanisms and processes that shape water resources management at the local scale (in this study, a sub-watershed of the Guadalquivir River basin) has important implications for the identification of the risks of various planning options, and in evaluation of the probability of demand failures under various climate scenarios. The contribution profiles in this study support the contention that the existing water deficit in the Guadalquivir River basin is unsustainable, and that a reduction in irrigated areas may be inevitable. Our data indicate that a mean temperature increase of 1°C in the low altitude parts of the region will result in a mean increase of 12% in the irrigation demand on outflows. Hence, farmers in the region will have to adopt more flexible responses to climate events, and ensure that the water is used in an efficient way.

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