Statistical Downscaling of Global Climate Model Outputs to Monthly Precipitation via Extreme Learning Machine: A Case Study

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Study Area and Data:

· Minab basin, Hormozgan province, Iran

· The total area of the basin is 10171 km^2. The study area has an arid and humid climate . The normal mean monthly maximum and minimum temperatures of the region are 42°C and 20°C.

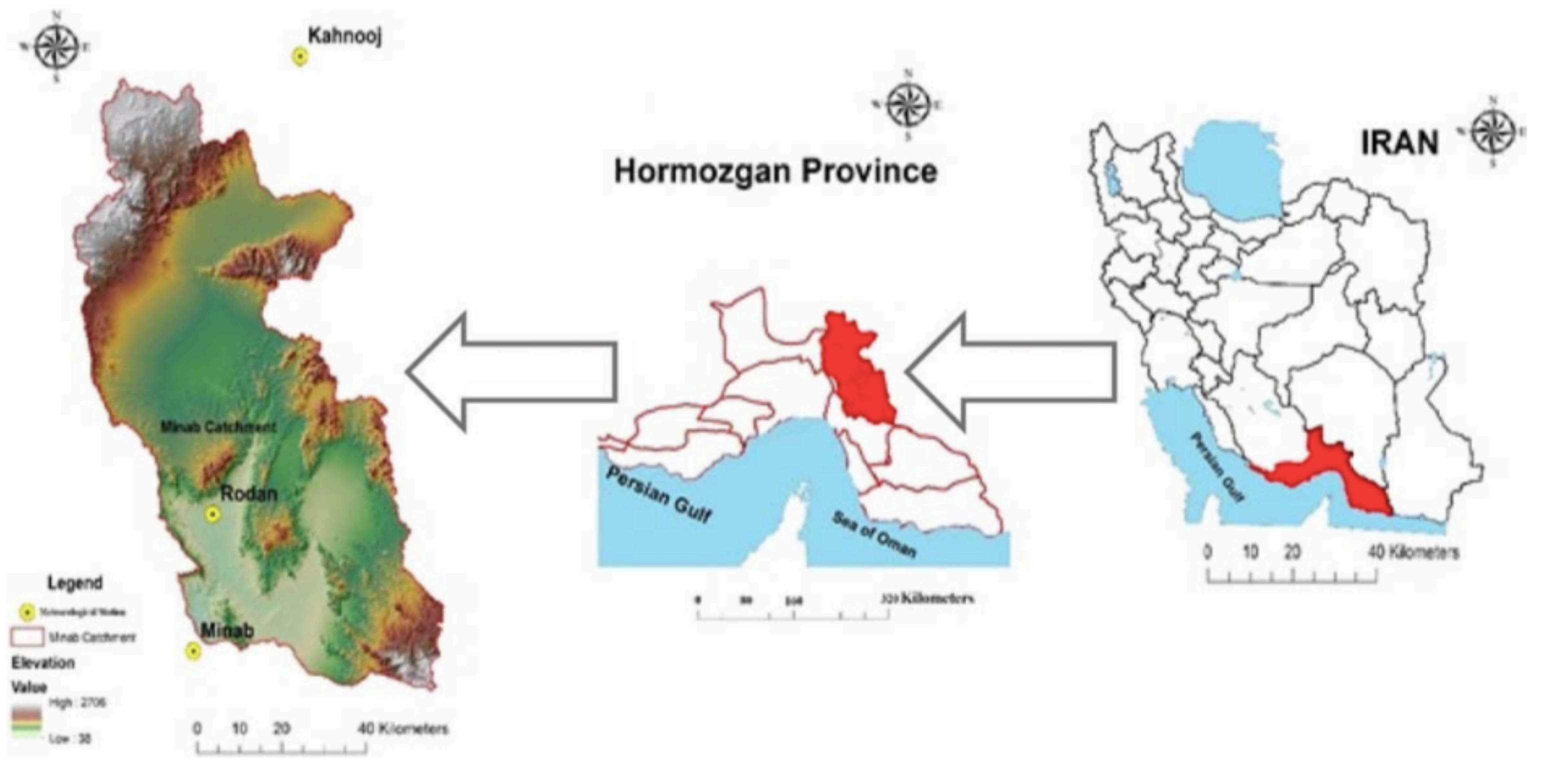

Figure 1. Minab basin and selected meteorological stations. [Color figure can be viewed at **wileyonlinelibrary.com**]

· Monthly reanalysis: NCEP/NCAR.

· Meteorological stations:

Table 1. Meteorological stations in study area.

Station name	Elevation (m)	Latitude (°N)	Longitude (°E)
Kahnooj	469.7	28° 03′	57° 75′
Rodan	200	27° 44′	57° 17′
Minab	29.6	27° 15′	57° 05′

Table 3. Optimal combination of predictors utilized in the downscaling models in each station.

Station	Large scale parameters
Kahnooj	Mean sea level pressure, 500 hPa Geopotential, 850 hPa Geopotential, precipitation
Rodan	Mean sea level pressure, 500 hPa Geopotential, 500 hPa Specific humidity, precipitation
Minab	Mean sea level pressure, 500 hPa Geopotential, air temperature (2m), precipitation

Methods:

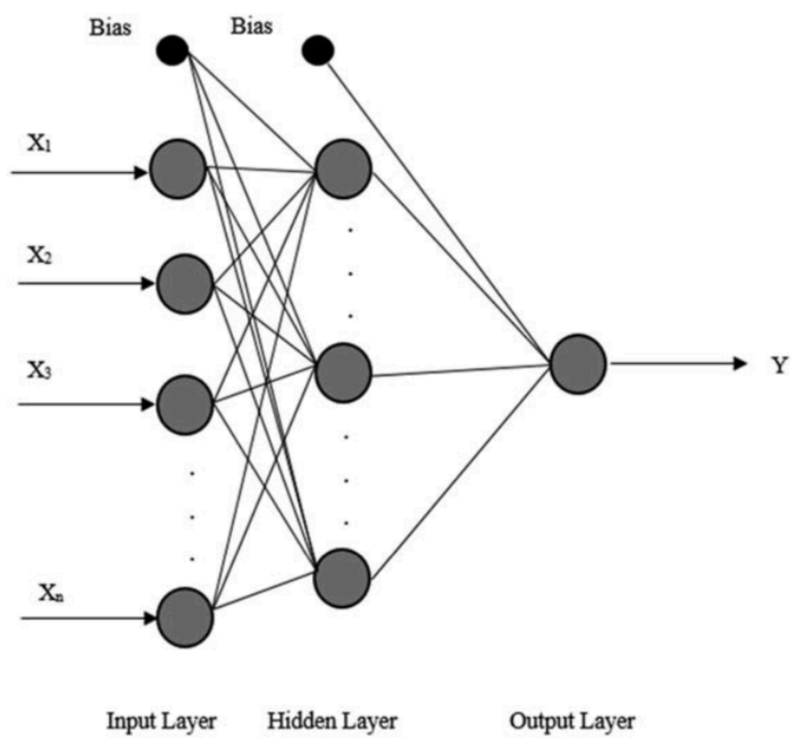

Figure 2. The topological structure of an extreme learning machine network.

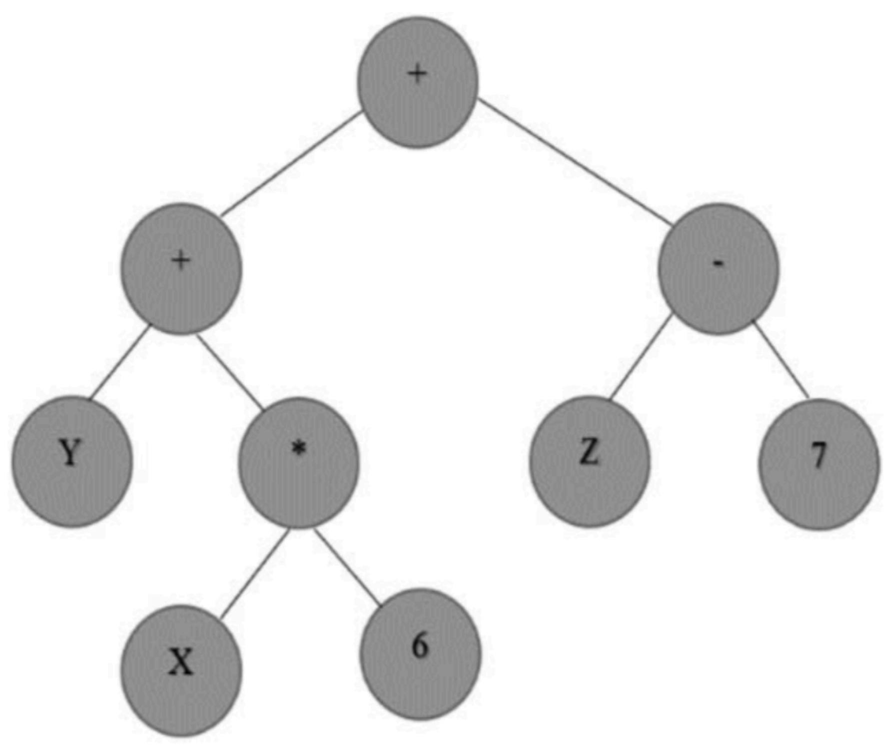

Figure 5. A typical function tree in Genetic Programing.

Results:

Table 4. Statistical parameters of model performance metrics in terms of RMSE, R^2, NS, and r for the downscaling models tested in the all stations.

		Training period				Testing period			
Station	Model	RMSE (mm)	R^2	NS	r	RMSE (mm)	R^2	NS	r
Kahnooj	ELM	20.204	0.764	0.758	0.874	16.2087	0.634	0.617	0.796
	ANN	24.444	0.652	0.646	0.807	17.6374	0.557	0.546	0.746
	QM	24.8048	0.6506	0.636	0.806	17.9926	0.548	0.537	0.7402
	GP	26.8736	0.577	0.572	0.759	19.1385	0.494	0.466	0.702
Rodan	ELM	22.7468	0.715	0.712	0.845	21.7672	0.645	0.634	0.803
	ANN	24.0428	0.68	0.679	0.824	24.5368	0.545	0.535	0.738
	QM	24.6555	0.678	0.662	0.823	25.2466	0.536	0.507	0.732
	GP	26.8746	0.6	0.599	0.774	26.3667	0.486	0.463	0.697
Minab	ELM	24.1803	0.738	0.73	0.859	19.1362	0.637	0.633	0.798
	ANN	28.0898	0.648	0.635	0.804	20.5233	0.586	0.577	0.765
	QM	29.1217	0.631	0.608	0.794	21.3539	0.576	0.543	0.758
	GP	31.4066	0.55	0.544	0.741	23.0068	0.481	0.469	0.693

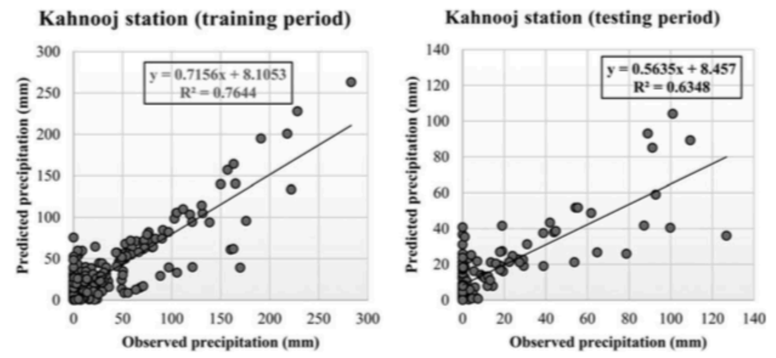

Figure 7. Scatter plots for training and testing phases of ELM-based model at Kahnooj station.

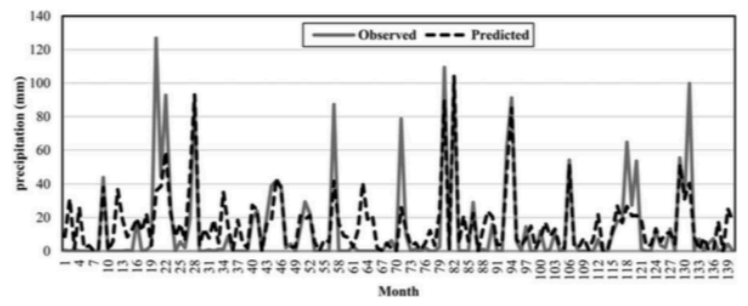

Figure 8. Observed precipitation and ELM- predicted precipitation in testing phase at Kahnooj station.

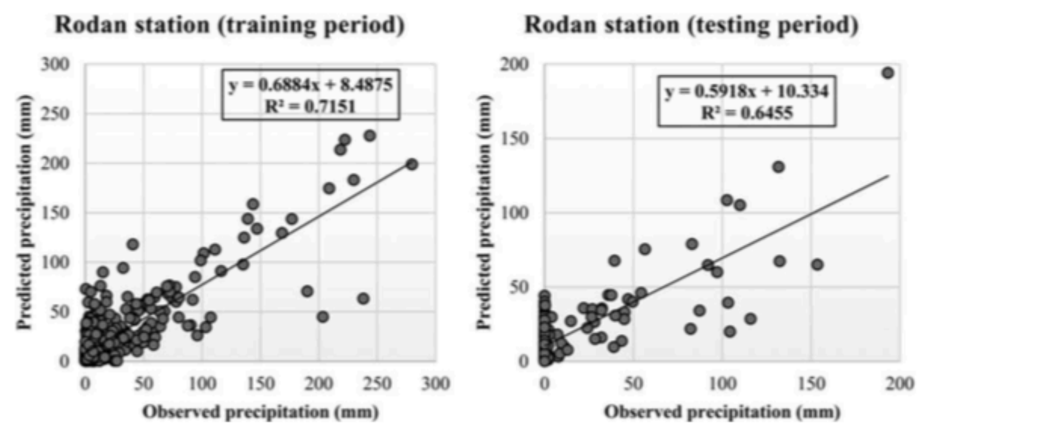

Figure 9. Scatter plots for training and testing phases of ELM-based model at Rodan station.

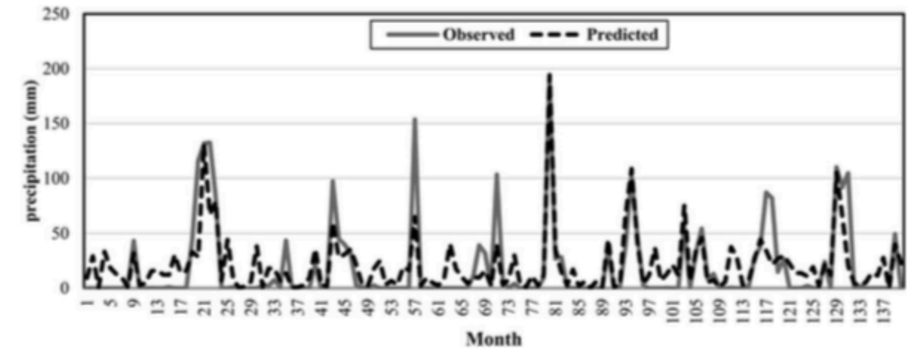

Figure 10. Observed precipitation and ELM- predicted precipitation in testing phase at Rodan station.

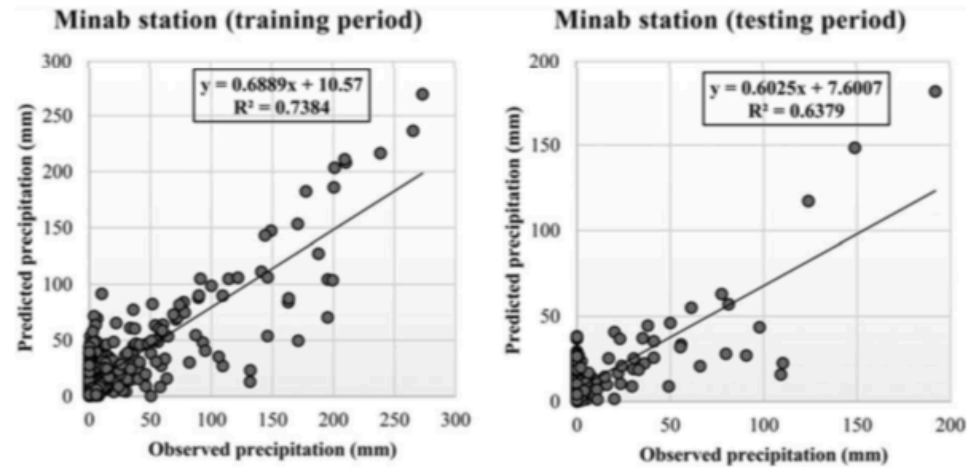

Figure 11. Scatter plots for training and testing phases of ELM-based model at Minab station.

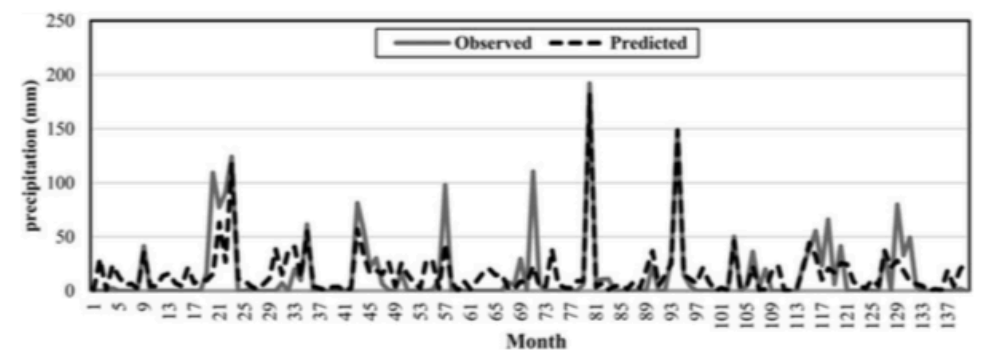

Figure 12. Observed precipitation and ELM- predicted precipitation in testing phase at Minab station.

Conclusion:

· ELM model performed better than the other models in downscaling precipitation for all stations.

· ELM required lower computation time and memory.

· ELM has the lowest training error and norm of weights.

An artificial neural network approach to rainfall-runoff modelling

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Hydrological sciences journal
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Overview:

· Feed forward network (information passes one way through the network from the input layer, through the hidden layer and finally to the output layer).

· Unfortunately, there are no fixed rules as to how many nodes should be included in the hidden layer.

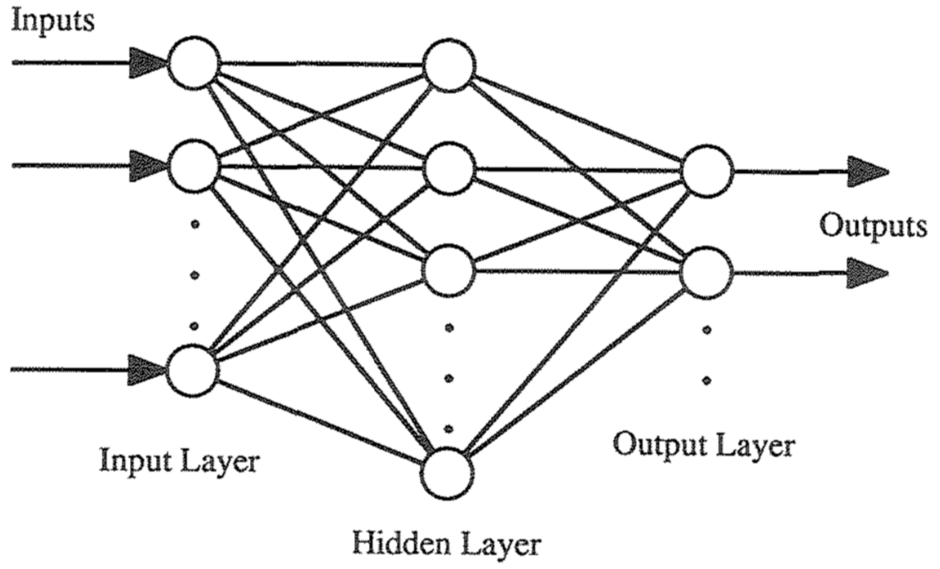

Fig. 1 A basic overview of artificial neural network topology.

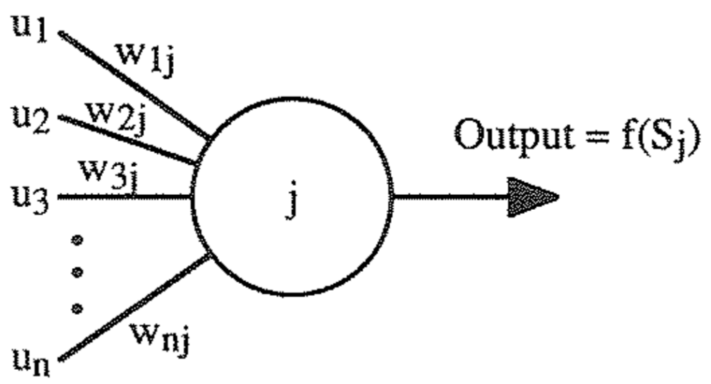

Fig. 2 An artificial neuron.

· $S_j = \sum_{i=1}^{n} w_{ij} u_j + w_{0j}$

· The activation function can be linear, discrete, or some other continuous distribution function. However, in order to use the back-propagation algorithm to train a network, this function must have the property of being everywhere differentiable.

· A practical rule of thumb is to set the weights and biases to random values in the range $(-2/\Omega, 2/\Omega)$ for a neuron with Ω inputs.

· The network calculates what it 'thinks' the output should be based on the inputs provided in the training pair.

· How much each neuron's weights and bias are adjusted in the back-propagation algorithm also depends on a learning parameter.

if the learning

parameter is too small

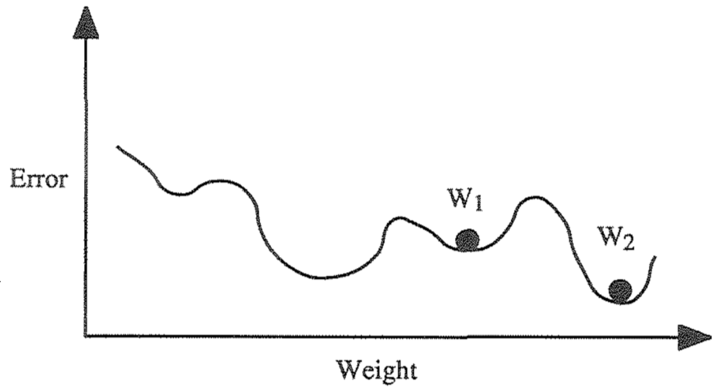

Fig. 3 Function showing weight *vs* error.

Study case:

Table 1 Hydrometric statistics for the Rivers Amber and Mole, UK.

	River Amber	River Mole
Gauge	Wingfield Park	Kinnersley Manor
Grid reference	SK 376520	TQ 262462
Catchment area (km^2)	139	142
Mean annual rainfall (mm)	789	793
Mean annual runoff (mm)	316	445
Mean flow (m^3 s^{-1})	1.4	1.95
10% flow (m^3 s^{-1})	2.9	4.2
Peak flow (m^3 s^{-1})	30.9	68.5
Max specific yields (m^3 s^{-1} km^{-2})	0.222	0.482

Source: *Hydrometric Register and Statistics 1986–1990* (NERC, 1993).

Table 4 ANN characteristics summary.

River	Input nodes	Hidden nodes	Output nodes	Standardization	Epochs	Learning parameter
Mole	7	5, 10, 20	1	Range, Sum of squares	500, 1000, 2000	0.1
Amber	15	5, 10, 15, 20, 30, 50	1	Range, Sum of squares	500, 1000, 2000	0.1

Results:

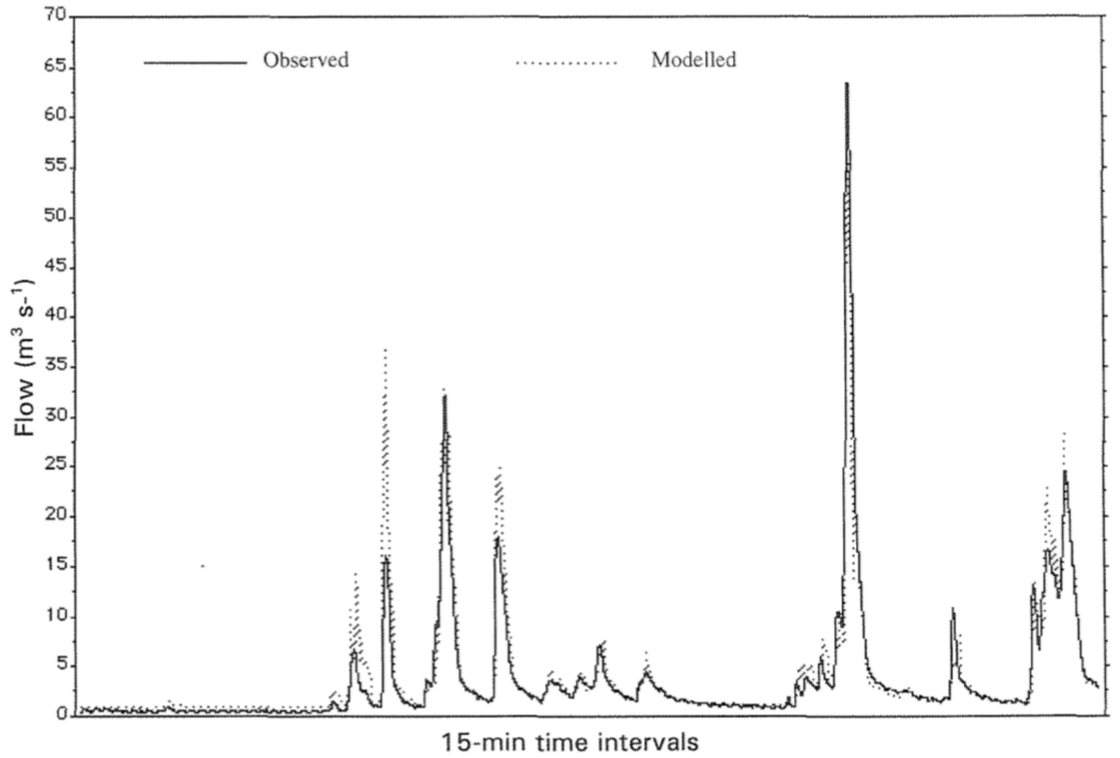

Fig. 5 ANN calibration results for the River Mole at Kinnersley Manor (23 September 1994–31 December 1994).

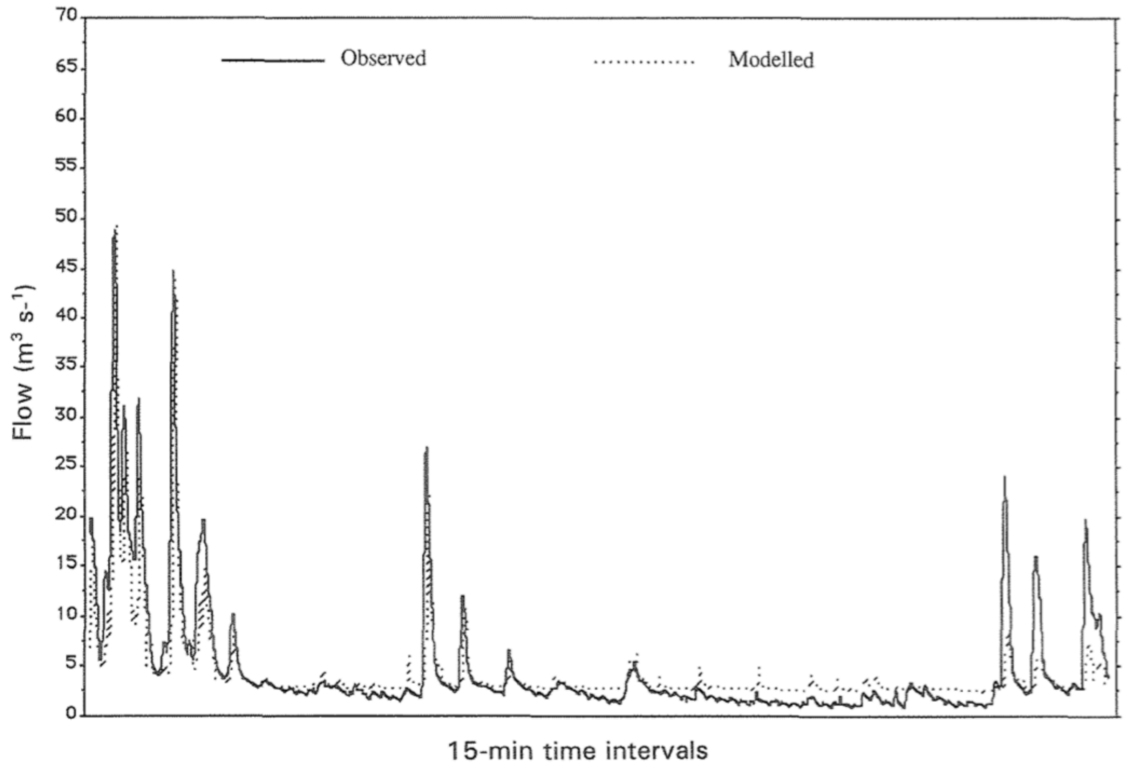

Fig. 6 ANN validation results for the River Mole at Kinnersley Manor (1 January 1994–10 April 1994).

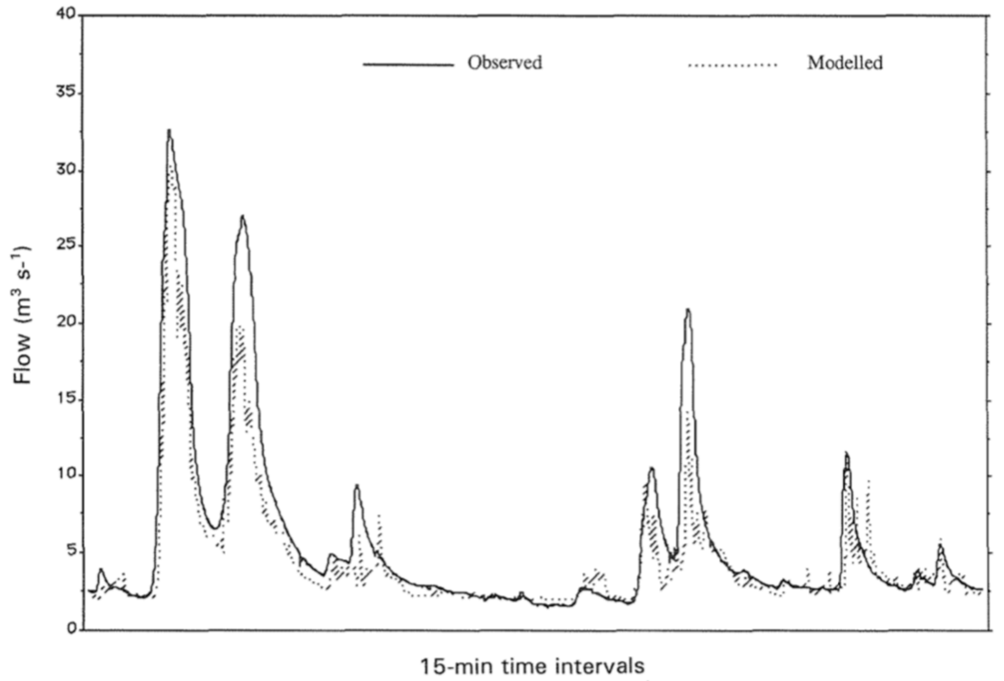

Fig. 7 ANN calibration results for the River Amber at Wingfield Park (22 January 1995–21 February 1995).

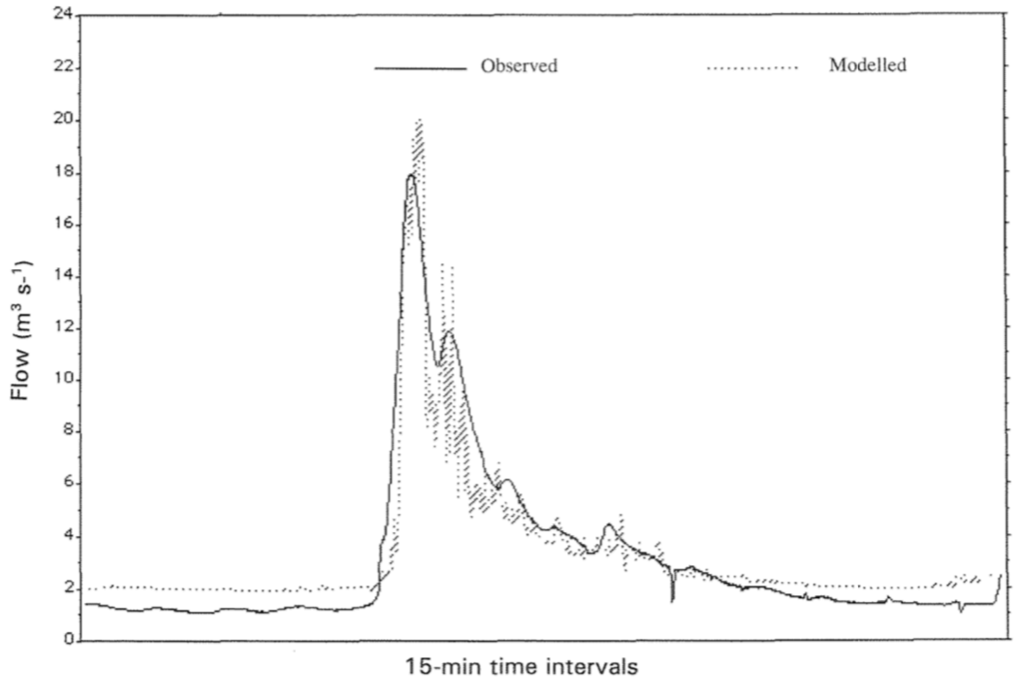

Fig. 8 ANN validation results for the River Amber at Wingfield Park (21 December 1994–5 May 1995).

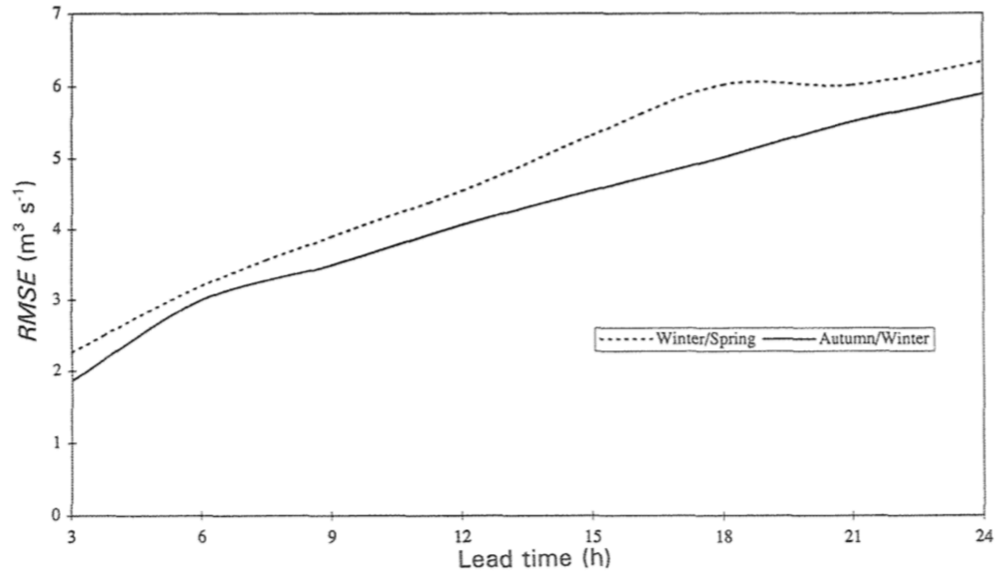

Fig. 11 ANN validation results obtained for the River Mole using 15-min precipitation and discharge series at time t_0 to forecast flows at time t_{0+n} (where n is 3, 6, 9, …, 24 h from present). The two lines are indicative of the different training periods used to calibrate the ANN (i.e. winter/spring *vs* autumn/winter).