WATER IN CELTIC COUNTRIES: Quantity, Quality and Climate Variability

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Guimarães

Portugal

Application of Artificial Neural Networks for river flow simulation in three French catchments

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Objectives

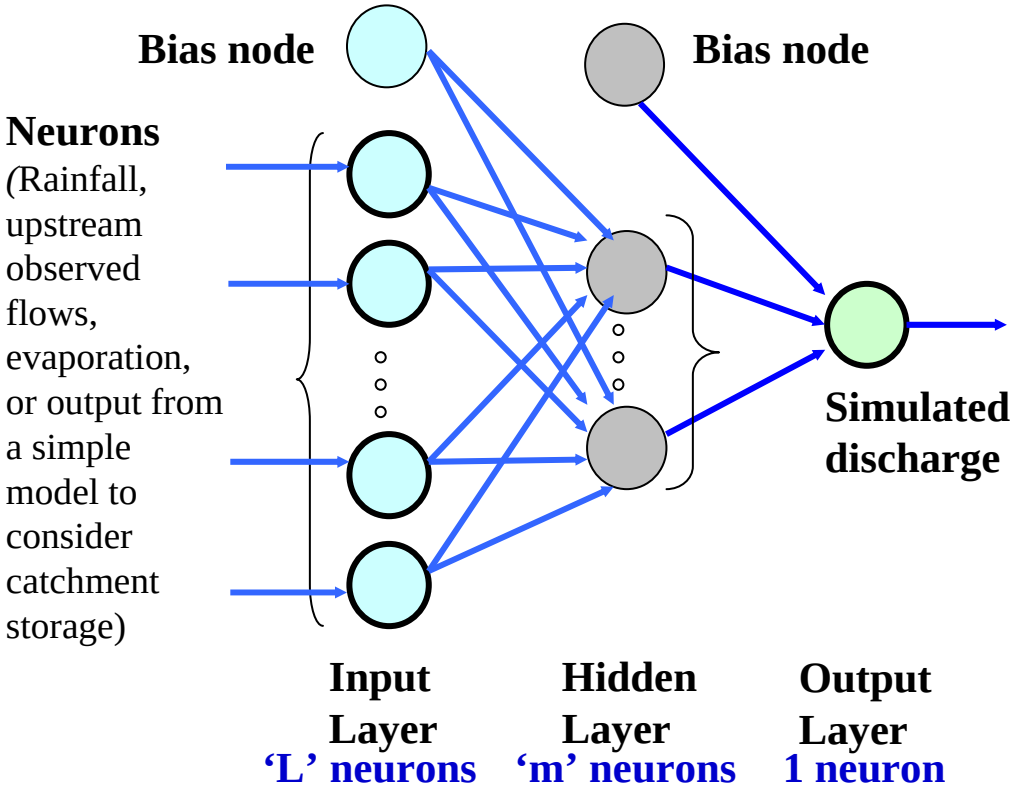
- **Application of Neural Networks for modeling runoff in the case of 3 French catchments**

- **Comparative assessment of the performance of neural network models when applied**
  - **i) as a stand-alone rainfall-runoff model (ANN), and**
  - **ii) as an output combination method (NNM), using the multi-model (consensus) approach**

<u>Note</u>: The structure of the network used for combining outputs of individual models, i.e. the NNM, is identical to that used for the individually applied ANN model

Artificial Neural Network used

- The ‘multi-layer feed forward network’ with one input layer, one output layer, and a hidden layer in between
- It is conceptually analogous to the biological neural network controlling functions of the human brain, consisting of highly interconnected networks of basic processing units (neurons)



Total no. of weights to be estimated = (L+1)m + (m+1): <u>Non-Parsimonious</u>

The SIMPLEX search method is used for estimation of the weights

Artificial Neural Network used

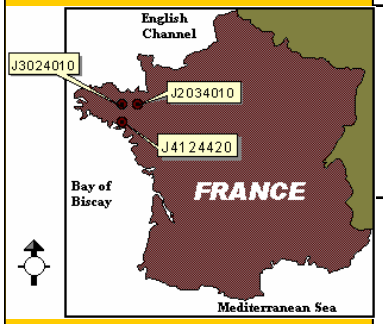
- **Inputs for the input layer are the recent past rainfall values, recent output(s) of the best individual model (other than the ANN model), and/or the recent past evaporation values**
- **The other model output is used to account for the storage effect in the catchment, thus avoiding consideration of all past rainfall inputs over the whole memory length of the system which would render the network even less parsimonious**
- **Neurons in the hidden and the output layer receive inputs y_i, which are transformed into the neuron outputs by the non-linear S-shaped activation/transfer function**

$$y_{out} = f\left[\sum\left(w_i y_i + w_o\right)\right] = \frac{1}{1+\exp\left\{-\sigma\sum\left(w_i y_i + w_o\right)\right\}}$$

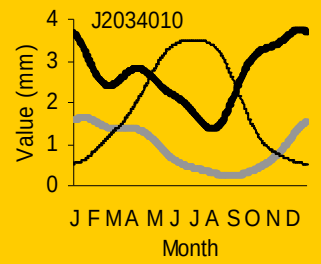
w_i: Input connection pathway weight

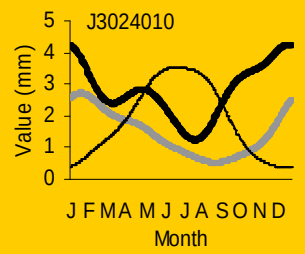
w_0: neuron threshold or bias (base-line value independent of inputs)

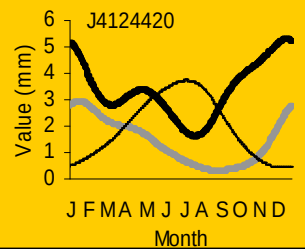
Summation extends from i=1 to i=N, the total no. of inputs to a neuron



Catchments used







Station Code/ Catchment	Station name	Area (km^2)	Length of longest stream (km)	Mean altitude (m)	Altitude at outlet (m)
J2034010	Le Guindy à Plouguiel	125	42.1	83	20
J3024010	Le Guillec à Trézilidé	43	11.6	85	35
J4124420	La Rivière de Pont-l'Abbé	32.1	9.0	84	15

Catchment	Period	Mean rainfall (mm/day)	Mean evaporation (mm/day)	Mean discharge (mm/day)	% of total no. of days R>E
J2034010	08/95-07/02	2.63	1.94	0.89	37.3
J3024010	08/95-07/02	2.78	1.88	1.45	38.7
J4124420	08/95-07/02	3.38	1.97	1.43	38.1

Other models and techniques used for comparison

Other rainfall-runoff models:

Conceptual quasi-physical model

- **SMAR: Soil Moisture Accounting & Routing model**

System theoretic models

- **Parametric Simple Linear Model (P-SLM)**
- **Non-Parametric Simple Linear Model (NP-SLM)**
- **Parametric Linear Perturbation Model (P-LPM)**
- **Non-Parametric Linear Perturbation Model (NP-LPM)**
- **Linearly-Varying Gain Factor Model (LVGFM)**

Techniques for combination of model outputs

- **Simple Average Method (SAM)**
- **Weighted Average Method (WAM)**
- **Neural Network method (NNM)**

performance evaluation criterion

Nash-Sutcliffe efficiency index R^2

Note: The split-record evaluation procedure was adopted

Results & Discussions

Values of performance index for the models in calibration and verification

Model	J2034010		J3024010		J4124420	
	R_c^2	R_v^2	R_c^2	R_v^2	R_c^2	R_v^2
P-SLM	47.75	54.42	31.44	37.29	50.89	54.66
NP-SLM	48.00	55.66	46.72	52.62	52.51	57.95
P-LPM	73.64	60.30	69.47	47.43	75.46	52.84
NP-LPM	75.70	69.19	70.11	53.98	82.90	73.34
SMAR	81.64	81.46	85.85	78.17	80.50	89.10
LVGFM	85.65	92.14	86.61	88.48	86.54	87.42
ANN	91.87	89.51	90.32	86.87	90.38	89.19

Neural network weights

Station Code	Input layer neurons		No. of neurons in hidden layer	Total no. of weights
	Nos.	Type		
J2034010	9	nR:4, nE:4, nS:1	3	34
J3024010	3	nR:2, nS:1	3	16
J4124420	5	nR:4, nS:1	5	36

nR: no. of rainfall inputs, nE: no. of evaporation inputs, nS: no. of SMAR outputs

Results & Discussions

Performance of Individual models

- Performances of both the Non-Parametric and the Parametric forms of the SLM are generally inferior
- Performances of both forms of the LPM are higher than their SLM counterparts
- Performance of the SMAR conceptual model is generally substantially higher than the linear models
- The LVGFM, which uses the the best amongst the 5 above models (i.e. the SMAR) as the auxiliary model, performs better than these 5 models.
- The ANN model, which also uses the output(s) of the SMAR model as input(s) to the neurons in the input layer, performs best amongst all 7 individual models

Results & Discussions

- Outputs from individual models are given equal weights in the SAM, and variable weights in the WAM
- For the NNM, the outputs from individual models are the inputs to the neurons in the input layer

Model Output Combination Techniques (MOCT)

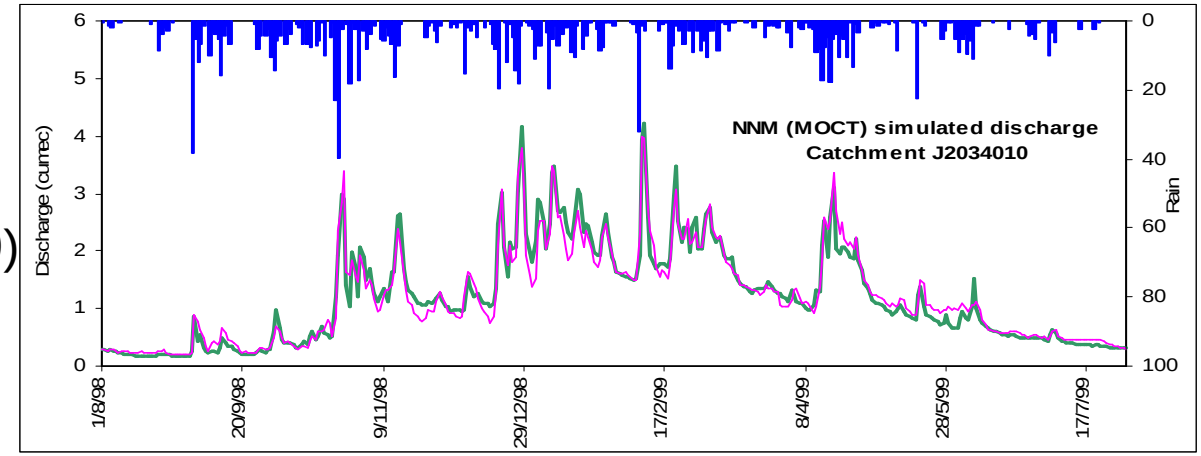
Values of performance index for

Technique for combining individual model outputs		J2034010		J3024010		J4124420	
		R_c^2	R_v^2	R_c^2	R_v^2	R_c^2	R_v^2
All 7 models	SAM	84.27	81.55	84.68	73.62	87.37	83.87
	WAM	94.05	92.14	92.73	88.62	93.55	94.24
	NNM	96.00	86.27	93.51	83.54	94.86	90.59
Best 6	SAM	87.53	84.30	87.50	77.09	89.73	86.59
	WAM	93.98	92.20	92.62	88.76	93.55	94.27
	NNM	95.15	86.39	93.40	84.62	94.28	90.81
Best 5	SAM	90.73	87.26	89.20	79.19	91.57	89.28
	WAM	92.51	91.23	92.00	88.11	93.41	93.64
	NNM	93.41	85.89	93.53	84.77	94.19	88.30
% improvement of the best MOCT on individual ANN		4.5		3.6		5.0	

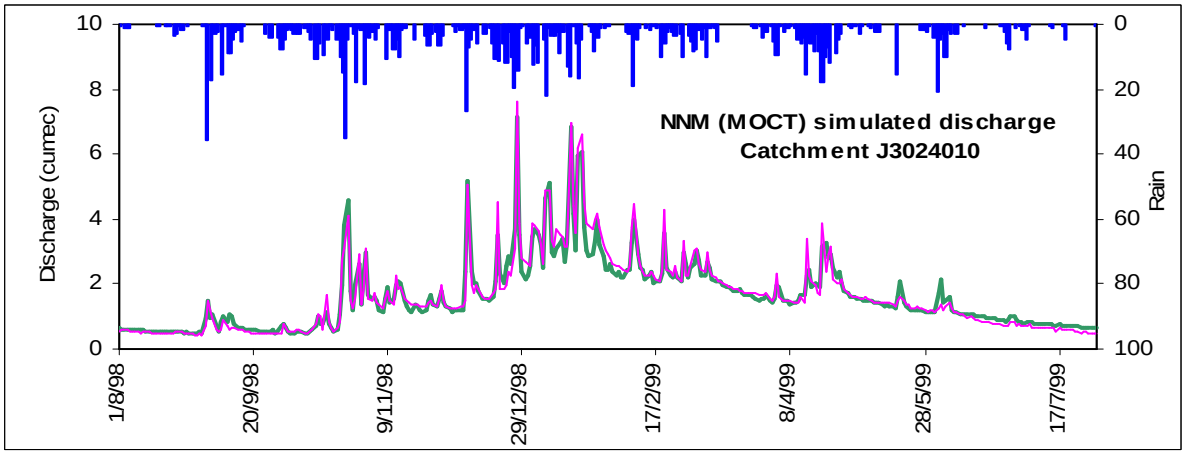
Results & Discussions

Observed and NNM-Simulated discharges for the three catchments

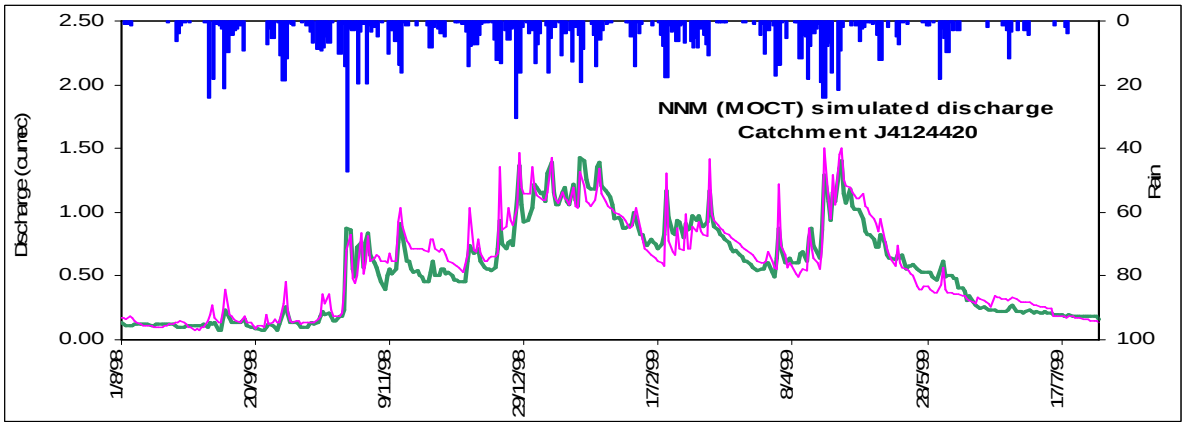
J2034010
(Aug 98 – Jul 99)



J3024010
(Aug 98 – Jul 99)



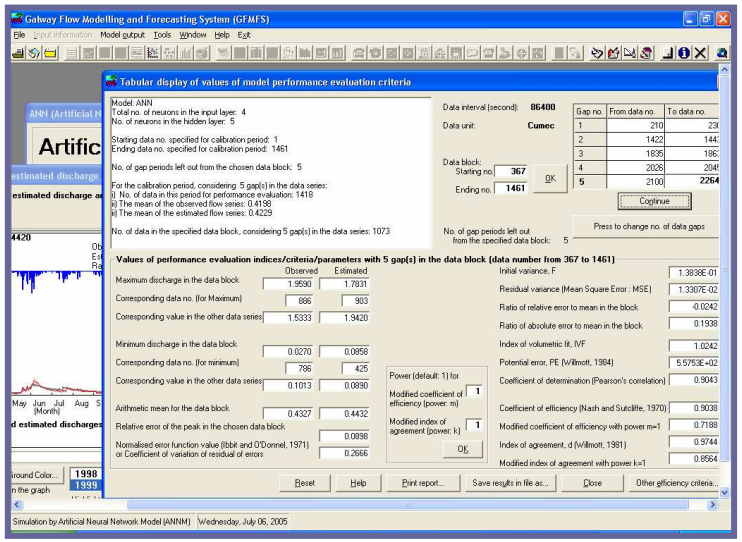
J4124420
(Aug 98 – Jul 99)



Rainfall
Obs. discharge
Sim. discharge

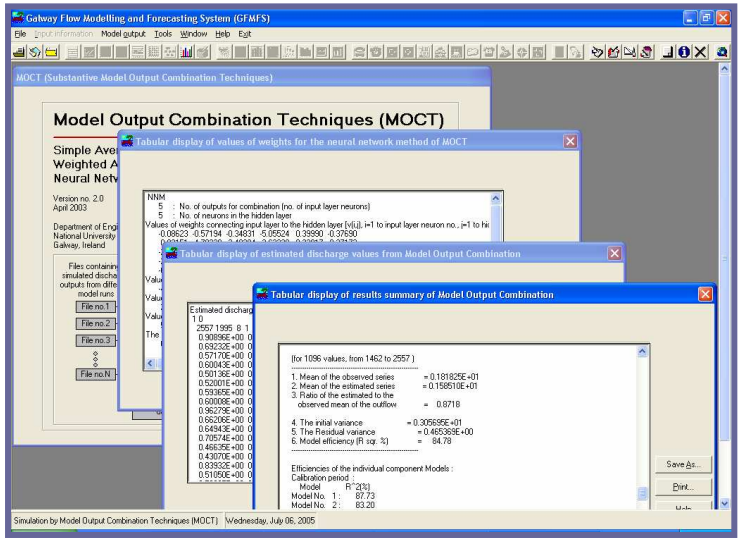
Results & Discussions

Screen shots of Windows from the GFMFS software package

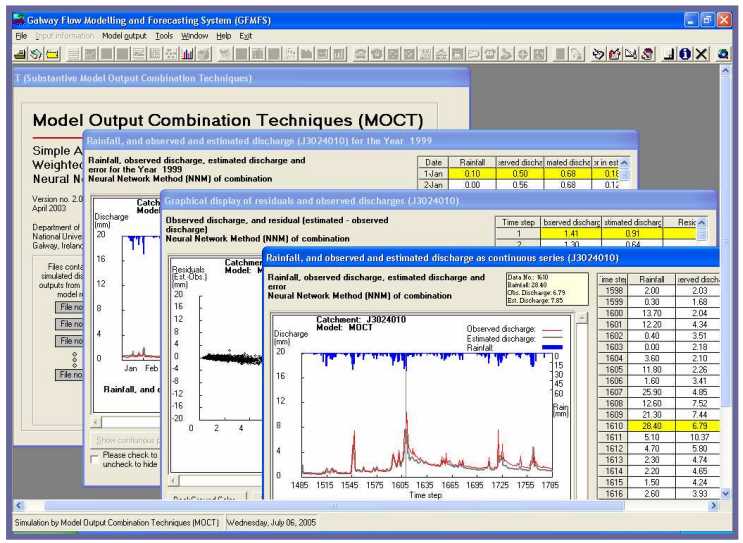


Window with values of performance evaluation criteria

Windows with tabular displays of results summary, calibrated values of NMM weights, and estimated discharge values



Windows with graphical displays of observed and NNM-simulated discharges, and scatter diagram



Conclusions

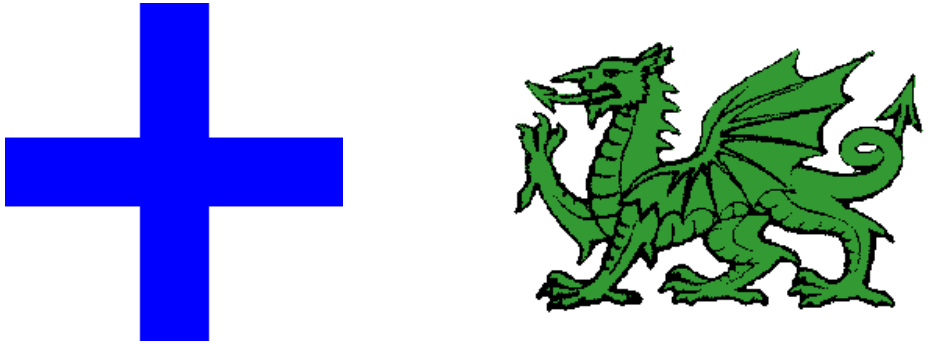
- **Although ANN models are substantially non-parsimonious, giving rise to greater complexity and corresponding difficulty in training, their flexible non-linear formulation results in significant improvement in model-fit and, in the case of 3 French catchments tested, offsets these weaknesses.**

- **This improved fit justifies the application of the ANN rainfall-runoff model for flow simulation in these 3 catchments**

Conclusions

- **Outputs from the rainfall-runoff models, used in different combinations in the MOCTs, are found to be useful for obtaining the best consensus simulation of the observed flows, whereby strengths of individual models are combined and perceptible weaknesses are suppressed**

- **Similar to its application as an individual rainfall-runoff simulation model, the neural network, applied for combining outputs from different individual models, also performs the best amongst the 3 combination techniques, and establishes its overall superiority for flow simulation in the 3 test catchments**



Thank you

for your attention!

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