Appraisal study to select suitable Rainfall-Runoff model(s) for the Nile River Basin

Bashar, K.E.
UNESCO Chair in Water Resources, Sudan, P.O Box 1244, Khartoum,
basharke@hotmail.com

F. Mutua
[2]University of Nairobi, Kenya , P.O. Box 30197, 00100 GPO Nairob, ifmutua@uonbi.ac.ke

D.M.M. Mulungu
University of Dar es Salaam,P.O.Box 35131,Tanzania , deorgm@yahoo.co.uk

T. Deksyos
Ministry of Water Resources, Ethiopia , P.O Box 5673, Addis Ababa, deksyost@hotmail.com

A. Shamseldin
University of Birmingham, UK

Abstract

This paper presents an appraisal study to select a suitable model(s) that can be used in forecasting flows in the rivers of the Nile basin.

Flow forecasting is an important step in river basin management in particular and water resources management in general. River flow models are used as components in actual flow forecasting schemes. They are also used in providing for efficient operation of storage reservoirs. Usually, flow forecasts are obtained in real time by transforming the input into a discharge using models. These forecasts may subsequently be modified or updated in accordance with the errors observed in the previous forecasts up to the time of making the new forecast.

The system analysis or black box approach depends on a prior assumption of flexible linear and time invariant relationship the expression of which can be obtained by the application of systems analysis approach to records. The conceptual model provides an alternative approach in which the input-output transformation goes through a series of steps.

In this appraisal study, systems and conceptual modelling techniques are applied to lake Victoria catchments (Simiyu, Sondu and Nzoia), Awash and the Blue Nile catchment up to Eddeim of the Ethiopian high lands. The models were applied in non-parametric and

parametric forms. Parameter optimisation is carried out by ordinary least squares, Rosenbrock, Simplex and genetic algorithm.

The areal rainfall which is the main input to these models was estimated using arithmetic mean. However, attempts to estimate the areal rainfall by the Thiesen polygon method was made but the improvement in the model performance can not justify the amount of work involved in making Thiesen's estimate.

It is shown that the simple assumption of linearity is not adequate in modelling the rainfall runoff transformation. However, in catchments which exhibit marked seasonal behaviour good results can be obtained with Linear Perturbation Model (LPM) which involves the assumption of linearity between the departures from seasonal expectations in input and output series.

The application of the GFFS (collection of systems and conceptual models) software proved to be possible with variable efficiencies in the Nile River basin. The LPM in non-parametric or parametric form, the LVGF model the ANN and the SMAR model can be used to forecast (reproduce). In catchments that exhibit marked storage effects e.g Sondu and Nzoia LPM and SMAR performed better than the other models. In Simiyu river it seems that the transformation can not be done under the assumption of linearity and hence the ANN performed better.

Within the range of the tested models LPM was found to be the best candidate model that can forecast the flows under a wide range of conditions ranging from marked seasonality to marked storage effects accounting for more than 90% of the initial variance.

1. Introduction

In recent decades, the advent of increasingly efficient computing technology has provided hydrologists with exciting new tools for the mathematical modelling of hydrological systems including, but extending far beyond, the more traditional river-flow forecasting applications. Elaborate physically-based distributed modelling, and elegant mathematical techniques using Artificial Neural Networks, Fuzzy systems, Wavelets, etc. are being used, all with high levels of complexity, but not necessarily with increased levels of efficiency attainment, particularly in the context of flow forecasting. Most such exercises are certainly significant from a research point of view, as they attempt to throw more light on the physical processes involved, but data demands, lack of parsimony in model parameters, and structural complexity can still be a major deterrent when it comes to applying these models in real-life problem solving. In the discharge forecasting context, even simple black-box type system-theoretic models, or physically-inspired lumped conceptual models, can produce better and more reliable discharge forecasting results than complex distributed models.

The Galway River Flow Forecasting System (GFFS) is a software package developed at the Department of Engineering Hydrology, National University of Ireland, Galway [O'Connor et al, 2001]. It comprises a suite of models for simulation, updating and real-time forecasting applications. The degree of structural complexity, associated parameter parsimony, and difficulty in objective function evaluation of these models, varies considerably. The models and techniques used in the present study, all from the GFFS package, are applied to five catchments in the Nile Basin representing variability in geographic location, climatic conditions, areal extent and various physiographical characteristics.

The objective of the research was to carry out an appraisal study to select candidate model(s) for use in the Nile basin. This is done by comparative studies involving diverse applications of the candidate models to catchments of the Nile basin and subject their performance to a specific criterion.

2. The Candidate Models

Three system-theoretic black-box models, an Artificial Neural Network Model, a simple conceptual Soil Moisture Accounting & Routing Model and the method of combination of outputs were used. Brief descriptions of these models are provided in the following section.

2.1 The Simple Linear Model (SLM)

2.1.1 Non-parametric modelling

The hypothesis of the SLM is introduced by Nash and Foley [1982]. The SLM approach assumes a linear time-invariant relationship between the total rainfall R_t and the total discharge Q_t. The input-output relationship for lumped, linear, time invariant system expressed in terms of a series of pulses or mean values over successive short intervals T, can be conveniently obtained from the response to unit pulse of duration T which is a convenient expression of the operation of the system. The discrete linear input-output relationship is expressed in terms of sampled pulse response by the convolution summation relation [Kachroo and Liang, 1992], which can be written after incorporating the model error term as

$$Q_t = \sum_{j=1}^{m} R_{t-j+1} h_j + e_t \qquad (1)$$

where Q_t and R_t are the discharge and rainfall respectively at the t^{th} time-step, h_j is the j^{th} discrete pulse response ordinate or weight, m is the memory length of the system, and e_t is the forecast error term.

2.1.2 Parametric Modelling-the Gamma Function Model

Constraint to the shape and volume of the estimated pulse response functions is obtained by parametric modelling where a solution is sought within the constraint of an assumed model form. Based on prior knowledge of the system behaviour the response function is represented by a suitable mathematical equation involving only a few parameters. The parameters must be estimated by optimization through a search in the space of reasonable parameter values.

The most popular impulse response function is given by

$$h(t) = \frac{1}{k\Gamma(n)} e^{-\frac{t}{k}} \left(\frac{t}{k} \right)^{n-1} \qquad (2)$$

where $\Gamma(n) = \int_0^\infty e^{-x} x^{n-1} dx$ is the gamma function of n.

The equation of the SLM for single input-single output will be

$$Q_t = G_f \sum_{j=1}^{m} R_{t-j+1} h_j + e_t \quad (3)$$

where h_j is given by equation (2) and G_f is the gain factor.

For multiple input-single output system under the constraints of the gamma function impulse response the parameters n, k and G_f must be found for each input.

2.2 The Linear Perturbation Model (LPM)

In the LPM [Nash and Barsi, 1983], it is assumed that, during a year in which the rainfall is identical to its seasonal expectation, the corresponding discharge hydrograph is also identical to its seasonal expectation. However, in all other years, when the rainfall and the discharge values depart from their respective seasonal expectations, these departures series are assumed to be related by a linear time invariant system. Thus the linear perturbation model uses the information contained in the observed seasonal variation of the hydrograph to reduce the dependence on linearity and increase the dependence on observed seasonal behaviour. The model assumes the following:

a. if each input function for each day of the year is equal to its expected value for that date R_d, the output will also equal its expectation for that date Q_d
b. the perturbations or the departure from the date expected input values are linearly related to the corresponding perturbations or departures from the date expected output values.

For a single input, the relation between the departure (i.e. perturbation) series of the LPM has the convolution summation form and can be written as

$$Q'_t = \sum_{j=1}^{m} R'_{t-j+1} h_j + e_t \quad (4)$$

where $R_t' = R_t - R_d$ and $Q_t' = Q_t - Q_d$ are the respective departures of rainfall and discharge from their seasonal expectations, e_t is the error output term and d = 1, 2, 3, …, 365. Model-estimated departure values are added to the seasonal expectations to give the estimated discharge series.

2.3 The Linearly Varying Gain Factor Model (LVGFM)

The LVGFM, proposed by Ahsan and O'Connor [1994] for the single-input to single-output case, involves only the variation of the gain factor with the selected index of the prevailing catchment wetness, but not the shape (i.e. the weights) of the response function. Using a time-varying gain factor G_t, the model output has the structure

$$Q_t = G_t \sum_{j=1}^{m} R_{t-j+1} B_j + e_t \quad (5)$$

where $\sum_{j=1}^{m} B_j = 1$

In its simplest form, G_t is linearly related to an index of the soil moisture state z_t by the equation $G_t = a + bz_t$, where a and b are constants. The value of z_t is obtained from the outputs of the naïve SLM, operating as an auxiliary model, using

$$z_t = \frac{\hat{G}}{\overline{Q}} \sum_{j=1}^{m} R_{t-j+1} \hat{h}_j \quad (6)$$

where $\hat{G}$ and $\hat{h}_j$ are estimates of the gain factor and the pulse response ordinates respectively of the SLM and $\overline{Q}$ is the mean calibration discharge.

2.4 The Artificial Neural Network Model (ANNM)

The *"multi-layer feed-forward network"* type of artificial neural network, used in this study, consists of an input layer, an output layer and only one *"hidden"* layer located between the input and the output layers [Shamseldin 1997]. Each neuron of a particular layer has connection pathways to all the neurons in the following adjacent layer, but none to those of its own layer or to those of the previous layer (if any).

Likewise, nodes in non-adjacent layers are unconnected. In the output layer, there is only one neuron, for the single output. Because the neural network itself does not incorporate storage effects, storage is implicitly accounted for by the use of the output series of the naïve SLM. For a neuron either in the hidden or in the output layer, each received input y_i is transformed to its output y_o by the mathematical transfer function

$$y_o = f\left(\sum_{i=1}^{M} w_i y_i + w_o\right) \tag{7}$$

where *f()* denotes the transfer function, w_i are the input connection pathway weights, M is the total number of inputs (which equals the number of neurons in the preceding layer), and w_o is the neuron threshold (or bias). The non-linear transfer function adopted for the neurons of the hidden and output layers is the widely-used logistic/sigmoid function

$$f\left(\sum_{i=1}^{M} w_i y_i + w_o\right) = \frac{1}{1+e^{s\left(\sum_{i=1}^{M} w_i y_i + w_o\right)}} \tag{8}$$

bounded in the range [0,1]. The neuron weights w_i, the threshold w_o and s can all be interpreted as parameters of the network configuration.

2.5 The Soil Moisture Accounting And Routing (SMAR) Model

The system type models such as SLM and LPM can fail to reproduce the observed hydrograph. The failure seems to lie in their model structure as no component that adequately accounts for evaporation and soil moisture effects in determining the volumes of runoff.

The SMAR Model is a development of the 'Layers' conceptual rainfall-runoff model introduced by O'Connell et al. [1970], its water balance component having been proposed in 1969 by Nash and Sutcliffe [Clarke 1994]. Using a number of empirical and assumed relations, which are considered to be at least physically plausible, the non-linear water balance (i.e. soil moisture accounting) component ensures satisfaction of the continuity equation, over each time-step. The routing component, on the other hand, simulates the attenuation and the diffusive effects of the catchment by routing the various generated runoff components through conservative linear time-invariant storage elements. For each time-step, the combined output of the two routing elements adopted (i.e. one for generated '*surface runoff*' as input and the other for generated '*groundwater runoff*' as input) becomes the simulated discharge forecast.

The water balance component of this model operates as a vertical stack of horizontal soil layers. Each layer can contain a certain amount of water at field capacity (see figure F1). Evaporation occurs from the top layer at a potential rate and from the second layer on

exhaustion of the top layer at the remaining potential rate multiplied by a parameter C whose value is less than unity. On exhaustion of the second layer evaporation proceeds from the third layer at the remaining potential rate multiplied by C^2 and so on. Thus, a constant potential evaporation rate applied to the basin reduces the soil moisture storage in a roughly exponential manner.

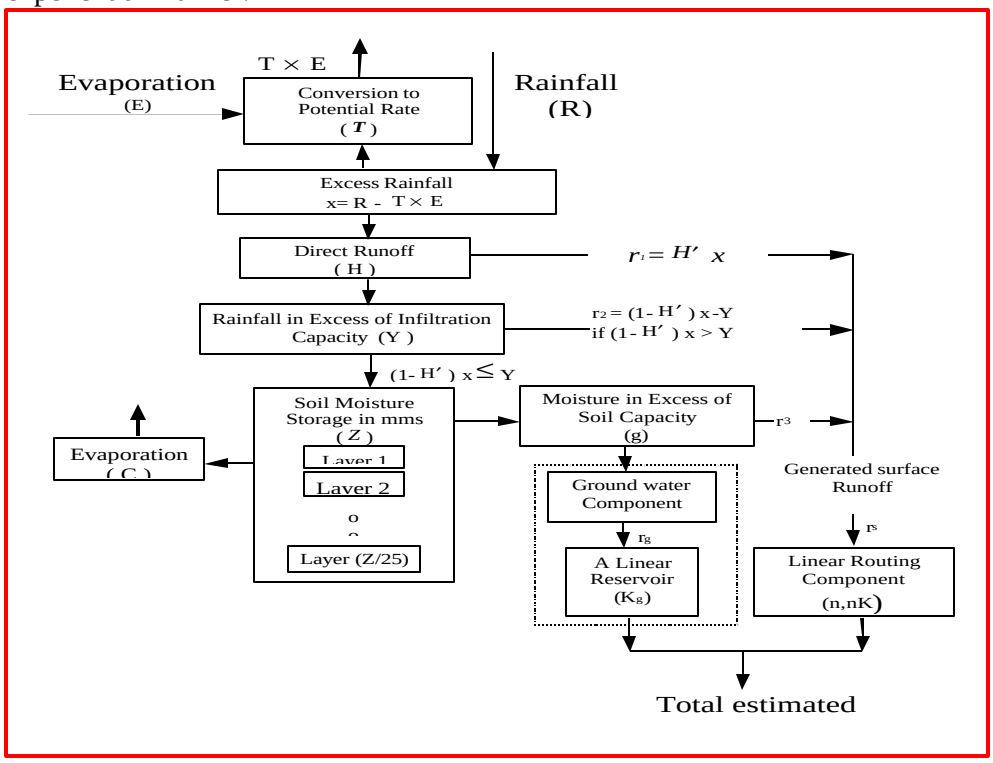


Figure (F 1): Schematic diagram of SMAR Model (Shamseldin et al 1997)

2.6 Methods of Combining the Forecasts of Different Models

Instead of relying on one individual model or switching between models, an alternative approach is to generate forecasts simultaneously from a number of different models and then combine these forecasts in an optimum manner. This can be done in several ways such as:

The Simple Average Method (SAM)

This is the simplest method for combining the outputs of different individual models. Given the output of N models, a combined estimate of discharge $\hat{Q}c_t$ of the t^{th} time period using SAM is given by:

$$\hat{Q}c_t = \frac{1}{N}\sum_{i=1}^{N}\hat{Q}_{i,t} \qquad (9)$$

SAM method given by equation (9) can produce forecasts that are better than those of the individual models (Shamseldin et al 1997, Makridakis et al 1982) and its accuracy depends mainly on the number of the models involved and on the actual forecasting ability of the specific models included in the simple average (Shamseldin et al 1997, Makridakis and Winkler 1983).

2.6.2 The Weighted Average Method (WAM)

The SAM method can be quite inefficient when some individual models selected for combination consistently produce more accurate forecasts than others (Shamseldin et al 1997, Armstrong 1989). In this case the use of a weighted average method would be preferable.
Granger and Ramanathan (1984) and Shamseldin et al (1997) used a weighted average method (WAM) for combining the outputs of N models using the formula:

$$Q_t = \sum_{i=1}^{N} a_i \hat{Q}_{i,t} + e_t \tag{10}$$

Where Q_t is the observed discharge of the t^{th} time period, a_i is the weight assigned to the i^{th} model estimated discharge $\hat{Q}_{i,t}$ and e_t is the combination error term.

Equation (10) can be expanded and written is a matrix form as:

$$\begin{bmatrix} Q_1 \\ Q_2 \\ Q_3 \\ \vdots \\ \vdots \\ Q_{k-1} \\ Q_k \end{bmatrix} = \begin{bmatrix} \hat{Q}_{1,1} & \hat{Q}_{2,1} & \cdots & \cdots & \hat{Q}_{N-1,1} & \hat{Q}_{N,1} \\ \hat{Q}_{1,2} & \hat{Q}_{2,2} & \cdots & \cdots & \hat{Q}_{N-1,2} & \hat{Q}_{N,2} \\ \hat{Q}_{1,3} & \hat{Q}_{2,3} & \cdots & \cdots & \hat{Q}_{N-1,3} & \hat{Q}_{N,3} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \hat{Q}_{1,k-1} & \hat{Q}_{2,k-1} & \cdots & \cdots & \hat{Q}_{N-1,k-1} & \hat{Q}_{N,k-1} \\ \hat{Q}_{1,k} & \hat{Q}_{2,k} & \cdots & \cdots & \hat{Q}_{N-1,k} & \hat{Q}_{N,k} \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \\ a_3 \\ \vdots \\ \vdots \\ a_{N-1} \\ a_N \end{bmatrix} + \begin{bmatrix} e_1 \\ e_2 \\ e_3 \\ \vdots \\ \vdots \\ e_{k-1} \\ e_k \end{bmatrix} \tag{11}$$

Equation (11) can be written as

$$Q = XA + E \tag{12}$$

where Q is output vector, X is the input matrix, A is the weight vector and E is the combination error vector.
This equation can be treated as a multiple linear regression model. The ordinary least squares (OLS) estimate the weights vector $\hat{A}$ is given by:

$$\hat{A} = \left[X^T X\right]^{-1} X^T Q \tag{13}$$

In the WAM, the sum of weights a is normally constrained to unity (Shamseldin et al 1997, Dickinson 1975) i.e.

$$\sum_{i=1}^{N} a_i = 1 \tag{14}$$

the OLS solution of equation (13) may not ensure the satisfaction of the constraints of equation (14) thus the method of constrained least squares (CLS) can be used to estimate the weights vector (Shamseldin et al 1997, Bruen 1985) as:

$$\hat{A}_{cls} = \left[X^T X\right]^{-1} \left[X^T Q + \frac{1}{2} b l \right] \tag{15}$$

where b is a unit vector a having a same dimension as the vector A and λ is the Lagrange multiplier given by (Shamseldin et al 1997):

$$l = 2\left[b^T \left(X^T X\right)^{-1} b\right]^{-1}\left[1 - b^T \left(\left(X^T X\right)^{-1}\right) X^T Q\right] \quad (16)$$

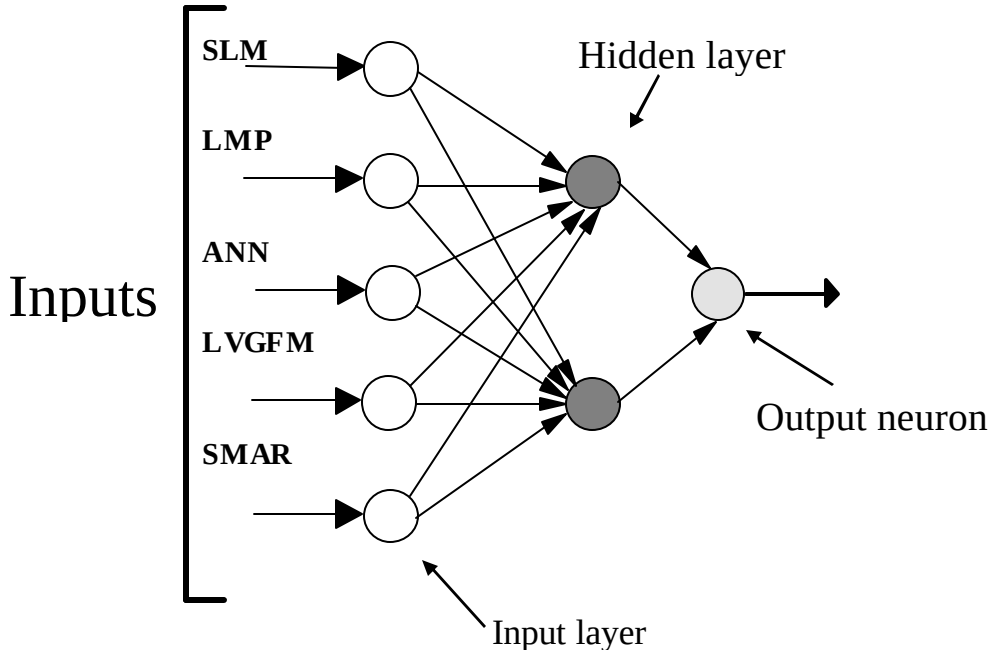
Shamseldin et al (1997) and Winkler (1989) pointed out that the main disadvantage of the WAM is that it may suffer from multi-collinearity problem which results in unstable estimates of the weights reducing the advantages obtained from combining the different models forecasts. The degree of multi-collinearity increases with the increase in the forecasting ability of the individual models as well as when the forecasts of the individual models used are very similar not necessarily being good.

2.6.3 The Neural Network Method (NNM)

The SAM and WAM methods are relatively simple methods of combining the forecasts. An alternative method is the NNM which can be used to test whether a more complex relationship such as a nonlinear function mapping of inputs into the network output, is needed for the combinations (Shamseldin et al 1997).

There are several types of neural networks available, however, the type used in this study is multi layer feedforward network. This type is very powerful in function modelling (Shamseldin et al 1997).

The multi layer feedforward neural network used consists of an input layer, an output layer and only one hidden layer between the input and output layers. A layer is usually a group of neurons having same pattern of connection pathways to the other neurons of adjacent layers. Each neuron in a particular layer has connection pathways to all the neurons in the next adjacent layer but non to those of the same layer (figure F2).



Figure(F2): Schematic diagram of the Artificial Neural Network model

The number of neuron in the input layer is equal to the number of elements in the external input array to the network. In this study the elements of the external array are the forecast of

selected models each of which is assigned to only one neuron. These inputs were transformed to outputs using a transfer function given by:

$$f(X_i) = X_i$$

where X_i is the i^{th} external input to the i^{th} neuron in the input layer. The outputs of these neurons in the input layer are distributed through connection pathways to the neurons of the single hidden layer.

The hidden neurons has no direct connection with either the external input or output of the network. Each neuron in the hidden layer receives its input through connection pathways from the neurons of the input layer and transmit their output along the connection pathways to all the neurons of the output layer. The output layer in turn accumulates the transmitted input and produce the network output. The number of neurons in the output layer equals the number of outputs expected from the network.

A neuron in the hidden or output layer receives inputs and transform it to output y_0 by a mathematical transfer function given by equation (7).
These network parameters are usually estimated by a procedure referred to in neural networks as training (Shamseldin et al 1997 and Hammestrom 1993) analogous to the calibration procedure in hydrological modelling.

The transfer function is usually nonlinear and the most widely used one is the logistic function given by equation (8).

3. The Model Efficiency Criteria

In this study, the performances of the selected models (SLM, LPM, LVGFM, ANN and SMAR) as well as the three methods of combining model outputs (SAM, WAM and NNM) are all evaluated using R^2 model efficiency criteria of Nash and Sutcliffe (1970). The R^2 reflects the amount of initial variance accounted for by the model. So it is closely linked to the sum of squares of the differences F between the estimated and observed discharges. The criterion is defined by:

$$R^2 = 1 - \frac{F}{F_0} = 1 - \frac{MSE}{MSE_0}$$

where F_0 is the initial variance of the discharges about their mean over the calibration period or some times called the initial mean square error (MSE_0) given by

$$F_0 = MSE_0 = \frac{1}{N}\sum_{i=1}^{N}(q_i - \overline{q})^2$$

where $\overline{q}$ is the mean observed discharge over the calibration period. F is the residual model variance (variance not accounted for by the model) or some times called the residual mean square error (MSE). It reflect the sum of the squares of the differences between the observed discharges q_i and the model estimates $\hat{q}_i$ given by:

$$F = MSE = \frac{1}{N}\sum_{i=1}^{N}(q_i - \hat{q}_i)^2$$

The initial variance F_0 can be visualized as the variance of a naïve model having a forecast all the time equal to the mean of the observed discharge. The quantities F and F_0 for the calibration period is estimated over that period. For the verification period the residual variance F is calculated over the period itself while the initial variance F_0 is calculated using

the mean discharge over the calibration period. The idea behind this calculation is that the naïve forecast in the verification period is the mean discharge of the calibration period.

Therefore, the R^2 can be regarded as a measure of the performance of the substantive relative to that of the naïve (primitive) model.

4. The Catchments

Five catchments were used in this study the details of which are shown in table 1. These catchments represent the main two sources of the Nile namely the Ethiopian high lands and the equatorial lakes. Two catchments were selected from the Ethiopian high lands, the Blue Nile (176,572 km^2) and the Awash (7,656 km^2). In the equatorial lakes three basins were selected, Simiyu (5,320 km^2) in Tanzania, Sondu (3,450 km^2) in Kenya and Nzoia (12,676 km^2) in Kenya. Topographically, there is a wide variation among these catchments which well represents the topography of the Nile basin. Climatologically, the selected catchments represents the whole scale from the arid to the tropical zones where the mean annual rainfall varies from few hundreds of millimetres to some thousands of millimetres.

Table (1): Information about the catchments used in the study and their concurrent data sets

Basin	Area (km^2)	Country	Rainfall Stations Used	The data sets			
				No. years	Starting year	Calibration	Verification
Nzoia	12,676	Kenya	12	10	1990	Jan 1990-Dec 1997	Jan 1998-July 1999
Sondu	3,450	Kenya	10	5	1970	Jan 1970-Dec 1972	Jan 1973-Dec 1974
Simiyu	5,320	Tanzania	5	9	1970	Jan 1970-Dec 1975	Jan 1976-Sept 1978
Blue Nile	176,572	Ethiopia/Sudan	10	7	1990	Jan 1990-Dec 1994	Jan 1995-Dec 1996
Awash	7,656	Ethiopia	9	12	1991	Jan 1991-Dec 1999	Jan 2000-Sept. 2002

5. Results and Discussion

Each of the five basic models is applied to each of the five selected catchments, using split-record evaluation, involving the use of calibration and verification periods. Roughly about two-thirds of the available data is used for calibration and one-third for verification. The method of combining outputs is also applied to each of the selected catchments using the outputs of the basic models applied in simulation mode (as distinct from the updating mode). In terms of increasing complexity, the SLM is the simplest, followed by the LPM in their non-parametric and parametric forms and the LVGFM. These three are system-theoretic in structure, and ordinary least squares solution is used for estimation of the pulse response function except for the parametric forms where the parameters were optimised. The SMAR model parameters are estimated using the three optimisation techniques, simplex, Rosenbrock and genetic algorithm. As for the ANN, the number of weights depends on the number of neurons chosen in the input layer and the hidden layer. If *'l'* is the total number of neurons in the input layer and *'m'* is that in the hidden layer, then the total number of weights to be estimated is *(l+1)m + (m+1) (Shamseldin et al 1997)*. As such, the ANN is the least parsimonious amongst the models chosen in the study. The simplex method of automatic optimisation is also used for calibration of the ANN. The results of performances of the

substantive models are shown in Tables 2 and 3 respectively for the simulation and updating modes.

From these results, it is clear that the simulation mode performance of the naïve SLM is, in each case, inferior to that of all other models. As expected, the LVGFM, which is a modification of the SLM, incorporating an element of linear variation of the gain factor G_t with the catchment wetness index at each time-step, performs consistently better than the SLM except for Nzoia and Sondu where the surface storage of the catchments might have affected the results. In the case of very large catchments, such as Blue Nile , the LVGFM, SMAR and ANN models have same order of performance with a slightly less efficiency in the case of SMAR. In the case of SMAR model the parameter lumping applied to large catchments such as the Blue Nile with such diverse physiographic, climatic and topographic variations has a negative effect on the model performance. On the other hand, the over-parameterisation of the ANN model, results on see-saw parameter effects which negatively impacts the model performance.

For catchments characterised by strong seasonality, the LPM in simulation mode , with its inherent component of seasonal variation, outperforms the LVGFM. For large catchments such as Blue Nile, having a catchment area of 176,572 km^2, and characterised by physiographical and hydro-meteorological variability, but displaying strong seasonality, the LPM performs better than both the SMAR, LVGFM and the ANN models. For smaller catchments, however, such as Awash, Nzoia and Sondu, characterised by a marked storage effects in their flow duration curves, the SMAR model performs consistently better than the other models. For Simiyu, the ANN was found to perform better than other models and the performance of LVGFM is just marginally higher than the rest of the models.

The SLM and LPM can also be applied in the updating mode in addition to the MOCT. The method of combined outputs is applied to the results of the simulation modes of the five substantive models. Table 3 shows the performance results of the models in updating mode applied to all the five catchments. It can be seen that the LPM consistently performed better than all the other models. It accounted for more than 90% of the initial variance.

These results indicate that simple models, involving fewer parameters or weights to be evaluated, and relying on simple mathematical procedures (e.g. the ordinary least squares solution), are often better in discharge forecasting than models which involve a significantly higher number of parameters or weights to be evaluated and which rely on complex mathematical computations (e.g. automatic optimization).

Table (2): The model efficiencies (in %) in simulation mode

Period	Basin	Method	SLM	LPM	VGFM	SMAR	ANN
Calibration	Nzoia	OLS	60.0	67.0	64.0	68.0	54.0
	Sondu	OLS	44.0	67.0	49.0	68.0	67.0
	Simiyu	OLS	32.3	39.4	49.9	46.5	52.7
	Blue Nile	OLS	77.8	92.1	91.2	90.5	91.8
	Awash	OLS	52.0	72.0	53.0	72.0	51.0
Verification	Nzoia	OLS	49.0	44.0	45.0	43.0	41.0
	Sondu	OLS	34.0	42.0	21.0	45.0	68.0
	Simiyu	OLS	24.8	31.6	41.8	31.0	40.9
	Blue Nile	OLS	76.0	91.1	89.0	89.2	90.7
	Awash	OLS	47.0	64.0	55.0	79.0	39.0

Table (3): The model efficiencies (in %) in updating mode

Period	Basin	Method	SLM	LPM	MOCT		
					SAM	WAW	NNM
Calibration	Nzoia	Parametric	96.0	97.0	98.0	96.0	97.0
	Sondu	Parametric	98.0	99.0	98.0	99.0	98.0
	Simiyu	Parametric	63.4	69.9	68.3	69.9	84.2
	Blue Nile	Parametric	98.2	98.6	89.9	92.4	92.4
	Awash	Parametric	48.0	76.0	81.3	82.9	82.8
Verification	Nzoia	Parametric	94.0	96.0	-	-	-
	Sondu	Parametric	89.0	90.0	-	-	-
	Simiyu	Parametric	73.6	71.6	73.1	71.6	60.8
	Blue Nile	Parametric	97.3	97.2	88.4	91.6	91.5
	Awash	Parametric	40.0	59.0	78.8	82.8	82.4

6. Conclusions

The performance of the naïve SLM is clearly inferior to that of all other models. For catchments, characterized by strong seasonality, the LPM outperforms the LVGFM. For large catchments with such seasonality, the LPM performs is even better than the SMAR model. For smaller catchments, however, the SMAR conceptual model performs consistently better than the LPM. The ANN, although characterized by a large number of weights (parameters), does not generally perform better than the simpler models. The SMAR model variants, having either nine or ten parameters, fail to adequately simulate the hydrological behaviour of the large catchments.

In conclusion, this study confirms that simpler models for continuous river-flow simulation can surpass their complex counterparts in performance. There is a strong justification, therefore, for the claim that increasing the model complexity, thereby increasing the number of parameters, does not necessarily enhance the model performance. It is suggested that, in practical hydrology, the simpler models, can still play a significant role as effective simulation tools, and that performance enhancement is not guaranteed by the adoption of complex model structures.

As a concluding statement, LPM in its updating mode can be used to safely forecast flows in the rivers of the Nile basin with a performance efficiency of more than 90% i.e. accounting for more than 90% of the initial variance.

7- Acknowledgments

This paper was prepared based on the research activities of the FRIEND/Nile Project which is funded by the Flemish Government of Belgium through the Flanders-UNESCO Science Trust Fund cooperation and executed by UNESCO Cairo Office. The authors would like to express their great appreciation to the Flemish Government of Belgium, the Flemish experts and universities for their financial and technical support to the project. The authors are indebted to UNESCO Cairo Office, the FRIEND/Nile Project management team, overall coordinator, thematic coordinators, themes researchers and the implementing institutes in the Nile countries for the successful execution and smooth implementation of the project. Thanks are also due to UNESCO Offices in Nairobi, Dar Es Salaam and Addis Ababa for their efforts to facilitate the implementation of the FRIEND/Nile activities.

8. References

Ahsan, M. and K.M. O'Connor, A simple nonlinear rainfall-runoff model with a variable gain factor, *Journal of Hydrology*, 155: 151-183, 1994.

Armstrong, J. S., Combining forecasts: the end of the beginning or the beginning of the end?, Int. J. Forecasting, 5: 585-588, 1989.

Bruen, M., Black box methods of systems applied to modelling of catchment behaviour. Ph.D. thesis, National University of Ireland, 1985.

Clarke, R.T., *Statistical Modelling in Hydrology*, John Wiley and Sons, 1994.

Granger, C. W. J. and Ramanathan, R., Improved methods for combining forecasts. J. Forecasting 3: 197-204, 1984.

Hammestorm, D., Working with neural networks. IEEE spectrum, 30: 46-53, 1993.

Kachroo, R.K. and G.C. Liang, River flow forecasting, Part 2, Algebraic development of *480* linear modelling techniques, *Journal of Hydrology*, 133: 17-40, 1992.

Makridakis, S. and Winkler, R., Average of Forecasts: some empirical results, Manage. Sci., 29(9): 987-996, 1983.

Makridakis, S., Andersen, A., Carbone, R., Fildes, R. Hibon, M., Lewandowski, R., Newton, J., Parzen, E. and Winkler, R., The accuracy of extrapolation (time series) methods: results of a forecasting competition. J. Forecasting, 1: 111-153, 1982.

Nash, J.E. and J.V. Sutcliffe, River flow forecasting through conceptual models, Part 1, A discussion of principles, *Journal of Hydrology*, 10: 282-290, 1970.

Nash, J.E. and J.J. Foley, Linear models of rainfall-runoff systems. In: 'Rainfall-Runoff Relationship', Proceedings of the *International Symposium on Rainfall-Runoff modelling*. Mississippi State University, May 1981, USA. Edited by V.P. Singh, Water Resources Publications pp.: 51-66, 1982.

Nash, J.E. and B.I. Barsi, A hybrid model for flow forecasting on large catchments, *Journal of Hydrology*, 65: 125-137, 1983.

O'Connell, P.E., J.E. Nash, and J.P. Farrell, River Flow forecasting through conceptual models. Part 2. The Brosna catchment at Ferbane, *Journal of Hydrology.*, 10: 317-329, 1970.

O'Connor, K.M., M. Goswami, G.C. Liang, R.K. Kachroo, and A.Y. Shamseldin, The Development of The 'Galway Real-Time River Flow Forecasting System (GFFS), The proceedings of the *19th European Regional Conference of ICID*, Czech Republic, 2001.

Shamseldin, A. Y., Application of a neural network technique to rainfall-runoff modeling, *Journal of Hydrology*, 199, 272-294, 1997.

Shamseldin, A.Y., K.M. O'Connor, and G.C. Liang, Methods for combining the outputs of different rainfall-runoff models. *Journal of Hydrology*, 197: 203-229, 1997.

Winkler, R. L., Combining forecasts: A philosophical basis and some current issues. Int. J. Forecasting, 5: 605-609, 1989.