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Comparison of ANN-NARX, SMAR-LTF and LPM-LTF Flood Forecasting Models in the Nzoia Basin, Kenya

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Abstract: Flooding is a perennial problem that occurs along several riverine environments, causing loss of property and human lives. The Nzoia Basin in Kenya is one of the areas prone to annual flooding, especially the lower reaches such as Budalang'i. This study assesses three flood forecasting techniques with a view of determining the most efficient model for flood forecasting in the Nzoia Basin. The three techniques considered are SMAR-LTF, ANN-NARX and LPM-LTF techniques. Each of the three simulation models was calibrated individually, initially without updating, then subsequently updated based on either of the two updating techniques (LTF or NARX). The study found that ANN-NARX forecasts had a slightly higher correlation to the observed discharge data when compared to the SMAR-LTF technique, although both had high coefficient of determinations ($r^2 > 0.9$) for up to 6 day lead forecasts. For LPM-LTF technique, forecasts had a high decay rate beyond one lead-day forecasts, with r^2 being less than 0.8, well below SMAR-LTF and ANN-NARX. This is consistently evident for the flood event periods considered during the study. It can thus be concluded that for flood forecasting in the Nzoia Basin, ANN-NARX is the best technique, although SMAR-LTF had close results to the ANN-NARX technique for all the 6 lead-day forecasts.

Keywords: ANN, SMAR, LPM, LTF, NARX, flood forecasting

1. Introduction

Flooding is one of the most common natural calamities of modern time. Approximately 70% of all disasters occurring in the world are hydro-meteorological events [1]. A flood is defined by [2] in three ways: Rise, usually brief, in the water level in a stream to a peak from which the water level recedes at a slower rate; relatively high flow as measured by stage height or discharge; rising tide.

Flooding affects a large part of the African continent, as many cities and settlements are concentrated on flood plains [3]. With climate change, especially the increase in storm frequency and rising sea level worldwide, flood events are likely to be more frequent and severe [4]. In Kenya, many parts of the country experience unexpectedly heavy rainfall in mid-April which continues through the end of May (the long rains period) and from September to November (the short rains period). The areas that are most prone to flooding disasters are the Lake Victoria Basin, comprising of Budalang'i in Western Kenya along the Nzoia River, the Kano plain along the Nyando River, and the lowland Tana River basin.

The Nzoia basin is prone to seasonal flooding, downstream of Rwambwa river gauging station. Currently, flood warning in the basin relies on the issuing of alerts when the river level at the Rwambwa monitoring station, just upstream of the flood plain, reaches certain pre-determined levels. The warnings are generated with a lead time of three days using Soil Moisture Accounting and Routing (SMAR) Model and Linear Transfer Function (LTF) updating procedure with inputs of lumped daily rainfall, evaporation, discharge and Quantitative Precipitation Forecasts (QPFs). This study assesses two additional flood forecasting techniques i.e. ANN-NARX and LPM-LTF so as to establish the best flood forecasting technique for the Nzoia Basin.

In principle, LPM-LTF uses linear models for simulation and updating while SMAR-LTF applies a non-linear model for simulation but a linear model for updating. ANN-NARX uses non-linear models for both simulation and updating. It is a known fact that flooding and related causes (factors) are non-linear in nature. Hence linear-based flood forecasting models are limited to shorter forecast duration. It is expected that non-linear models e.g. ANN-NARX would make improvements in the forecast duration but such improvements may be basin-based and must be determined for practical applications.

The Nzoia River basin is located in Western Kenya and is part of the Lake Victoria basin as shown in Figure 1. The basin lies between latitudes 1° 30'N and 0° 05'S and longitudes 34° 00' and 35° 45'E and contributes enormously to the shared waters of the Trans-boundary Lake Victoria. The basin has a catchment area of about 12,900 km^2, with the river having a length of about 334 km up to its mouth in the Lake Victoria [5].

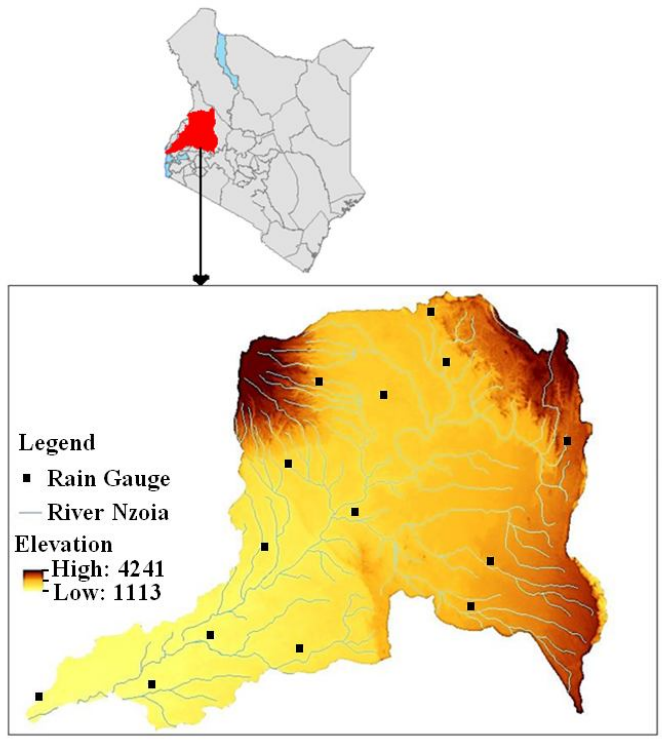

Fig.1. The Nzoia River Basin (Elevation is given in m)

River Nzoia originates largely from Cherangani Hills, at a mean elevation of 2,300 m above mean sea level and drains into Lake Victoria at an altitude of 1,100 m. Its main tributaries include: Lusumu, Kipkarren, Kuywa, Koitobos, Noigamet, and Moiben. The climate of the basin is mainly tropical humid with mean annual day temperature variations between 16°C in the highland areas (Cherangani hills and Mt. Elgon) to 28°C in the lower areas. The mean annual night temperatures vary between 4°C in the highland areas to 16°C in the semi-arid areas. The mean annual rainfall varies from a minimum of 600 to a maximum of 2,700 mm [5].

In its upper reaches, the river flows in a slightly meandering V shaped valley. The width of the channel is about 40 m with a bed gradient of 1 in 240. The channel width increases to 50 m in the middle, with a bed gradient of 1 in 390. The bed gradient flattens further to1 in 3,400 as the river meanders through a wide flood plain and the Yala Swamp. The channel width increases to 70 m and the height of the banks reduces considerably, which causes spilling of floodwaters over the banks and consequent flooding of large areas on either side [5]. Recent major flood events in Nzoia basin occurred in April-May 2003, October-November 2008 and October November 2011.

2. Theoretical Background of Simulation models and Updating Procedures

Two system theoretic black-box models i.e. Artificial Neural Networks (ANNs) and Linear Perturbation Model (LPMs) and one conceptual model i.e. Soil Moisture Accounting and Routing (SMAR) Model were considered for this study. Two updating procedures were also used: Linear Transfer Function (LTF) and Non-linear Auto-Regressive Exogenous-Input Model (NARXM).

2.1 Simulation Models

2.1.1 Linear Perturbation Model

This model exploits the seasonal information inherent in the observed rainfall and discharge series [6]. 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. The relation between the departures/perturbation series of the LPM may be represented algebraically by the convolution summation equation [6],

$$Q_i' = \sum_{j=1}^{m} R_{i-j+1}' \, h'_j + e_i \qquad (1)$$

where R_i' and Q_i' are the rainfall departures and the corresponding discharge departures from their seasonal expectations respectively, h'_j is the *j-th* discrete pulse response ordinate or weight and e_i is the forecast error term.

2.1.2 Soil Moisture Accounting and Routing Model

The SMAR model is a lumped quasi-physical conceptual rainfall-evaporation-runoff model introduced by [7], with two main modules: water-balance and routing components. Using a number of empirical and assumed relations, the non-linear water balance component preserves the balance between the rainfall, evaporation, generated runoff and the changes in the various layers of soil moisture storage. The routing component simulates the attenuation and the diffusive effects of the catchment by routing the various generated runoff components (outputs from the water balance component), through linear time-invariant storage elements. For each time-step, the combined output of the two routing elements adopted becomes the simulated (un-updated) discharge forecast produced by the SMAR model.

The optimisation procedures for the calibration of the SMAR model are: the classic gamma distribution (Nash-cascade) model [8], Negative Binomial distribution [9], and the Inverse Gaussian distribution [10] for flashy catchments. The choice of three automatic optimization algorithms, i.e. the genetic algorithm [11], the Rosenbrock method [12] and the Simplex method [13] are available for the calibration of the SMAR model.

2.1.3 Artificial Neural Networks

A multi-layer feed-forward network consisting of an input layer, output layer and 3 hidden layers was used. Each neuron of a particular layer has connection pathways to the following adjacent layer, but none to those of its own layer or to those of previous layer(s). The output layer has only one neuron for the single output, the simulated discharge.

For a neuron either in the hidden or in the output layer, the received inputs Y_i are transformed to its output Y_{out} by a mathematical transfer function of the form [14],

$$Y_{out} = f\left(\sum_{i=1}^{M} w_i Y_i + w_o\right) \qquad (2)$$

where $f\,(\ldots)$ denotes the transfer function, w_i is the input connection pathway weight, M is the total number of inputs (which usually equals the number of neurons in the preceding layer), and w_o is the bias (a base-line value independent of the input).

The non-linear transfer function adopted for the neurons of the hidden layer and also that of the output layer is the logistic function, i.e. a form of sigmoid function, given by [14],

$$f\left(\sum_{i=1}^{M} w_i Y_i + w_o\right) = \frac{1}{1+e^{-\sigma\left(\sum_{i=1}^{M} w_i Y_i + w_o\right)}} \qquad (3)$$

which is bounded in the range [0,1], implying that the network output is likewise bounded in that range, σ being a scaling parameter of the transfer function.

2.2 Updating Procedures

2.2.1 Linear Transfer Function

It is also referred to as Auto-Regressive Exogenous-input Model (ARXM). It is a linear input-output model that enables the forecasting of future values of a time series on the basis of recent past values, and values of one or more exogenous inputs. It is widely applied in river flow forecasting due to its flexibility and LTF being parsimonious in the number of parameters used [15].

For a forecast lead-time of one data interval, the LTF output updating procedure while incorporating a residual updated discharge forecast error term e_{i+1}^{LTF} can be expressed as [16],

$$Q_{i+1} = \sum_{k=1}^{p} a_k\, Q_{i-k+1} + \sum_{k=0}^{q} b_k\, \hat{Q}_{i-k+1} + e_{i+1}^{LTF} \quad (4)$$

$$\hat{\hat{Q}}_{i+1|i} = Q_{i+1} - e_{i+1}^{LTF} = \sum_{k=1}^{p} a_k\, Q_{i-k+1} + b_0\, \hat{Q}_{i+1|i} + \sum_{k=1}^{q} b_k\, \hat{Q}_{i-k+1} \quad (5)$$

where Q_{i+1} is the as-yet-unmeasured discharge for the $(i+1)^{st}$ time step, $\hat{Q}_{i-k+1}$ is the current and most recently observed discharges, $\hat{Q}_{i+1|i}$ is the one-step-ahead simulation model discharge forecast of the substantive rainfall-runoff model, $\hat{\hat{Q}}_{i+1|i}$ is the one-step ahead discharge forecast made at the current i^{th} time step, p , q are the orders of the auto-regressive and the exogenous input parts of the LTF, a_k , b_k are the corresponding coefficient parameters of these two parts. A generalized equation can be given as,

$$\hat{\hat{Q}}_{i+l|i} = \sum_{k=1}^{l-1} a_k\, \hat{\hat{Q}}_{i-k+l|i} + \sum_{k=l}^{p} a_k\, Q_{i-k+l} + \sum_{k=0}^{l-1} b_k\, \hat{Q}_{i-k+l|i} + \sum_{k=l}^{q} b_k\, \hat{Q}_{i-k+l} \quad (6)$$

LTF was used in the updating of simulation discharge for both the SMAR and LPM models.

2.2.2 The Non-linear Auto-Regressive Exogenous-Input Model

In non-parametric form, the one-step-ahead NARXM-neural network updating procedure may be expressed as [17],

$$Q_{i+1} = h\left(Q_{i}, Q_{i-1}, \dots, Q_{i-p+1}, \hat{Q}_{i+1|i}, \hat{Q}_{i}, \dots, \hat{Q}_{i-q+1}\right) + e_{i+1}^{NARXM} \quad (7)$$

$$\hat{\hat{Q}}_{i+1|i} = Q_{i+1} - e_{i+1}^{NARXM} \quad (8)$$

where h denotes a non-linear functional relation and e_{i+1}^{NARXM} is the residual error of the corresponding updated discharge-forecast.

Discharge estimates over the selected forecast lead-times can be obtained using the NARXM-neural network updating procedure by the recursive application,

(5)

$$\hat{\hat{Q}}_{i+l|i} = h\left(\hat{\hat{Q}}_{i+l-1|i}, \hat{\hat{Q}}_{i+l-2|i}, \dots, \hat{\hat{Q}}_{i+1|i}, Q_{i}, \dots, Q_{i-p+l}, \hat{Q}_{i+l|i}, \hat{Q}_{i+l-1|i}, \dots, \hat{Q}_{i+1|i}, \hat{Q}_{i}, \hat{Q}_{i-1}, \dots, \hat{Q}_{i-q+l}\right) \quad (9)$$

The input layer receives the external input array to the network and each of the elements of this array is designated to one (and only one) of the input neurons. In the case of one-step-ahead forecasting, the external inputs (i.e. the exogenous inputs) to the network are the simulation-mode discharge forecasts $\hat{Q}_{i+1|i}, \hat{Q}_{i}, \dots, \hat{Q}_{i-q+1}$ and the current and previous recently observed discharges $Q_{i}, Q_{i-1}, \dots\dots, Q_{i-p+1}$ as demonstrated in Fig. 2.

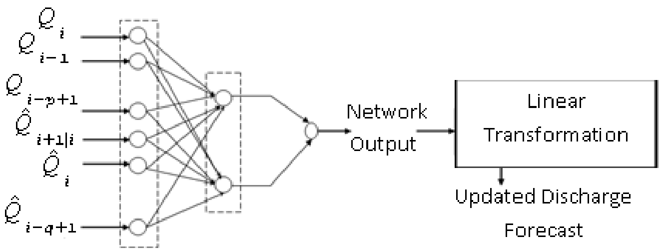

Fig. 2. Schematic diagram for the multi-layer feed-forward neural network used as an output updating procedure for one-step-ahead

Each neuron in the input layer produces a single output that, in its entirety, becomes an input to the hidden layer. The hidden layer enhances the ability of the network to model non-linear processes [18]. Each hidden neuron has an input array, which consists of the outputs of the input layer neurons. The hidden neuron produces only a single output, which becomes an input array to the output layer. The transformation of its input array, by each neuron of the hidden layer, to a single output is achieved by a mathematical non-linear transfer function, which introduces non-linearity into the operation of the network. The same transformation function is normally used for all of the hidden layer neurons. Although the NARXM has greater flexibility than the linear LTF for the same number of inputs, it is a less parsimonious model structure than the LTF [17].

3. Materials and Methods

3.1 Description of Data Sets

For this study, the lower reach of River Nzoia that runs from Rwambwa river station was selected due to the availability of quality water level sensors at that station which record the water level every 10 minutes. The data used was provided by Kenya Meteorological Service (KMS). They included: lumped daily areal evaporation rates, areal rainfall over the basin and river discharge data at Rwambwa gauge station, all for a 6 year period. The distribution for the calibration and verification is detailed in Table 1.

Table 1. Data availability and the periods for calibration and verification for the catchments chosen for the study

	Whole Data Series	Calibration Period	Verification Period
Length of Record (Years)	6	4	2
No. of Data	2,192	1,461	731
Duration	Jan. 1st 2008 to Dec. 31st 2013	Jan. 1st 2008 to Dec. 31st 2011	Jan. 1st 2012 to Dec. 31st 2013

The procedure adopted was in line with WMO conventions [19] which adopt an updating procedure for conducting river flow forecasts as shown in Figure 3.

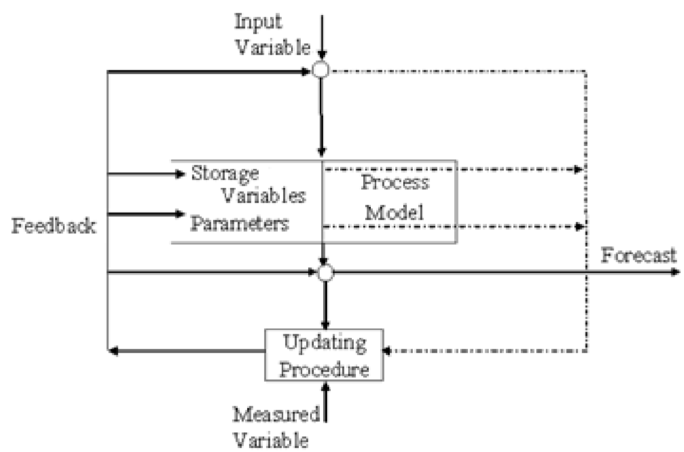

Fig.3. Simulated real-time inter-comparison of hydrological models [19].

3.2 Data Processing

Data gaps in the discharge series were synthetically filled using the following approach:

i) Initially assuming -9.99 as the data value for each data gap. This was to differentiate the data gap from a data record of zero.

ii) Calibrating each model iteratively until the model performance in two successive tests converged. The discharge values used for filling the gaps in each iteration were the previous discharge estimates of the data values simulated in the previous iteration run. For each model, the series having the highest r^2 performance value was adopted for filling the original gaps in the series.

Table 2. Initial model parameter specifications for SMAR

Model Param.	Description	Initial Value
Z	The combined water storage depth capacity of the layers (mm)	25
T	A parameter (less than unity) that converts the given evaporation series to the model-estimated potential evaporation series.	0.5
C	The evaporation decay parameter, facilitating lower evaporation rates from the deeper soil moisture storage layers	0.5
H	The generated *'direct runoff'* coefficient	0.1
Y	The maximum infiltration capacity depth (mm)	10
N	The shape parameter of the Nash gamma function *'surface runoff'* routing element; a routing parameter	1
nK	The scale (lag) parameter of the Nash gamma function *'surface runoff'* routing element; a routing parameter	1
G	The weighting parameter, determining the amount of generated *'groundwater'* used as input to the *'groundwater'* routing element.	0.15
K_g	The storage coefficient of the *'groundwater'* (linear reservoir) routing element; a routing parameter	10

Once the gaps were filled, simulation and subsequent updating were carried out. Each of the three models (SMAR, ANN and LPM) was applied to the Nzoia basin, initially for split-record evaluation, involving the use of calibration and verification periods and subsequently by recalibration of the same model structures over the entire available record. This was achieved using the sum of the original calibration and verification periods but retaining some aspects of the original calibration results, such as memory length of response function, and number of harmonics where applicable.

For ANN, multi-layer feed-forward architecture was adopted for integrated ANN simulation and updating. The number of input neurons for the observed rainfall, evaporation and discharge, and hidden layer neurons were specified as 3 for each of the mentioned layers. This was informed by other studies on flood forecasting in various catchments, although one hidden neuron has shown to be sufficient [20]. The output layer had one neuron; the updated discharge values. NARXM was used for the updating process.

For SMAR, the starting values for the model parameter description were defined as shown in Table 2. The Simplex algorithm was then applied to optimize these starting values based on the rainfall and evaporation data input. The model was then calibrated based on the optimized parameters. The calibration resulted in non-updated discharges. The Linear Transfer Function (LTF) was then used as the updating technique to provide lead-time forecasts.

For LPM, the harmonics of the rainfall and discharge series i.e. H_R and H_Q were both specified as 10 based on a trial-and-error process which yielded a high correlation for both data series. An integrated simulation and updating process was then carried out. The Linear Transfer Function (LTF) was then used as the updating technique to provide lead-time forecasts.

4. Results and Discussion

4.1 Whole Data Series

The forecast results are shown in Figure 4. The comparison was based on the coefficient of determination (r^2).

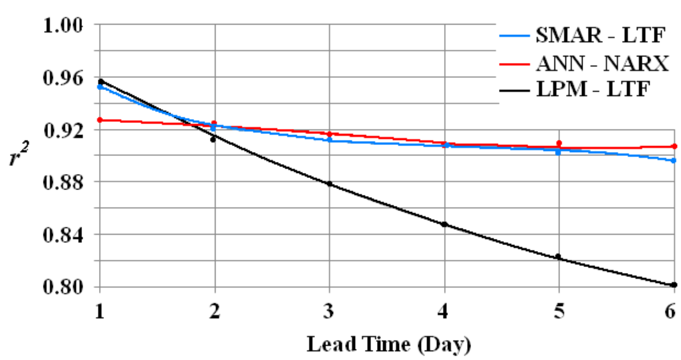

Fig. 4. Comparison of r^2 for each model for the whole data series

From Fig. 4, it is noted that for one lead-day forecast, LPM outperforms the other two models. Beyond one lead-day forecasts, ANN outperforms SMAR and LPM. This phenomenon can be explained from the hydrological process, which is a non-linear process. Since non-linearity increases as the lead-time period increases, for one lead-time forecast, linear systems such as LPM may outperform non-linear systems such as ANNs. LPM being a linear technique and the simulation results updated using LTF, a linear technique, results in a high rate of decay. This explains the sharp decline in forecast prediction, well below the other two models.

For SMAR, a conceptual hydrological model, it is able to simulate the non-linear hydrological process, and subsequent LTF updating results is able to forecast at better accuracies than LPM, although it is slightly below ANN. However, forecasts produced from SMAR-LTF have high correlation strength i.e. $r^2 > 0.9$. For ANN, the rate of decay over the lead-time period is slower compared to SMAR or LPM, since NARX is a non-linear model hence can fit non-linear systems better than LTF or other linear functions.

The RMSE of the differences between predicted and observed discharge was computed for each model for each lead time prediction. The lead-day forecast errors are shown in Figure 5.

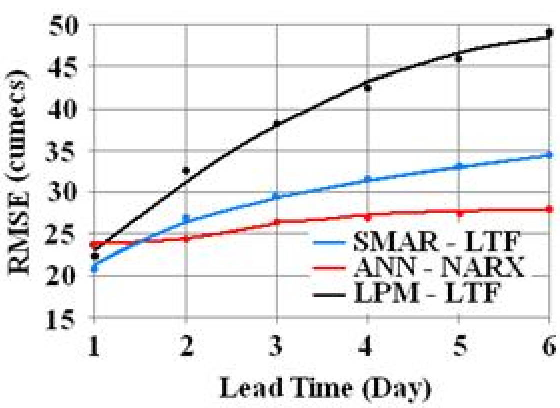

Fig. 5. RMSE for the three models for the whole data period

From Figure 5, ANN-NARX has a lower RMSE compared to the other two models, more so beyond one-lead day forecasts. This can be attributed to the ability of ANN to map non-linear phenomena such as hydrological cycle. SMAR-LTF follows in second place. Since SMAR is a conceptual hydrological model, it simulates the non-linear hydrological process using optimized hydrological parameters which represent the hydrological process. This is why the RMSE is relatively lower compared to LPM-LTF which is a linear model which considers seasonal variations.

Major recent flood events witnessed in the Lower Nzoia basin were in October-November 2008 and October-November 2011. An analysis of these periods was also carried out to assess the efficiency of the three models during the flood events.

4.2 October-November 2008 Floods

Figure 6 shows the performance of the three models with respect to forecasts for the period 1st Oct. 2008 to 30th November 2008.

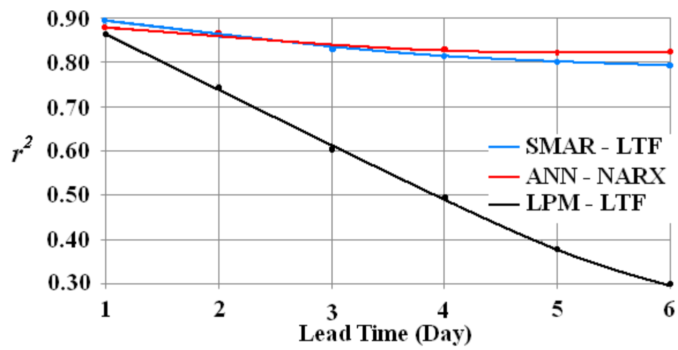

Fig. 6. Comparison of r^2 for each model technique for Oct –Nov 2008 period

ANN-NARX outperforms both SMAR-LTF and LPM-LTF for lead forecasts beyond one day, although SMAR-LTF is close to ANN-NARX forecasts. For LPM-LTF forecasts, the rate of decay is high, since both the simulation and updating techniques are linear in nature.

4.3 November - December 2011 Floods

Figure 7 shows the performance of the three models with respect to forecasts for the period 1st Oct. 2011 to 30th November 2011. ANN-NARX again outperforms both SMAR-LTF and LPM-LTF for lead forecasts beyond one day, although SMAR is close to ANN forecasts. For LPM-LTF forecasts, the rate of decay is high, because both the simulation and updating techniques are linear in nature. However, the forecast correlations are stronger for all 3 techniques compared to those of October-

November 2008 flood period. This can be attributed to better simulation results beyond the starting point, October-November 2008 being closer to the starting point, January 1st 2008 compared to the October-November 2011 period.

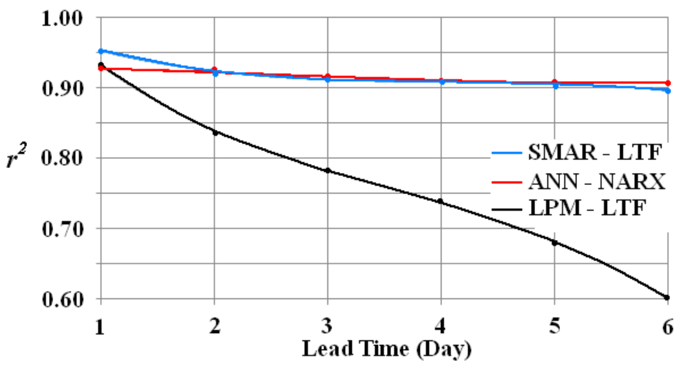

Fig. 7. Comparison of r^2 for each model technique for October – November 2011 period

5. Conclusions

This study compared three flood forecasting techniques i.e. SMAR-LTF, ANN-NARX and LPM-LTF in the Nzoia Basin. The three models were calibrated, verified and an updating procedure applied to each of the three models so as to produce lead-time forecasts for up to 6 lead-days. For one lead-day forecast, LPM-LTF was shown to slightly outperform both ANN-NARX and SMAR-LTF when considering the whole data series. All techniques however had high correlations greater than 0.90. Beyond one lead-day forecasts, ANN-NARX was shown to outperform both SMAR-LTF and LPM-LTF lead forecasts. However, for ANN-NARX and SMAR-LTF, the results were generally high in all lead-time predictions i.e. r^2> 0.9 when compared to LPM-LTF forecasts which had a high decay rate.

When the forecast period was focused on the flood event periods of October-November 2008 and October-November 2011, ANN-NARX and SMAR-LTF were found to have fairly high correlations with the observed data i.e. r^2> 0.80 for all lead forecasts compared to LPM-LTF which beyond one lead-day forecast had a correlation less than 0.8. It can thus be concluded that ANN-NARX outperforms the other two techniques with SMAR-LTF forecasts close to those of ANN-NARX in all the 6 lead-day predictions in the Nzoia Basin. SMAR-LTF performs better than LPM-LTF in the study area.

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