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Estimation of Likely Impact of Climate Variability on Runoff Coefficients from Limpopo Basin using Artificial Neural Network (ANN)

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ABSTRACT: Forecasting future response behaviour of a semi-arid catchment in terms of runoff coefficient being trivial, an attempt has been made to apply an Artificial Neural Network (ANN) model to forecast the runoff coefficients (ROC) for the Limpopo catchment system in Botswana. ROCs computed from 1971 to 2000, by the water balance technique have been used to develop the optimal network architecture with appropriate choice of the size of input vectors, number of hidden layers and number of neurons in the hidden layers, training algorithms and transfer functions for the network. Based on its performance in terms of reproducibility of the water balance runoff coefficients, the network was used to forecast the runoff coefficients up to 2016. For the decades between 1971-1980, 1981-1990 and 1991-2000 the average runoff coefficients were found to be 0.40 to 0.41 and 0.47 respectively. The average forecast runoff coefficients for the decade 2001-2010 and the period 2011-2016 were found to marginally increase to likely values of 0.48 and 0.50 respectively. This may therefore need an appropriate watershed management strategy to conserve soils and runoff from the basin.

1 INTRODUCTION

In past two decades or so, the world has been witnessing a substantial rise in the number of weather related disasters and in 2002 alone, as many as 700 natural disasters were experienced, 600 of them being due to weather related events such as droughts, floods, windstorms, rain-intensities and temperature resulting in economic losses to the US \$ 53 millions out of a total of US\$ 70 millions (OFDA, 2003). Even a semi-arid country like Botswana has also been in its grip and has been observing disasters due to Droughts and Floods which between the years 1965 and 2000 have affected over 4.5 million people resulting in financial loss to the tune of US \$ 3.5 millions (EM-DAT, 2004). Reasons for such disasters in Southern Africa are varied; they range from natural climate variability due for instance, to ENSO events to management related factors such as increased risk of flooding due to land degradation. However, recent evidence show that disasters are increasingly linked to climate extremes generally attributed to global temperature change leading to climatic variability, primary to which are anthropogenic emissions of green house gases.

Further consequences of increased temperature can be observed through higher evaporation, depletion of soil moisture, increase in consumptive use by crops or increase the phenomenon of evapo-transpiration, leading to uncertainties in water resources planning and management. Frederick and Major (1997) have also reported that not only the timing and magnitude of the global temperature changes are uncertain, but also less is known about the climate change and their impacts at basin and watershed levels. General Circulation Models (GCMs) the principal tools relating changes in atmospheric chemistry to changes in climatic variables such as temperature and precipitation; though project that a 1.5 to 4.5 °C rise in global mean temperature would increase the global mean precipitation about 3 to 15%. However, this is not applicable to all regions, particularly the sub-tropics. For Southern Africa majority of models show net drying of upto 15% for two thirds of the continent including Botswana (IPCC, 2001). It is projected also that, some lower latitude basins, may experience reductions in runoff due to a combination of increased evaporation and decreased precipitation. Even in areas with increased precipitation, higher evaporation rates may lead to reduced runoff. As a result, hydrological uncertainties attributed to changing atmospheric chemistry are likely to persist in the foreseeable future.

In view of this, an attempt has been made in this paper to assess the likely effect of the climatic variability on runoff from one of the major river systems of Botswana, the Limpopo basin, which is a major source of food security and source of many other economic activities for a large section of the population of Botswana. Since the country is experiencing rapid urbanization which has risen from about 18% in the year 1981 to more than 50% in 2001 and basin is also undergoing a rapid transformation in its land use. Two major aspects that can affect the runoff from this catchment are the effect of land use and the climatic variability in the region. To marginalize the cross cutting effects due to these two to some extent, i.e. effects due to changes in climate and land-use, it has been proposed to use a ratio between total flow and total rainfall over the catchment in a year to represent the lumped flow characteristics of the basin with the assumption that the forecasted runoff coefficient by and large will be as a result of the overall effect of the two. Since, the time series of the runoff coefficients will usually be small and may be non-stationary; using time-series models to forecast some ten or twenty time steps ahead may not be possible or will yield erroneous results. So an attempt to use the artificial intelligence through development of models like the Artificial Neural Network (ANN) has been attempted, such that the results of this study can assist in development of policies for proper watershed management.

2 STUDY AREA

Botswana is a completely landlocked country located between latitudes 18° S and 27° S and longitudes 20° E and 29° E. The country shares a boarder with Zimbabwe in the northeast, South Africa in the south to southeast, Namibia in the west, and Zambia in the north. The country is more or less gently undulating uplands with occasional rocky outcrops. The narrow southeastern part is the hard veldt while the rest and major part of the country is the sand veldt. The eastern part has most of the country's population in contrast to the sparsely populated sand veldt. The hard veldt has the most fertile soils and good rains. The Limpopo catchment lies on the hard veldt eastern part covering an area of about 80 000 km^2 (about one-eight area of Botswana). It provides water for the capital city Gaborone, the largest urban centre and rural settlements. The Limpopo River is not only the major source of water in the eastern Botswana but also has strategic importance to countries like, South Africa, Zimbabwe and Mozambique through which it flows out to the Indian Ocean. The basin experiences an average annual rainfall between 450 and 550 mm south-westerly with temperatures varying between 37°C in summer and 10°C in winter. Additionally the area experiences very high rates of evaporation, which stands at an average of about 1400 mm per year. In spite of the fact that the eastern part has better rains and have appreciable flow as compared to the sand veldt areas, present water supplies for the country as a whole relies heavily on groundwater resources that are becoming stressed. Unless development and growth, especially over the eastern part of the country is put on brake, additional water resources will have to be found to supply the growing demand.

3 METHODOLOGY

3.1 *The Water Balance Computation*

When a catchment is ungauged or the hydrological cycle is subjected to the effects of human interference, one of the methods found very useful in estimating runoff coefficient is the Water Balance Method (Thornthwaite and Mather, 1955). Besides its reasonable representation of the physical processes through integration of the effects of climate and land-use, the main advantage of this method lie in its simplicity and fewer data requirements. Also, in view of the fact that the method works very well for areas (cells) representing uniform soil and climatic characteristics, this method is often applied through a multi-cell representation of the catchment as suggested by Fischer et al, (1996). Such cells, however, can be obtained by superimposing contours of long-term rainfall, evapotranspiration on the soil map of the catchment. Computed runoff from each cell is then lumped at the outlet to obtain the final runoff, hence the runoff co-efficient (Parida et al., 2003). However, the output from each cell computed by this model is sensitive to one of the factors, which is used for allocation of Total Available Moisture for Runoff (TARO) between Detention (DET) and Runoff (RO). This factor being sensitive to the cell size needs to be calibrated such that the sum of square of deviation between the observed and the computed flows was the least. However previous studies carried out for a sub-catchment of the Limpopo, it has been found that a factor of 0.45 is quite reasonable (Parida et al., 2003)

3.2 *Method of Artificial Neural Network:*

Artificial Neural Network comprises of a network of neurons and takes the cue from their biological counterparts, in the manner that neurons being capable of learning can be trained to find solutions, recognize patterns, classify data and even forecast future events (Clair and Ehrman, 1998). As a result of these, such networks have found wide application in simulating highly complex relationships and as such found wide application in modelling many hydrological problems including rainfall-runoff modelling and stream flow forecasting (Shamseldin ,1997; Zealand et al, 1999; Uvo et al., 2000; Anmala et al, 2000; Hsu et al., 2002 and Riad et al., 2004)

Such a network usually comprises of many layers arranged in series, each layer containing one or a group of neurons each of which have the same pattern of connections to the neurons in the other layer(s) (Shamseldin, 1997). The first and last layers are used for input and output variables and the intermediate layers are usually connoted as the hidden layer which can be one or many, depending on the complexity of the problem. The weights to a neuron are automatically adjusted by training the network according to a specified learning rule until it properly simulates the past data or performs the desired task (Furundzic, 1997. Shamseldin, 1997, Zealand et al, 1999). Mathematical functions, known as neuron transfer functions, are used to transform the input to output for each neuron. The log-sigmoid transfer function is commonly used for hidden layer neurons, especially with the back propagation algorithm (The Mathworks Inc., 2002).

Two separate stages are involved in the hidden (intermediate) and output layers in transformation of their respective inputs to output. Firstly, an input to a neuron is multiplied by its corresponding weight, and the total sum of those input products, to such neuron, plus a constant term yields the neuron net input. The second stage entails transformation of the net input into output. The optimum network architecture (Plant Model) can then be used to predict future behaviour (forecasting) of the plant. An optimization algorithm is used to select the control input that optimizes future performance. Figure 1 shows a typical example of one hidden layer feed forward neural network architecture.

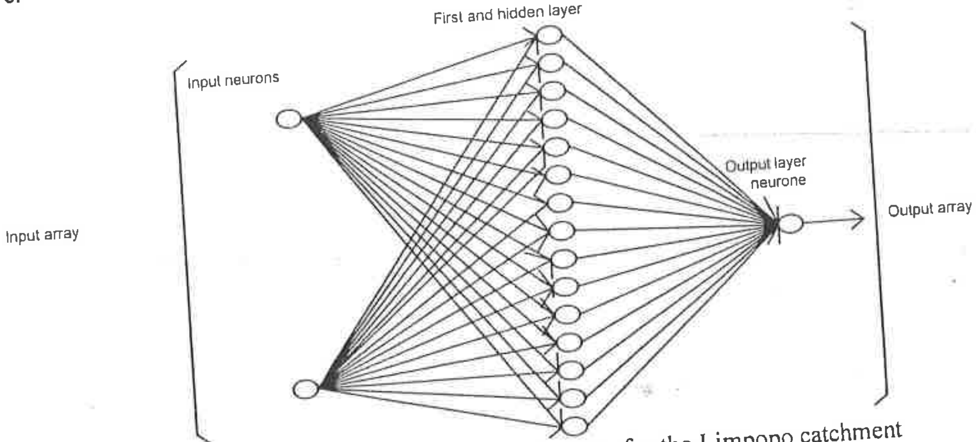

Figure 1. A typical Network architecture for the Limpopo catchment

4 ANALYSIS AND DISCUSSION OF RESULTS

4.1 *Water Balance Technique*

A total of 75 cells were delineated and the water balance study was undertaken for each cell from 1971 to 2000. This was done with assumptions of average uniform soil properties, rainfall and evaporation over each cell, a typical example of which (for cell 64 and year 1981) has been given in Table 1. Knowing the total runoff and total rainfall for a given cell, the runoff co-efficient for a given year can be calculated, hence for all other cells in that particular year. Then these coefficients for a given year were weighted using the fractional area represented by the respective cells to the entire catchment and the yearly runoff coefficient computed, hence for the entire period between 1971 and 2000 as given in Table 2. From the results, it was seen that for the decade between 1971 and 1980 the runoff coefficients averaged at 0.40. This average subsequently changed to 0.41 and 0.47 for the decades 1981-1990 and 1991-2000 respectively.

Table1. A typical table for runoff coefficient computation for cell 64 and year 1981using Water balance Method.

	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEPT	OCT	NOV	DEC	TOTAL (mm)
P	200	173	166	59	34	0	0	0	57	56	87	45	877
PET	86	76	87	55	56	58	65	76	87	99	98	100	943
P-PET	114	97	79	4	-22	-58	-65	-76	-30	-43	-11	-55	
APWL	0	0	0	0	22	80	145	221	251	294	305	360	
SM	112	112	112	112	91.78	54.31	30.17	15.17	11.56	7.838	7.096	4.314	
ΔSM	107.7	0	0	0	-20.2	-37.5	-24.1	-15	-3.61	-3.73	-0.74	-2.78	
AET	86	76	87	55	54.21	37.47	24.15	15	60.61	59.73	87.74	47.78	
DEF	0	0	0	0	1.79	20.53	40.85	61	26.39	39.27	10.26	52.22	
SURP	6.319	97	79	4	0	0	0	0	0	0	0	0	
TARO	6.319	100.2	129.1	68.54	34.27	17.13	8.567	4.284	2.142	1.071	0.535	0.268	372.4
RO	2.844	45.07	58.09	30.84	15.42	7.711	3.855	1.928	0.964	0.482	0.241	0.12	167.6
DET	3.475	55.09	70.99	37.7	18.85	9.424	4.712	2.356	1.178	0.589	0.295	0.147	

P=Precipitation; PET=Potential Evapotranspiration; APWL=Available Potential Water Loss; SM=Soil Moisture; ΔSM=Change in Soil Moisture; AET=Actual Evapotranspiration; DEF= Deficit; SURP=Surplus; TARO=Total Available for Run Off; RO= Run off; DET=Detention (All values are in mm)

4.2 Application of ANN

Application of ANN was undertaken in two stages viz: development of optimal network architecture using the water balance computed ROCs and forecasting up to 2016 to match with the Vision 2016 of this country.

4.2.1. Network Development and Validation of ROCs:

The network design was undertaken using two input variables viz: the two major climatic variables playing in the process of runoff generation namely the basin rainfall and evaporation. Such vectors for different years were placed in a matrix of concurrent vector of output runoff coefficients computed from the water balance. The popularly known back propagation algorithm was used with log-sigmoid transfer function for the hidden layer as it was found the best in optimising the performance function. However, the linear transfer function (purelin) was used for the output layer. The number of neurons in the input and output layers were decided based on the number of input variables and the target variable respectively. The optimum network architecture was arrived with one hidden layer containing fifteen neurons while using Automated regularisation with early stopping as the training algorithm. Further, with the help of principal component analysis, this architecture was found to be the best at 0.001 significance level when two components were used as can be seen from Table 3, suggesting that both the input variables were retained.

The ROC data was divided into three equal sub-sets for training, validation and testing. The network converged after 511epochs with Mean Squared Error (MSE) of 0.1682 for training the subset. Optimization of the performance function for training, validation and testing subsets are shown in Figure 2.The output runoff coefficients obtained through simulation of the developed network has been shown in Fig. 3 and were found to have a very good correlation between the target runoff coefficients (i.e. the ROCs computed from water balance model) at 0.914 .

Table 2. Water Balance computed Runoff Coefficients for Limpopo catchment between 1971 and 2000.

Year	Runoff Coeff	Year	Runoff Coeff	Year	Runoff Coeff
1971	0.4	1981	0.35	1991	0.39
1972	0.29	1982	0.38	1992	0.35
1973	0.47	1983	0.35	1993	0.50
1974	0.46	1984	0.34	1994	0.43
1975	0.37	1985	0.48	1995	0.60
1976	0.56	1986	0.40	1996	0.55
1977	0.35	1987	0.52	1997	0.59
1978	0.21	1988	0.38	1998	0.43
1979	0.48	1989	0.36	1999	0.40
1980	0.37	1990	0.56	2000	0.45

Table 3. Comparisons of best network architectures at different significance levels

No	Sig. Level	MSE	PCs used	Total PCs available
1	0.001	0.168206	2	2
2	0.1	0.359038	2	2
3	0.2	0.241234	2	2
4	0.3	0.782144	1	2
5	0.4	0.750538	1	2
6	0.5	0.768733	1	2
7	0.6	0.670193	1	2
8	0.7	0.677308	1	2

MSE = mean squared error; PCs = Principal components

Figure 2. The output of the best minimized performance function adopted for the study

4.2.2 Forecast of ROCs

After development of the optimal network, the model predictive control was used for forecasting, which uses the previous plant input i(t) and output, a(t) to predict future values of the plant output $a_m(t+1)$. The last value in an output array, $a_m(t+1)$, is used to estimate proportionate values of i(t+1) and $a_p(t+1)$ which are then added to the inputs in forecasting for $a_m(t+2)$. This was repeated until the forecasting reached the end of the chosen design period i.e. the year 2016. Use of such a type of controller though requires a significant amount of on-line computation (because of optimization algorithm performed at each sample time to compute the optimal control input) is quite efficient in formulation of forecasts. The plot of simulated and forecasted ROCs together have been shown in Figure 4. It was observed that the forecasted runoff coefficients showed a marginal upward trend with value of 0.0004, which is of the order 0.1 % rise/year. If the results are compared with the previous decadal averages of ROCs, it can be seen that the average for the decade 2001-2010 was found to change to a likely value of 0.48 and then to 0.50 for the period 2011-2016.

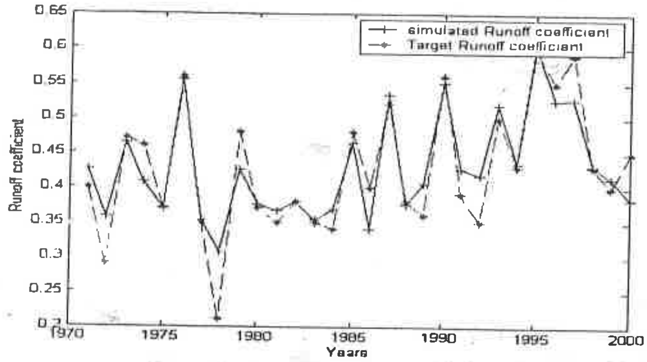

Figure 3. Target and simulated runoff coefficients plotted together for the entire study period

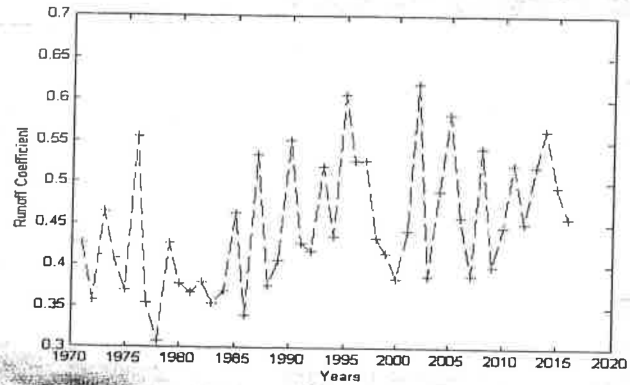

Figure 4. Runoff Co-efficients from 1971-2016 for the Limpopo catchment

5 CONCLUSIONS

The following conclusions have been drawn from this study undertaken to evaluate the likely impact of climate change on Runoff-coefficients from the Limpopo Catchment in Botswana:

i. For the period 1971-2000 for which climatic (such as rainfall and evaporation) and soil characteristics (such as field moisture capacity) data were available, ROCs were computed using multi-cell water balance technique and have been given in Table 2.

ii These ROCs were used to develop an Artificial Neural Network model. Optimal network most suited for this catchment was arrived at, a three layer feed forward network with two, fifteen and one neuron in the input, hidden and output layers respectively and Automated regularization with early stopping as the training algorithm and log-sigmoid transfer function for hidden and purelin for the hidden and output layers respectively. The relevance of the number of input variables was justified using Principal Component Analysis. Forecast of ROCs up to 2016 (Vision Year of Botswana) was undertaken using model predictive control.

iii. Average ROC for the period 1971-1980 was found to be 0.40, which for the decades 1981-1990 and 1991-2000 were found to have changed to 0.41 and 0.47 respectively. However, such averages during the forecast period i.e. decade 2001-2010 and 2011-2016, were found to be 0.48 and 0.5 respectively. From these decadal averages it can be seen that, the most rapid increase per year has been in the decade 1971-1980, which stands at an average increase of 9 % per year. The succeeding decades have average annual percentage increases of 4.7, 6.1, 4.7, and 3.8 respectively over its previous decadal averages.

iv. The last two figures of ROCs in particular being in the forecast period, suggests that there is a decreasing trend in the percentile increase over its previous decade, indicating that there is likelihood of decreasing yield from this catchment during the coming years. In view of this, it is imperative to undertake some of the catchment management strategies such that the yield from the catchment is harnessed with utmost efficiency.

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