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A Review of Models for Evaluation of Climate Change Impact on Water Resources

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Authors' contributions

This work was carried out in collaboration among all authors. Authors AWS and AAM designed the study and developed the equations. Authors AWS and DOO wrote the protocol, prepared the draft of the manuscript and managed literature searches. Author DOO further managed the analyses of the study and literature searches. All authors read and approved the final manuscript.

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Review Article

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ABSTRACT

The use of models to simulate or predict impact of climate change on water resources management is very vital due to continual increase in global warming which invariably affects most important natural resources in the environment. This paper provides an overview of the existing models used for evaluating climate change impact on water resources management. It also compares their relative advantages and drawbacks. It was found that no model can perform satisfactorily the assessment of climate change impact; hence it may be necessary to use one model to compliment the weakness of another. Global Circulation Model (GCM) is not easily accessible in developing countries due to sophistications and processes involved in running it. Moreso, the nature of available data and cost of acquiring it is high. The main advantage of Water Balance (WATBAL) model is that it can model climate change impact in water resources but its major drawback is that it requires many inputs of hydro-meteorological parameters. Regression and Artificial Neural Network (ANN) models are readily available and not too expensive. They can model climate change impact on water resources and hydropower operation. However, the drawback is that enormous data are required for ANN model calibration and operation. It is

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imperative therefore to anticipate and efficiently prepare for future water resources management and suggest necessary measures to mitigate the effect of climate change.

Keywords: ANN; BILAN; data; GCMs; regression and WATBAL.

1. INTRODUCTION

Impact of climate change on water resources is a very crucial issue due to its importance to human existence. Climate change is caused by natural and anthropogenic factors due to emission of greenhouse gases. Climate change affects man and his environment and constantly modifies temperature and precipitation thereby altering the quantity and quality of runoff in rivers. Flooding or drought may result from climate change in the environment. Study had shown that impact of climate change was noticed in River Niger, Nigeria when the annual yield of the river at Kainji reservoir had steadily decrease from 46 x 10^9 m^3 in 1970 to 26 x 10^9 m^3 at the peak of 1973 drought [1]. Also there has been drastic reduction in electricity generation at Kainji hydropower station over the years and this may be due to shortage of water in the reservoir among other factors as a result of climate change. It is imperative therefore to study the impact of climate change on water resources and hydropower operation in order to confirm the aforementioned climate change impact and suggest necessary measures to mitigate its effect. The ability to anticipate and efficiently prepare for future water resources management challenges is currently limited by imprecise regional climate change models and long-term weather forecasts. Uncertainty about future climate conditions makes it more difficult to optimally prepare for and adapt to associated changes in water resources availability and quantity.

Climate change refers to a change in the state of the climate that can be identified by changes in the mean and the variability of its properties that persists for an extended period, typically decades or longer. It is also defined as any change in climate over time whether due to natural variability or as a result of human activity [2]. The changes in climate variables such as precipitation and temperature have hydrological impacts that will influence reservoir management. In the same perspective, drinking water supplies, flood risks, irrigation and hydropower production will be affected at various levels [3,4,5]. Assessment of climate change impact on water resources and hydropower reservoir operation is an enormous task that requires the use of model due to large volume of data involved and spatial and temporal variability in hydro-meteorological parameters. The various models such as Water Balance (WATBAL), Global Circulation Model (GCM), BILAN model, Regression models and Artificial Neural Network (ANN) model used in literature for evaluating impact of climate change on water resources and hydropower reservoir operation are reviewed in this paper.

Assessment of climate change impact on the river runoff is often based on input data from climate scenarios [6]. Impact of climate change on the seasonal distribution of runoff in mountainous basins in Slovakia was assessed using conceptual lumped mathematical model WATBAL [7]. Vulnerability of water resources to climate change of Lake Tana in Ethiopia was assessed using WATBAL model [8]. Hay and McCabe studied the hydrological effects of climate change in the Yukon river basin using WATBAL model in the United State of America [9]. The data used for the analysis are temperature and the precipitation data. Salami assessed the impact of climate change on the water resources of Jebba hydropower reservoir using hydro-meteorological parameters, Mann-Kendall, Regression and reduction pattern to examine trend and fluctuation in the selected parameters [10].

2. MODELS

2.1 Regression Models

Regression models are statistical tools used to model the relationship between two or more variables. It usually contains one independent variable and one or more dependent variable(s) Regression models provide the scientist with a powerful tool which allows predictions of future events to be made with information about past or present events. The scientists employ these models because, it is less cumbersome and time saving in using it to model and predict. There are basically two major regression models namely linear and multiple regression models. Salami et al. [11] assessed the impact of climate change on the water resources of Jebba hydropower reservoir using hydro-meteorological variables. Statistical analyses were carried out to measure dispersion and central tendency, while the regression and Mann-Kendall analysis were adopted to detect trends. Makanjuola et al. [12] studied the impact of climate change on surface water resources of Oyun and Asa streamflow in Ilorin using statistical analysis, Mann-Kendall and regression to detect the significance of the trend in each variable. Reduction pattern analysis was used to depict the fluctuation of the variables over time. McBean and Motiee assessed the impacts of climate change on the water resources of North America using long term regression analyses and Mann-Kendall statistics [13].

2.2 Linear Regression Model

A linear regression model is a statistical tool that is used to model relationship between one independent and one dependent variable. Equation 1 is the simple linear regression equation that can be used to predict property of one variable based on another. There are some assumptions which must hold when formulating a linear regression model.

$$Y = aX + b + \varepsilon \tag{1.1}$$

where:

X = Independent variable
a = Parameter estimate for variable X
Y = Dependent variable
b = Least square estimate of the intercept
ε = Error term (negligible)

The value of constants a and b are obtained from the Equations 1.2 and 1.3

$$a = \frac{n\sum(XY) - \sum X \sum Y}{n\sum(X^2) - \left(\sum X\right)^2} \tag{1.2}$$

$$b = \frac{\sum Y - b\sum X}{n} \tag{1.3}$$

where:

n = Total observation
∑ = Summation

2.3 Multiple Regression Model

Multiple regression model is a statistical tool for modeling variables with one independent and two or more dependent variables. Equation 1.4 is a multiple regression model which can be used to assess the effect of climate change on river runoff. The model was used to assess the overall impact of meteorological parameters such as precipitation, temperature and evaporation on the runoff in some selected locations in the Nigeria ecological zone [1].

$$Y = a_1 + b_1X_1 + b_2X_2 + b_3X_3 + ... + b_nX_n \tag{1.4}$$

where:

X_1, X_2,…, X_n = *Set of independent variables*
Y = Dependent variable
a_1, b_1, b_2,…,b_n = *Parameter constants*
ε = Error term (negligible)

2.4 Water Balance (WATBAL) Model

WATBAL model is an acronym for the water balance rainfall-runoff model. It is an integrated lumped distributed model developed for assessing the effect of climate change on the water resources of lakes, rivers and reservoirs. The model has two key components: (1) water balance that uses functional relations for estimating water movement in a basin and (2) estimation of potential evapotranspiration using Priestly-Taylor, Thornthwaite or modified Penman. Tarekegn and Tadege carried out a study on the assessment of the effect of climate change on the water resources of the Lake Tana sub-basin in Ethiopia using WATBAL model [14]. Generally WATBAL is expressed as a differential equation while the potential reserves of the basin are grouped into one block called the maximum storage capacity.

The model is distinct because evapotranspiration in the water balance may be determined using one of the analytical methods mentioned above. Any estimate of climate change impact on water resources depends on the ability to relate changes in actual evapotranspiration to predicted changes in precipitation and potential evapotranspiration [15]. WATBAL model is developed from Equation 1.5 for water balance [16]. Chirila et al. [17] carried out a study on the impact of possible climatic change on surface water resources in the Buzau and Lalomita river basins using WATBAL model. The main advantage of WATBAL model is that it can model climate change impact on water resources. However, its major drawback is its choice of estimating potential evapotranspiration and it requires the input of many hydro-meteorological parameters. The conceptual diagram of the WATBAL model is shown in Fig. 1.

$$P = Q + E + \Delta s \quad (1.5)$$

where:

P = precipitation
Q = runoff
E = Evapotranspiration
Δs = water change

2.5 BILAN Model

BILAN model can be used for assessing water balance components in monthly or daily time step in a river basin. Fig. 2 is a structure of the BILAN model whose inputs are basin precipitation, air temperature and relative air humidity while its output is the total streamflow. The model simulates water budget at three vertical levels: on land surface, in soil layer and in groundwater aquifer. Three water balance algorithms that are applied were developed for winter, snow melting and summer conditions. Surface water balance depends on evapotranspiration, which is determined by meteorological conditions using empirical values that have been derived for different climate zones. Excess water (precipitation minus evapotranspiration) forms direct runoff or infiltrates to deeper zone, where it is divided into interflow and groundwater recharge. Parameters of the model are determined by two-step optimization, which is aimed at attaining a good fit between the observed and simulated river flows [18]. The parameters that significantly affect the total runoff are calibrated in the first step while the second step includes those parameters that affect distribution of the runoff into its components. The calibration by using results of base flow measurements can alternatively be applied if such data are available. Results of the simulations for affected and non affected input series give information for assessing the climate change impacts on output series of the model. These include potential evapotranspiration, basin evaporation, three components of river flow (surface runoff, interflow and base flow), groundwater recharge and three components of water storage (in snow cover, soil layer and groundwater aquifer). This model has similar advantages and drawbacks as WATBAL.

2.6 Global Climate Models (GCMs)

Global climate models are also known as general circulation models (the acronym GCMs). GCMs are mathematical models which simulate the fluid dynamics and physics of the earth atmosphere, oceans and land surfaces. Scientists have developed these models to a state of sophistication such that they reproduce many observed features of the current climate. The most powerful supercomputers are required for analysis. Thousands of climate researchers use global climate models to better understand how global changes such as increasing greenhouses gases or decreasing Arctic sea ice will affect the earth. The models are used to look hundreds of years into the future so that the impact of climate change on the earth planet can be predicted.

The global climate models are able to simulate the large scale features of the climate and they produce a facsimile of the observed annual cycle and other variations of earth climate. Nevertheless the models used in studying greenhouse warming problem are not perfect. Global climate models used around the world do not completely agree on all aspects of climate variability or sensitivity and they all have serious deficiencies. Accuracy of GCMs, in general, decreases from climate related variables, such as wind, temperature, humidity and air pressure to hydrologic variables such as precipitation, evapotranspiration, runoff and soil moisture, which are also simulated by GCMs [19]. To run a GCM, there is need for input parameters. This information includes solar radiation, volcanic emissions and human-produced emissions of greenhouse gases. This information for the 20th century is available but of course emissions that will be in the future is not. The model output is better presented using supercomputer because it is typically many gigabytes large. All climate models must make some assumptions about how the earth works. However, in general, the more complex a model, the more factors it takes into account and the fewer assumptions it makes [13].

There are many different GCMs used worldwide. Although there are similarities between them, they do not produce exactly the same results from a given set of inputs. Different results from different models are source of uncertainty in climate research. Jose and Cruz carried out a preliminary and limited assessment of the Angat reservoir and Lake Lanao in Philippines water resources through the application of general circulation models (GCM) [20]. The hydrological model was used to simulate the future runoff-rainfall relationship. Eman et al. [21] studied the evaluation of climate changes impacts within the Blue Nile river sub-basin using the RegCM3 Regional Climate Model to simulate interactions between the land surface and climatic processes. The quality of the models is judged by how well they can represent the present climate. When several models of relatively good quality agree on a particular result, then the results can be judged as robust. It is such robust results that have been used to both attribute global warming to anthropogenic climate change, and to produce future projections of climate change. It is also important to identify where models do not agree and thus where uncertainty is higher [22].

2.7 Artificial Neural Networks (ANN) Model

Artificial Neural Networks (ANNs) model are collection of non-linear mapping structures based on the function of human brain. They are powerful modelling tools used especially when the underlying data relationship is not known. The model can identify and learn correlation patterns between input data set and corresponding target values. The model is very suitable where the training data are readily available. The model is now being increasingly recognised in the area of classification and prediction where regression model and other related statistical techniques have traditionally been employed. Elgaali and Garcia used neural networks to model the impacts of climate change on water supplies in Colorado Arkansas river basin under two GCM-based climate change scenarios [23]. The two scenarios are from the Hadley Centre for Climate Prediction and Research (HAD) and from the Canadian Climate Centre (CCC). Demirel and Booij studied the identification of an appropriate low flow forecast model for the Meuse River in Netherlands based on the comparison of output uncertainties of different models [24].

Three models were developed for the Meuse River such as multivariate model, linear regression model and Artificial Neural Network (ANN) model. The uncertainty in these three models is assumed to be represented by the difference between observed and simulated discharge. Pulido-Calvo et al. [25] carried out a study on Water Resources Management in the Guadalquivir river basin, Southern Spain using ANN model to simulate the inflow and outflow in a water resources system under shortage of water. The hydro-meteorological data used for the study are streamflow, precipitation and temperature data from various gauging stations. Poff et al. [26] carried out a study on stream hydrological and ecological responses to climate change with ANN model. The model was used to evaluate the hydrological responses of two streams with different hydro-climatological data in the north-eastern part of the United States. ANN model requires large volume of input and output data for model calibration. For instance, two-third of the data is used for calibration/training [27].

Solaimani assessed the rainfall-runoff prediction based on ANN in Jarahi Watershed in Iran [28]. The study was aimed at modelling the rainfall-runoff relationship in the catchment area. Dibike and Solomatine studied the river flow forecasting using ANN model in the Apure river basin in Venezuela [29]. Two types of ANN architectures namely multilayer perceptron network (MLP) and radial basis function networks (RBF) were implemented. The data used for the analysis are weekly precipitation, evapotranspiration and runoff for the period of five years (1981-1985). ANNs are recognised as a powerful tool for data analysis and they are constructed with layers of units which are termed multilayer ANNs. A layer of units composed of units that perform similar function. There are three layers in the ANN model namely: the input units also known as independent variables, the hidden layer and the output layer corresponding to the dependent variables. ANNs model normally use learning techniques to train data before analysis, the most widely used learning technique is back propagation algorithm. Back propagation algorithm uses the earlier generated output data to adjust the network weighs in order to minimise the error in the predicted training data. There are two major types of neural network architecture namely: Multilayer Perceptron (MLP) and Radial Basis Function (RBF). The main difference between RBF and MLP networks are as follows [30]:

i. The RBF network has one hidden layer and activation functions of neurons and is Gaussian function with particular centre and spread.
ii. There are no weights between input layer and hidden layer of RBF and the distance

between each pattern and centre vector of each neuron in hidden layer is used as an input of Gaussian activation function.

iii. In this network, activation functions of output neurons are simple linear functions and because of this reason linear optimum algorithms can be used. The network has been made to improve the processing rate and prevent fall in local minimums associated with the learning process in MLP network.

Equations 1.6 to 1.8 are ANN expression model; the expressions are used in simulating the impact of climate on streamflow in the Bosten Lake using ANN model [31].

$$y = f\left(u_j\right) \tag{1.6}$$

$$u_i = \sum w_i x_i - \theta_j \tag{1.7}$$

$$f(u) = \frac{1}{1+\exp(-u)} \tag{1.8}$$

where:

y = Runoff output
f = Logistic sigmoid function
u_j = Interconnected neurons
w_i = Weight of xi (I = 1, 2, 3,…n)
x_i = Input variables
Θ_j = Critical value

where:

S_{max} = Maximum reserves
P_{eff} = Effective precipitation
R_d = Direct runoff
R_s =SURFACE runoff
R_{ss} = Sub- surface runoff
E_v =Evapotranspiration
R_b =Baseflow
z = Relative depth of water

3. MULTILAYER PERCEPTRON

This is the most commonly used neural network computing technique. The architecture of a typical multilayer neuron is shown in the Fig. 3. Basically Multilayer Perceptron (MLP) consists of three layers: input, hidden and output. Input layer is a unit where data are introduced to the model, hidden layer is a unit where the data are processed while the output layer is the unit where the result for a given input are produced [32]. Each layer of the MLP is made up of several nodes and the layers are interconnected by set of correlation weights.

3.1 Radial Basis Function

Radial Basis Function (RBF) is the second neural network modelling architectural technique. It is a supervised and feed forward neural technique. Fig. 4 is the architectural sketch of the RBF. It is a three layer network; input, hidden and output,

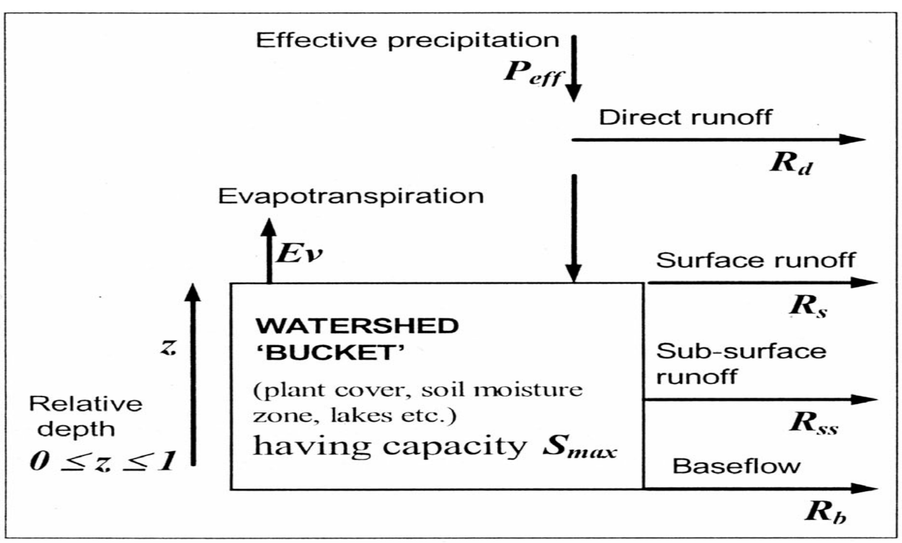

Fig. 1. Conceptual sketch of WATBAL model
Source: Kilkus [15]

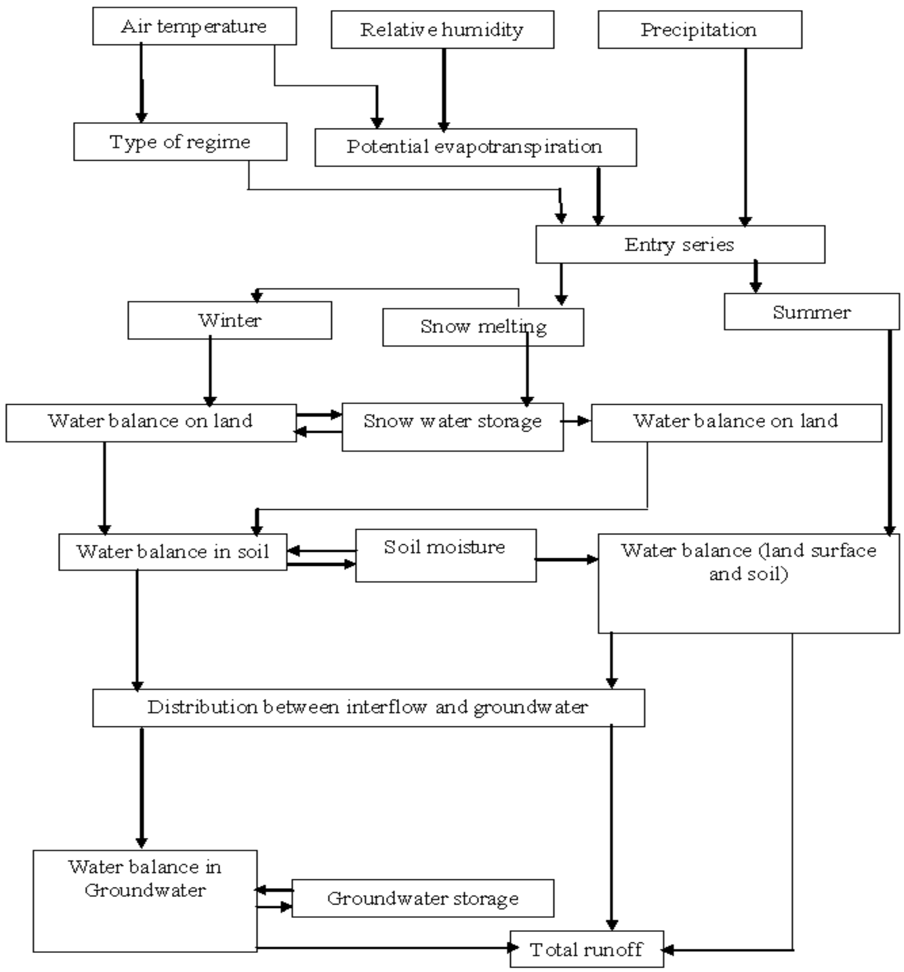

Fig. 2. Structure of Bilan model
Source: Horáček et al. (2008)

where data are introduced to the model, processed and result for a given input are produced respectively. The hidden layer consists of a number of nodes and a parameter vector called a 'centre' that can be considered as the weight vector. Training of RBF network implies finding the set of basis nodes and weights for the RBF network in order to find the best fit to the trained data.

3.2 Designing of ANN Models

Designing of ANN models follows a number of systemic procedures. In general there are five basics steps adopted for the ANN model: (1) collecting data (2) pre-processing data (3) building the network (4) training (5) test performance of model as shown in Fig. 5.

4. DATA COLLECTION

Collection and preparation of data is the first step in designing ANN models. The data required for the model are monthly temperature (ºC), precipitation (mm), evaporation (mm) and runoff (m^3/s) for a longer period [31].

4.1 Data Pre-processing

After data collection, three data pre-processing procedures are conducted to train the ANN model efficiently. These procedures are: (1) solve the problem of missing data (2) normalize data and (3) randomize data. The missing data are replaced by the average of neighbouring values in the same year. Normalization procedure before presenting the input data to the model is generally a good practice since mixing

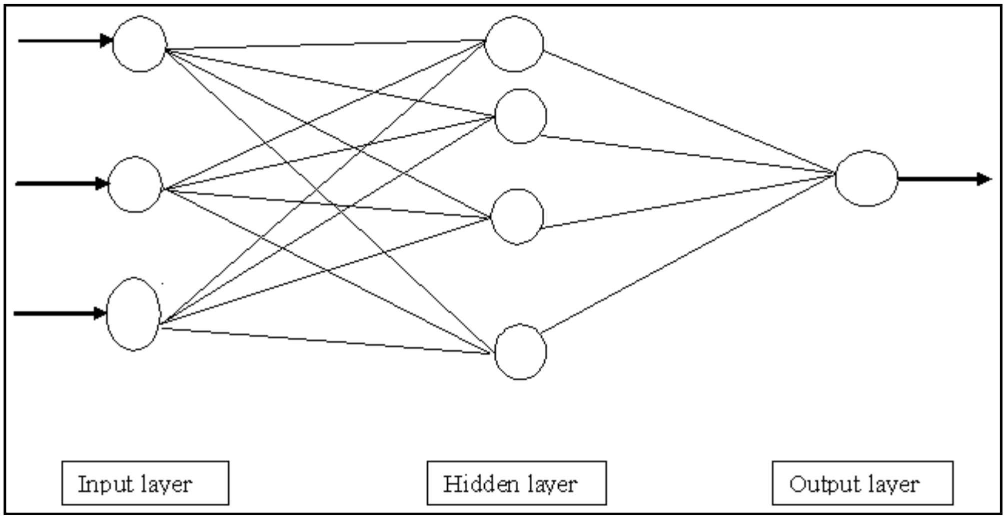

Fig. 3. MLP network
Source: Harun et al. [32]

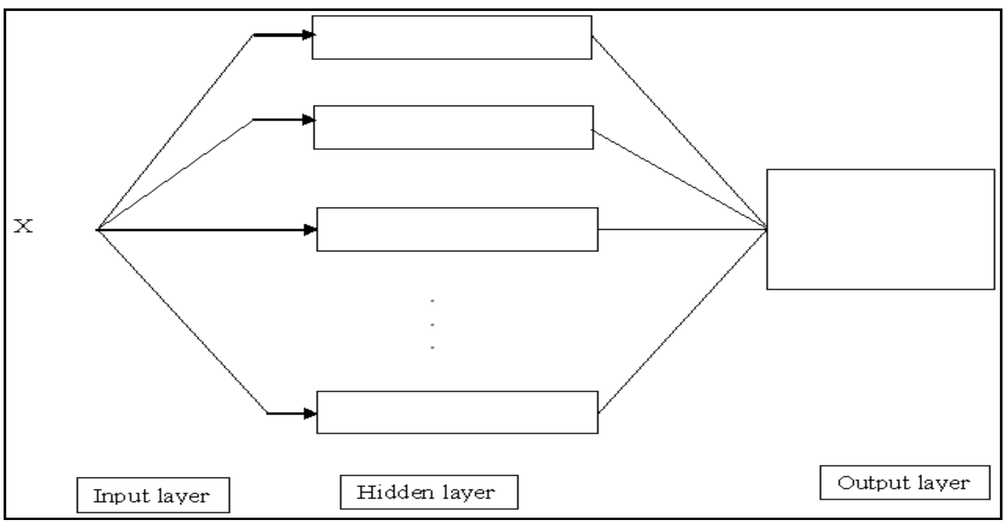

Fig. 4. RBF network
Source: Adapted from Dibike and Solomatine (1999)

variables with large magnitudes and small magnitudes will confuse the learning algorithm on the importance of each variable and may force it to finally reject the variable with the smaller magnitude [35].

4.2 Network Building

In building the network for the ANN the number of hidden layers, neurons in each layer, transfer function in each layer, training function, weight/bias learning function and performance function are specified before applying the model. MLP network approach is more preferable to RBF because of its accuracy [36].

4.3 Network Training

The process of training ANN model involves the adjustment of the weights in each node using a specified error value in order to make the actual outputs (predicted) close to the target (measured) outputs of the network. The training period is normally longer than the validation and testing periods [31,32]. The data required for the ANN model calibration is normally larger than the one required for model validation/testing and forecasting/predicting. As a rule of thumb about two-third of the input and output data are required for model calibration while the remaining data are used for the validation and testing [27].

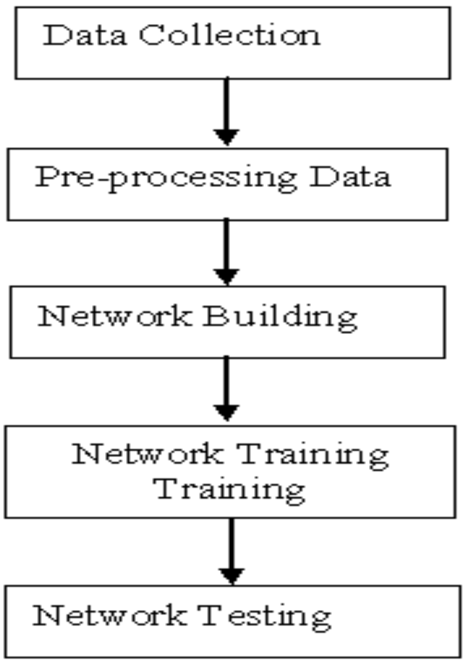

Fig. 5. Basic flowchart for designing ANN model

Source: Al Shamisi et al. [27]

4.4 Network Testing

Network testing is applied to ANN model in order to test the performance of the developed model. At this stage unseen data are exposed to the model in order to evaluate the performance of the developed ANN models quantitatively and verify whether there is any underlying trend in performance of ANN models. Statistical analyses involving the coefficient of determination (R^2), the root mean square error (RMSE), the mean relative error (MRE) and mean absolute error (MAE) are to be computed. RMSE provides information on the short term performance which is a measure of the variation of predicated values around the measured data. The lower the RMSE, the more accurate is the estimation. MRE is an indication of the average deviation of the predicted values from the corresponding measured data and can provide information on long term performance of the models. The lower the MRE the better is the long term model prediction. A positive MRE value indicates the amount of overestimation in the predicated global solar radiation (GSR) and vice versa [27]. Equations 1.9 to 2.1 are the statistical coefficients used for determining the performance of the ANN model.

$$MSE = \left[\frac{1}{n} \sum_{i=1}^{n} \left(y_{pi} - y_{oi} \right)^2 \right]^{\frac{1}{2}} \tag{1.9}$$

$$MAE = \frac{1}{n} \sum_{i=1}^{n} \left| y_{pi} - y_{oi} \right| \tag{2.0}$$

$$MRE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{y_{pi} - y_{oi}}{y_{oi}} \right| \tag{2.1}$$

where:

ypi = Predicted output value
yoi = Observed output value
n = Number of observation
∑ = Summation

5. CONCLUSION

The paper provides an overview of the existing models used for evaluating the impact of climate change on water resources and hydropower reservoir operation. It also compared their relative advantages and drawbacks. It was found that no model can perform satisfactorily in the assessment of climate change impact; hence it will be necessary to use one model to compliment weakness in another. Some models are readily available while others are not. GCMs models are not easily accessible in developing countries due to sophistications in the processes involved in running it, nature of data and high cost, but it can model climate change impact on water resources. The main advantage of WATBAL and BILAN models is that they can model climate change impact in water resources. However, its major drawback is its choice of estimating potential evapotranspiration which requires many input hydro-meteorological parameter. Regression and ANN models are readily available and not too expensive. They can predict climate change impact on water resources and hydropower operation and can even predict future impacts. The major shortcoming is that they require enormous data of about thirty years for calibration. It is more preferable in modeling non-linear relationships between climatic parameters and runoff.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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