OPTIMIZATION TECHNIQUE FOR ESTIMATING AVAILABLE GOUNDWATER DURING THE DRY SEASON FOR IRRIGATION FARMING SYSTEM IN LAPAI; NIGER STATE, NIGERIA

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Abstract
This paper addresses some predominant problems peculiar to Lapai irrigation site such as the problem of determining groundwater level during the dry season for irrigation purpose. The objective is to estimate the quantity of the groundwater during the dry season for irrigation system. The mass balance model equation was solved, the climatic data obtained from Nigeria metrological station was trained, tested and analysed by Artificial Neural Network (ANN) to estimate the quantity of the groundwater available during the dry season in the selected irrigation field. The results obtained for the estimation of the quantity of the groundwater showed that there is considerable amount of water that is sufficient to irrigate intercropping irrigation farming system in Lapai irrigation site and the performance of the models was evaluated using Mean Square Error (MSE). Result shows that the ANN techniques were well suited for groundwater estimated level.

Keywords: Aquifer, Simulation, Groundwater Level

Introduction
Groundwater is essential and highly valuable for domestic, industrial and irrigation use in Arid and Semi- arid region. Groundwater modelling is not only important for environmental protection but also maintaining the groundwater equilibrium system, controlling groundwater level fluctuation, and protecting against severe Land subsidence. These resources commonly are free from pathogenic factors, and have high quality, usually do not need chemical treatment (Moharram *et al.,* 2015). Groundwater is one of the natural resources that are the most important for human and for the environment. They provide potable water supply as well as water for industrial and agricultural use. They also ensure the environmental flow of rivers, lakes and wetland areas, contributing to the sustenance of biodiversity (Campbell & Konikow, 2013)., Groundwater resources assessment, accurate estimate required to ensured evaluation of the groundwater resources for productive uses (Felix *et al.,* 2014). Oluseyi *et al.* (2015) developed estimation of groundwater using empirical formula in Odeda local government area of Ogun state, Nigeria. They determined groundwater and groundwater recharge coefficient through a case study using empirical methods applicable to the tropical zone. They collected the related climatological data between January 1983 and December 2014 in Ogun Osun River Basin Development Authority (OORBDA) Ogun State Nigeria.

Irrigation
Irrigation is the science of artificial application of controlled amount of water for plant at needed intervals. Irrigation helps to grow agricultural crops, maintain landscape, and re-vegetate disturbed soil in dry area. Nigeria has not been left out among the committee of African nations which are battling with food crisis and food security. For any nation to stand fit for economic development such nation must take her Agricultural sector serious in which irrigation practices are paramount not only in solving hunger crisis but also economic recovery and employment creation (Geir, 2017).

In this paper we propose to estimate groundwater level during the dry season in Lapai for irrigation purpose.

Model formulation

Statistical Indices

Statistical indices correlation coefficient (R), Mean Square Error (MSE), Epoch, were used to evaluate the best fitting between observed and predicted data.

Artificial Neural Network

An artificial neural network (ANN) is a computational mode based on the structure and function of biological neural networks. Information that flows through the network affects the structure of the ANN because a neural network changes. An artificial neural it is the layer which is responsible for extracting the required feature from the input data. Andrej *et al.* (2018) defined Artificial Neural Network (ANN) as a mathematical model that tries to simulate the structure and functionalities of biological neural networks.

Neuron with Vector Input

A neuron with a single R- element input vector shown below:
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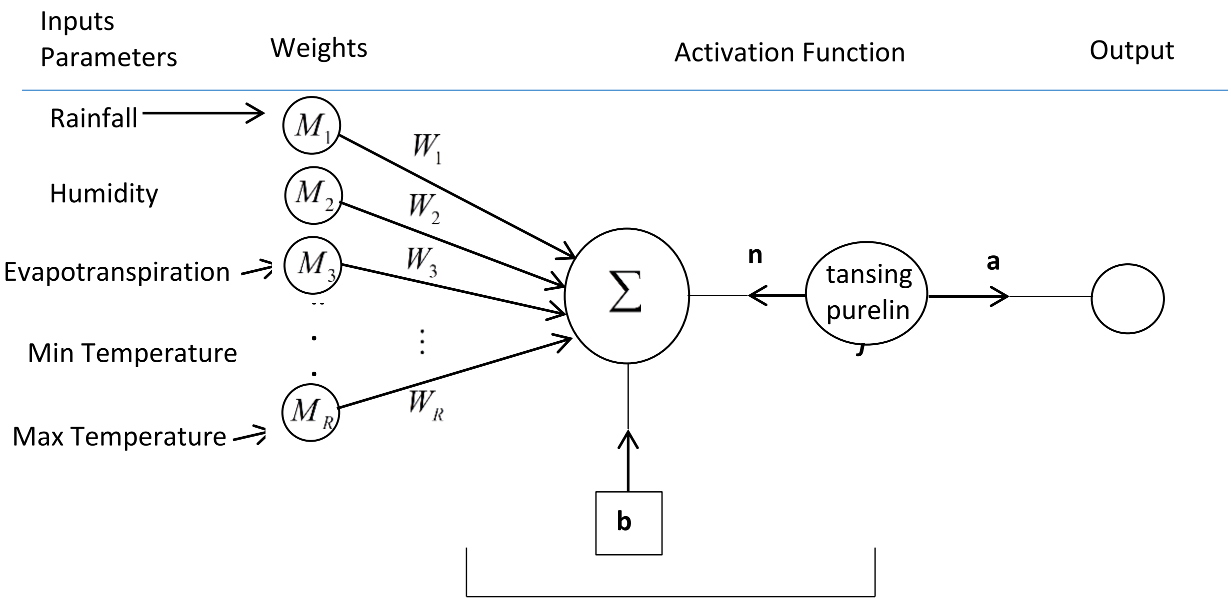

Figure1 Graphical representation **a = *f* (WX + b)**

The individual element inputs $M_1, M_2, M_3............M_R$ are multiplied by the weight $W_{I1}, W_{I2}, W_{I3}, ...W_{I,R}$ and the weight values are fed to summation junction. The sum is simply $W \times M$, the dot product of the single row matrix Wand the vector M. The neuron a bias b which summed with the weighted input to form the net input n. This sum n is the argument of the transfer function f.

$$n = W_{I1,}M_1 + W_{I,2}M_2 + ..., + W_{I,R}M_R + b \qquad (1)$$

Levenberg - Marquadt

The Levenberg - Maquadt algorithm developed by Kenneth Levenberg and Donald Marquadt in (1963) and provides a numerical solution to the problems of minimizing linear function. The algorithm is fast and has stable convergence. Levenberg – Marquadt algorithm is suitable for training small and medium size problems. The update rule of Levenberg – Marquadt algorithm is:

$$W_{k+1} = W_k \left(J^T J + \mu I \right)^{-1} J_k e_k \qquad (2)$$

where,

$W = weight\ of\ neural\ network$

$J = jacobian\ matrix\ to\ be\ \min imize$

$\mu = scalar\ that\ control\ the\ leaning\ process$

3. Estimation of the groundwater level and quality

Estimation of the groundwater level and quality during the Dry season (from November to April), at irrigation site based on the quantity of water available in the selected irrigation sites. We therefore considered the mass balance equation as:

$$I = J \pm S\frac{dh}{dt} \qquad (3)$$

where,
$I =$ rainfall (input)
$J =$ evapotranspiration (output)
$\frac{dh}{dt} =$ change in groundwater level with respect to time
$S = Storavity$
$S\frac{dh}{dt} =$ storage change of groundwater with respect to time.
For period without recharge, the groundwater level is expressed as:

$$\frac{dh}{dt} = c\left(h - h_0\right) \qquad (4)$$

where,
$h =$ groundwater level
$h_o =$ standard groundwater level
$c =$ constant
Integrate equation (4), we have

$$\int \frac{dh}{(\mathrm{h} - \mathrm{h}_0)} = \int cdt \qquad (5)$$

$$e^{\ln\left(h - h_o\right)} = ct + k \qquad (6)$$

$$h - h_0 = e^{ct}.\mathrm{e}^k \qquad (7)$$

$$h = h_0 + Be^{ct} \qquad (8)$$

where;
B = constant
Substituting $c(h-h_0)$ in equation (4) into (3) we have:

$$I = J \pm Sc\left(h-h_0\right) \tag{9}$$

I = 0, in equation (9), then equation (9) becomes

$$J + Sc(h-h_0) = 0 \tag{10}$$

Simplifying (10) we have,

$$J = -sc(h-h_0) \tag{11}$$

Substitute $-sc(h-h_0)$ in equation (11) for J in equation (3) we have:

$$I = -Sc(h-h_0) + \mathrm{S}\frac{dh}{dt} \tag{12}$$

Simplifying equation (12), we have:

$$I = S\frac{dh}{dt} - Sc(h-h_0) \tag{13}$$

Simplifying equation (13), we have:

$$I = S\left[\frac{dh}{dt} - c(h-h_0)\right] \tag{14}$$

Results and discussion

Groundwater Level Estimate Results

The model was applied to estimate the Groundwater available for the period of the dry season in Lapai, study area, the Rainfall, Humidity, evapotranspiration, the minimum and maximum temperature data from tables at the index were used for Artificial Neural Network and fifteen different algorithms were obtained and compared to run our model given by the equation (3.9)

Groundwater Level estimate in Lapai

Table 1: Shows the evaluation of all fifteen networks for the observation well as given by the equation (14) in Lapai

Neural	N1	N2	Epoch	LR	R-Train	R-Test	R-All	MSE	Data %
FFLM	5	5	100	0.9	0.75	0.88	0.85	3.94	80-20
FFRP	5	5	100	0.9	0.65	0.70	0.66	4.35	80-20
FFSCG	5	5	100	0.9	0.45	0.62	0.55	4.07	80-20
FFBFG	5	5	100	0.9	0.44	0.55	0.50	4.02	80-20
FFCGF	5	5	100	0.9	0.50	0.63	0.61	4.04	80-20
RNLM	5	5	100	0.9	0.45	0.56	0.60	4.11	80-20
RNRP	5	5	100	0.9	0.51	0.53	0.56	4.16	80-20
RNSCG	5	5	100	0.9	0.64	0.44	0.64	4.04	80-20
RNBFG	5	5	100	0.9	0.52	0.57	0.60	4.08	80-20
RNCGF	5	5	100	0.9	0.60	0.56	0.65	4.49	80-20
CFLM	5	5	100	0.9	0.55	0.43	0.56	4.26	80-20
CFRP	5	5	100	0.9	0.56	0.62	0.68	4.01	80-20
CFSCG	5	5	100	0.9	0.35	0.54	0.45	4.20	80-20
CFBFG	5	5	100	0.9	0.43	0.56	0.55	4.32	80-20
CFCGF	5	5	100	0.9	0.56	0.51	0.60	4.11	80-20

N1=numbers of neurons in the first hidden layer, N2= numbers of neurons in the second hidden layer, LR = learning rate, MSE = mean square error, R= correlation coefficient between network output and network target outputs in training and testing.

Table 1 shows the achievements by Artificial Neural Network (ANN) model in Lapai irrigation sites. The depth to groundwater for all fifteen networks by various training algorithm are compared. It is observed from the Table 1. that Feed Forward Levenberg Marquardt (FFLM) is the best overall performance for groundwater estimated in Lapai with mean square error of 3.94 and the corresponding correlation coefficient of 0.85 and by the Cascade Forward network with Resilient Back propagation (CFRP) trained with the same algorithm known as the second best with mean square error (MSE) of 4.01 and corresponding correlation coefficient of 0.68.

The following graphs are the first best five estimated algorithm shown in the table 1 above as given by the equation (14) in Lapai irrigational site.

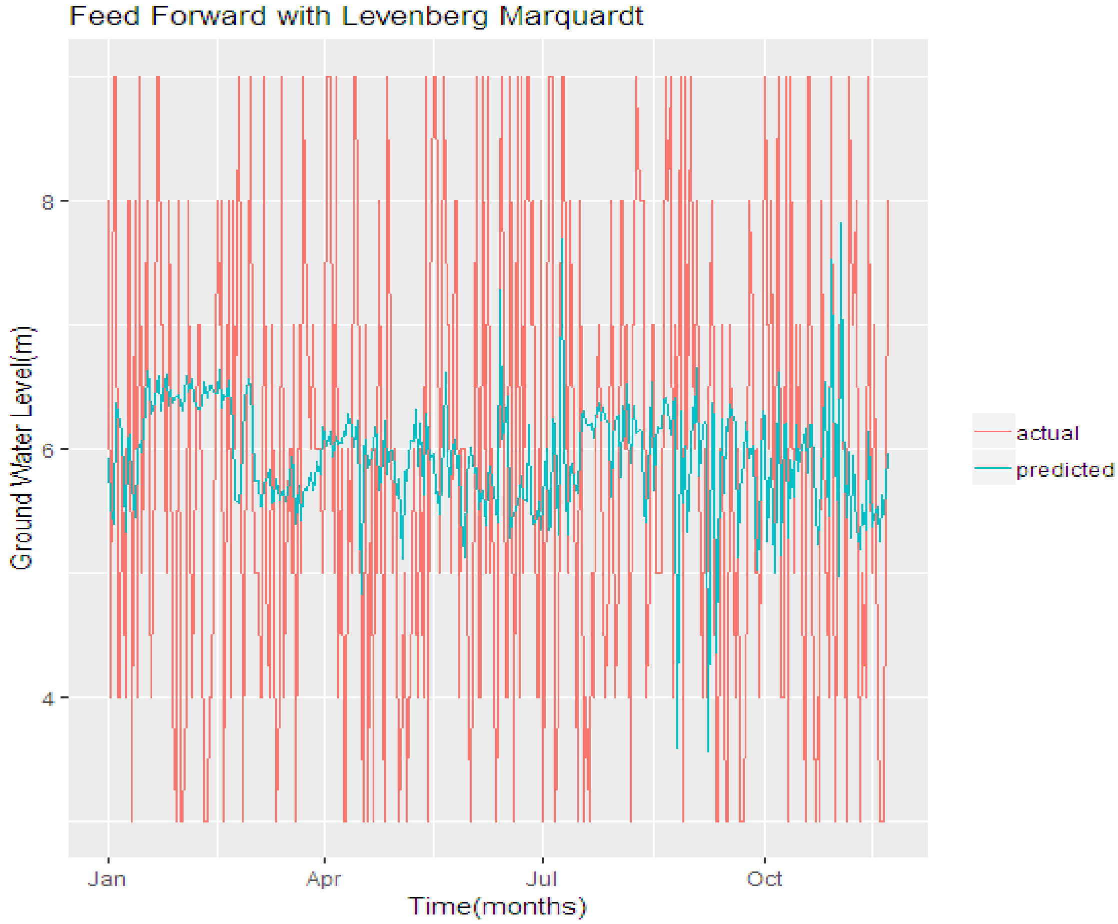

Figure 2: Hydrograph of the Groundwater for the Best Performance Algorithm in Lapai

Figure 2 shows the hydrograph of groundwater level (m) against time (month) in Lapai. The actual groundwater level in Lapai study area during the dry season (November – April) is $5.93\times10^{6}\ ft^{3}$ (cubic feet) and the estimated groundwater level in Lapai study area during the dry season is $5.94\times10^{6}\ ft^{3}$ (cubic feet).The graph shown that the estimated groundwater is sufficient to practice intercropping farming system during the dry season and livestock farming. However, the estimated groundwater volume can be used for planning a large scale irrigation farming as the standard groundwater consumptive use for rice crop is within

200mm per day, meanwhile conversion shows that $1ft^3$ = 28316846.711688. It is observed from the graph that the Feed Forward Neural Network with Levenberg Marquardt is the best algorithm that estimated groundwater levels in Lapai, the depth to groundwater increases from `December and reached its highest level in April but it is lowest in September.

Figure 3: is the graph of the second best estimated algorithm (Cascade Forward with Resilient Back propagation is the second best algorithm that estimated) with Mean Square Error of 4.01 in the Table 1 as given by the equation (14) in Lapai.

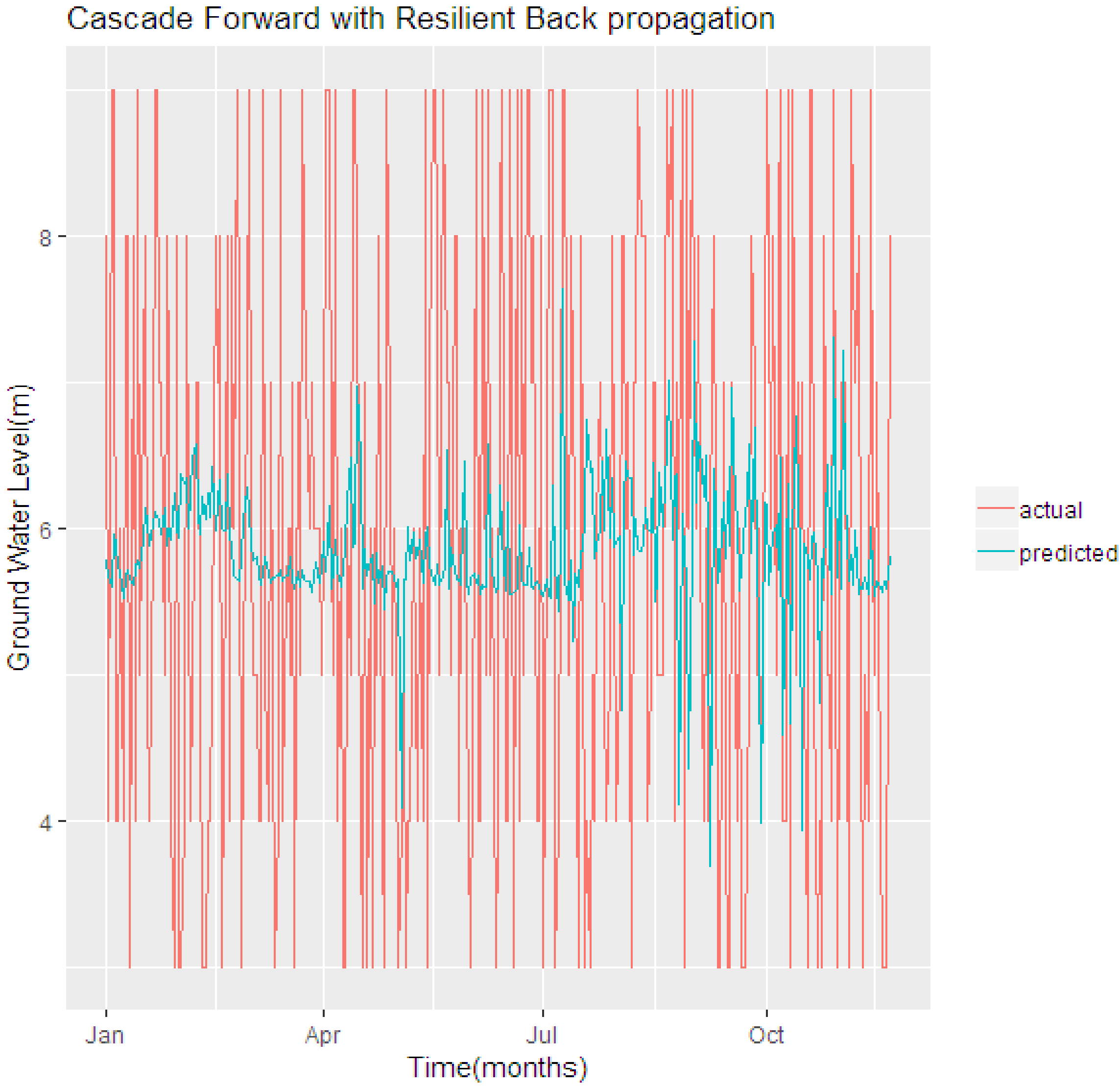

Figure 3: Hydrograph of the Groundwater for the Second Best Performance Algorithm Lapai

Figure 3 shows the hydrograph of groundwater level (m) against time (month)in Lapai.it is observed from the graph that the Cascade Forward with Resilient Back propagation is the second best algorithm that estimated groundwater levels, the depth to groundwater increases from `December and reached its highest level in April it is lowest in September.

Figure 4 is the graph of the third best estimated algorithm (Feed Forward Neural Network with BFCG quasi Network) with Mean Square Error of 4.02 in the Table 1 as given by the equation (14) in Lapai.

Figure 4: Hydrograph of the Groundwater for the Third Best Performance Algorithm Lapai

Figure 4 shows the hydrograph of groundwater level (m) against time (month) in Lapai.it is observed from the graph that the Feed Forward Neural Network with BFCG quasi Network is the third best algorithm that estimated groundwater levels in Lapai, the depth to groundwater increases from `December and reached its highest level in April but it is lowest in September.

Figure 5 is the graph of the fourth best estimated algorithm (Feed Forward Neural Network with Fletcher Reeves Conjugate Gradient) with Mean Square Error of 4.04 in the Table 1 as given by the equation (14) in Lapai.

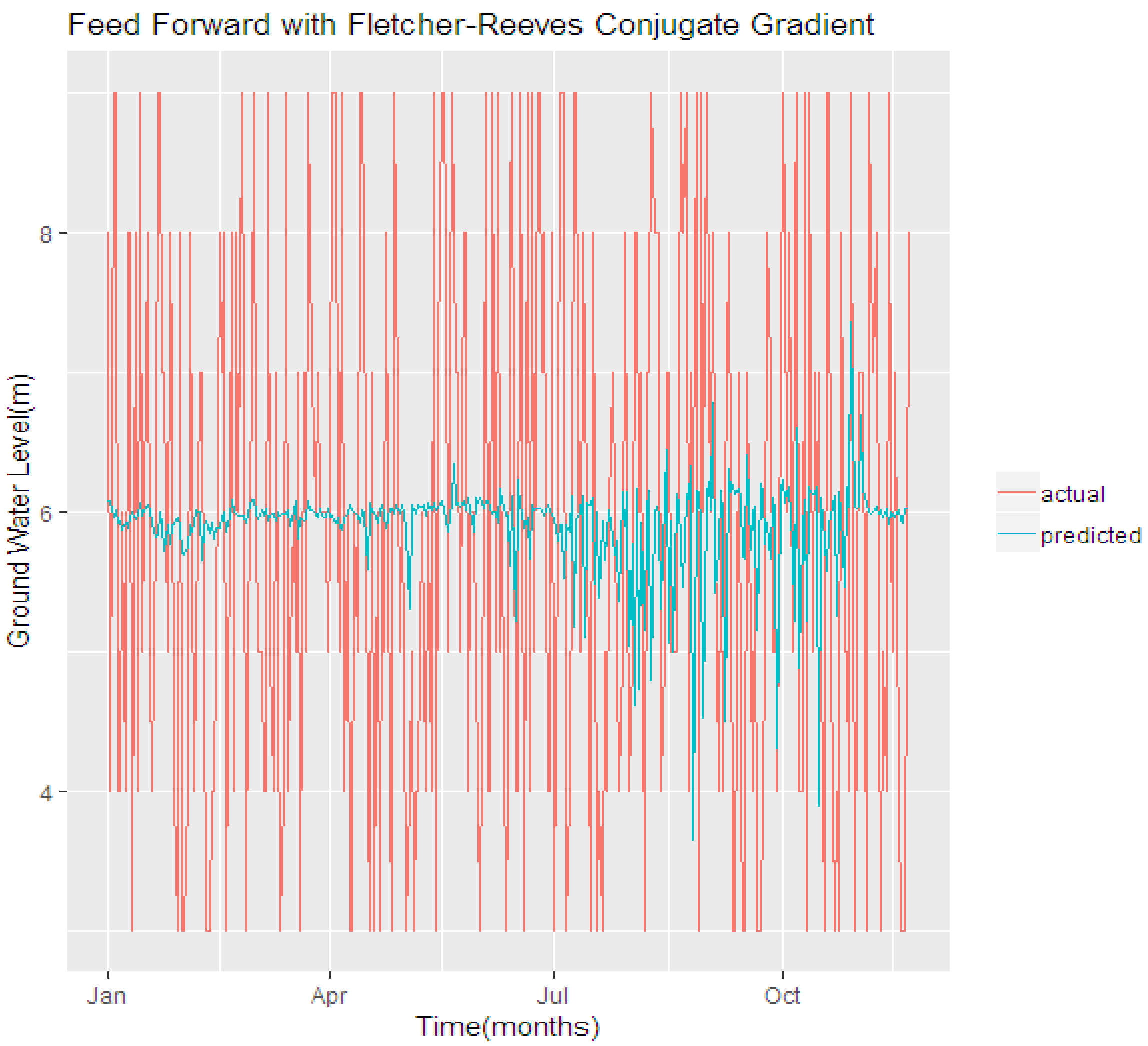

Figure 5: Hydrograph of the Groundwater for the Fourth Best Performance Algorithm Lapai

Figure 5 shows the hydrograph of groundwater level (m) against time (month) in Lapai. It is observed from the graph that the Feed Forward Neural Network with Fletcher Reeves Conjugate Gradient is the fourth best algorithm that estimated groundwater levels in Lapai, the depth to groundwater increases from `December and reached its highest level in April but it is lowest in September.

Figure 6 is the graph of the fifth best estimated algorithm (Feed Forward with Fletcher Reeves Conjugate Gradient is the Fifth best algorithm) with Mean Square Error of (4.07) in the Table 1 as given by the equation (14) in Lapai.

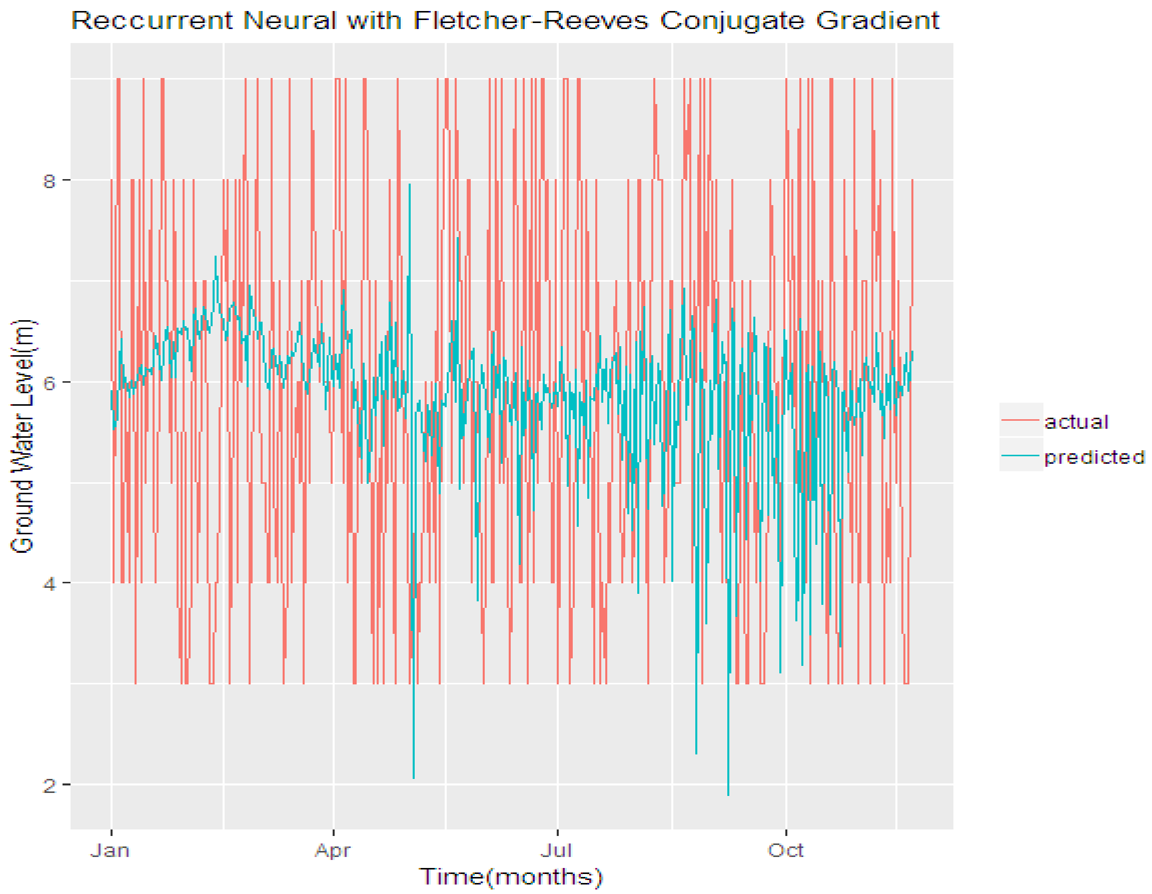

Figure 6: Hydrograph of the Groundwater for the Fifth Best Performance Algorithm Lapai

Figure 6 shows the hydrograph of groundwater level (m) against time (month) in Lapai. It is observed from the graph that the Feed Forward with Fletcher Reeves Conjugate Gradient is the Fifth best algorithm that estimated groundwater levels in Lapai, the depth to groundwater increases from `December and reached its highest level in April but it is lowest in September.

Conclusion

The main purpose of this study is to proffer solutions to estimation of the quantity of groundwater available during the dry season in Bida Basin, five climatic data obtained from Nigeria metrological station Abuja were used to trained and tested in Artificial Neural Network. Result from the analysis showed that the Feed Forward Levenberg algorithm is best overall performance out of the fifteen algorithm being compared in Lapai irrigation site. The actual and the estimated groundwater level are 5.93×10^6 (cubic feet) and 5.94×10^6 (cubic feet).

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