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AN ARTIFICIAL INTELLIGENCE BASED DROUGHT PREDICTIONS IN PART OF THE TROPICS

Aiyelokun Oluwatobi[1*], Ogunsanwo Gbenga[2] and Fabiyi Oluwafunbi[3]

[1] *Department of Civil Engineering, University of Ibadan*
[2]*Department of Information Communication Technology, Tai Solarin University of Education, Ijagun*
[3]*Department of Geography and Environmental Management, Tai Solarin University of Education, Ijagun*

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Abstract: There are indications that anthropogenic activities of man have tremendously increased extreme weather conditions resulting from global warming. This study therefore aims to determine the possibility of drought, its frequency, persistence and severity in Southwest Nigeria. The study employs the use of secondary data such as rainfall records from Ijebu-Ode station covering a period of 40 years (1974–2013) for drought computation while other parameters such as temperature, potential evapotranspiration and relative humidity were used for Artificial Neural Network (ANN) based modeling and prediction of drought. The frequency of drought events was calculated using the Standardized Precipitation Index (SPI). The SPI was calculated for 3, 6, 9, 12, and 24 months' time steps, and findings shows that all time steps had an increasing trend which signify excess rainfall and flooding in years to come except, the 3 month time step for the month of April that shows a significant decreasing trend, indicating an increase in drought. ANN was further used to model the drought for the 3-month time step for the month of April. Prediction of the year 2045 shows that there would be periods of severe dryness. The study concludes that the hypothesis of increasing rainfall in the tropics due to climate change does not hold for all areas and time steps, since there is indication that drought will persist in few months in years to come. Finally, more intensive study should be done to ascertain possibility of unforeseen droughts in the tropics where rainfall has been forecasted to persist.

Keywords: tropics; drought; standardized precipitation index; trend and ANN

* Correspondence to: Aiyelokun Oluwatobi. E-mail: aiyelokuntobi@gmail.com

INTRODUCTION

Variability of climatic elements due to global warming has continued to catch the interest of individuals and groups from diverse disciplines, encouraging interdisciplinary research on environmental issues related to climate change. Variability in rainfall patterns affects agricultural production, water supply, transportation, the entire economy of a region, and the existence of its people Oduro-Afriyie and Adukpo, 2006). In regions where the year-to-year variability is high, people often suffer great calamities due to floods or droughts (Oduro-Afriyie and Adukpo, 2006). There are indications that anthropogenic activities of man have tremendously increased extreme weather conditions resulting from global warming. Since damage due to extremes of rainfall cannot be avoided completely, a forewarning could certainly be useful (Nicholls, 1980; Oduro-Afriyie and Adukpo, 2006).

Dry events are meteorological extremes characterized with too less availability of water than normal. Drought is a temporary aberration within the natural variability and may be regarded as an insidious hazard of nature (Karavitis *et al.*, 2011). It is a disastrous natural phenomenon that has significant impact on socio-economical, agricultural, and environmental spheres (Khadr *et al.*, 2009). Droughts generally result from a combination of natural factors that can be enhanced by anthropogenic influences (Karavitis *et al.*, 2011). The primary cause of any drought is a deficiency in precipitation, and, in particular, the timing, distribution, and intensity of this deficiency in relation to the existing water storage, demand, and use (Karavitis *et al.*, 2011). This deficiency may result in water shortages necessary for the functioning of natural eco-systems, and/or pertaining to human activities (Karavitis *et al.*, 2011).

National Aeronautics Space Administration (NASA) scientists have detected the first signs that the tropical rainfall is on the rise (Manish and Pandey, 2011); it was further stipulated that in tropics, where nearly two thirds of the rain falls, there has been an increase of 5% (Manish and Pandey, 2011). On the contrarily, past research has shown that West Africa region which is located in the tropics has experienced a marked decline in rainfall from 15 to 30% depending on the area (Niasse, 2005). It has also been established that long-term trend of rainfall series of West and Central African showed major climatic discontinuity (Uduak and Edem, 2012). The aforementioned analysis lead to a thoughtful investigation of the possibility of dry events using rainfall of different time scales for Ijebu-Ode region, which is situated within the tropics.

One of the widely used methods for meteorological drought assessment is the Standardized Precipitation Index (SPI) developed by McKee *et al.* (1993). This method has the ability to quantify the precipitation deficit for multiple time scales, reflecting the impact of precipitation deficiency on the availability of various water supplies. This versatility allows the SPI to monitor short- term water supplies, such as soil moisture, important for agricultural production, and long- term water resources such as ground water supplies, steam-flow and reservoir levels.

The applications of artificial neural network (ANN) techniques in environmental studies have recently received increasing attention. The ANN has the capability to identify complex nonlinear relationships between input and output data sets without the necessity of understanding the nature of the phenomena and without making any underlying assumptions regarding linearity or normality (Abudu *et al.*, 2011). ANN also has the capability to handle noisy data (Meher, 2014). The ability to predict extreme weather events including droughts is immensely important in order to mitigate their effects (Gayan and Upul, 2009). This paper therefore aims to determine the possibility of drought, its frequency, persistence and severity in Southwest Nigeria using SPI for eight time scales, as well as to model and to further forecast drought using ANN.

DESCRIPTION OF THE STUDY AREA

Ijebu-Ode is located approximately around latitude 6° 47° and longitude 3° 58°E in South Western Nigeria (**Fig. 1**). It has an area of 192 km^2 and a population of 154, 032 at 2006 census, it is bounded in the North by Ijebu North, bounded in the East by Ijebu East Local Government, bounded in the West by Odogbolu Local Government and in the South by Epe Local Government Council of Lagos State. The study area experiences humid tropical climate which is characterized by alternate wet and dry season seasons like the rest of Nigeria. Ijebu-Ode region on annual basis is under the influence of hot-wet tropical maritime airmass during the rainy season (April-October) and hot-dry tropical continental airmass during the dry season (November-March) the following year. Rainfall is generally heavy with peaks occurring in July and September (double maxima) coupled with high temperature, high evapotranspiration and high relative humidity. The mean annual rainfall is between 1575 mm and 2340 mm. The rains may be unduely prolonged in some years while their onset may be delayed as "AUGUST BREAK" is usually experienced between late July and Mid-August.

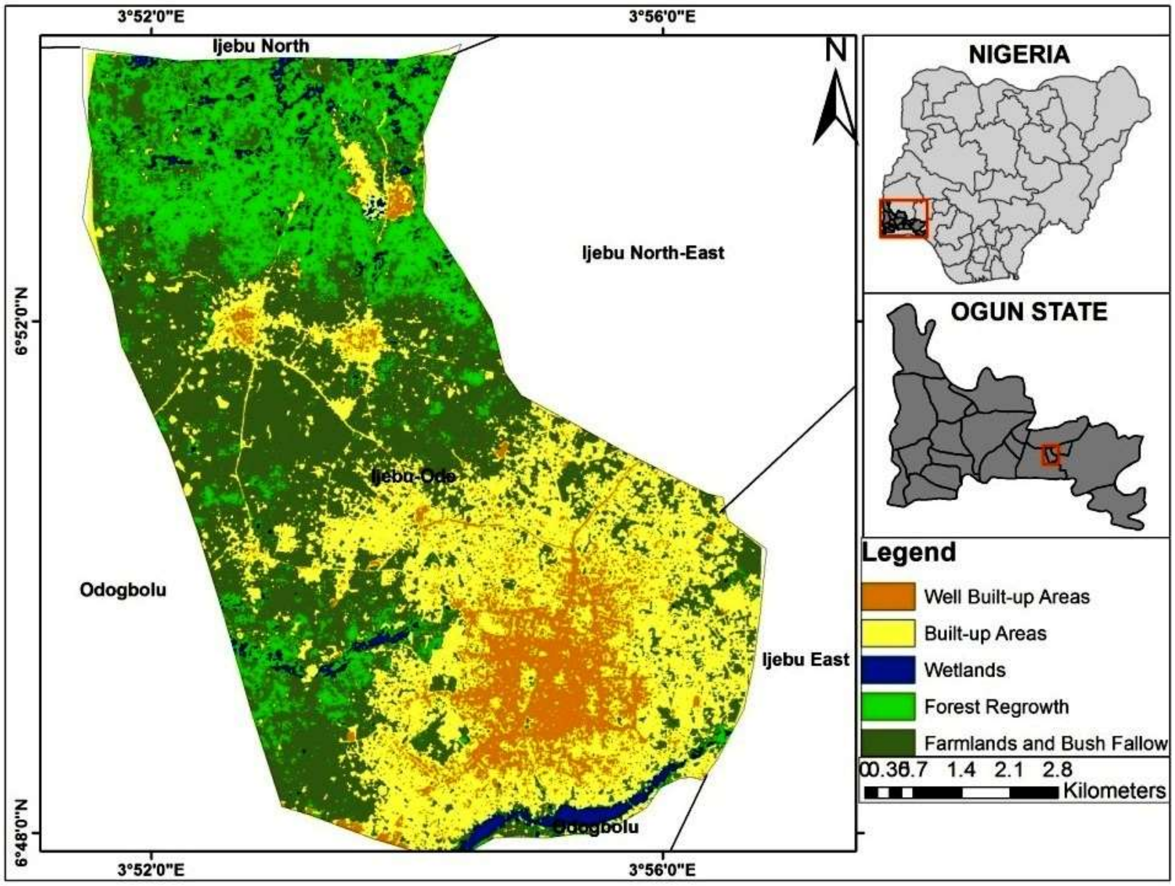

Fig. 1 Map of the study área.

METHODOLOGY

Materials

Data for Ijebu-Ode rainfall station was obtained from the Nigeria Meteorological Agency (NIMET) station in Ijebu-Ode, Ogun State. The time series of meteorological data covering 40 years for rainfall and 22 years for maximum and minimum temperature, wind speed, sunshine duration, and relative humidity were obtained covering 1975 to 2013 and 1991 to 2012, respectively.

Standard Precipitation Index (SPI)

The SPI was developed by Mckee *et al.* (1993) to quantify precipitation anomaly with respect to long-term normal conditions for multiple time scales (Du *et al.*, 2012). SPI can be calculated at various time scales on which precipitation deficits/surpluses can affect different aspects of the hydrologic cycle, which is the main advantage of the SPI (Du *et al.*, 2012). This advantage is crucial because it can reflect the natural lags in the response of different water sources, such as river discharge and storage, to precipitation anomalies (Paulo *et al.* 2003). Lloyd-Hughes and Saunders (2002) described the detailed calculation of SPI. The most commonly used distribution for SPI calculation is the two-parameter gamma distribution with a shape and scale parameter, which is defined by its probability density function:

$$G(x) = \frac{1}{\beta^{\alpha}\tau(\alpha)}\int_0^x x^{\alpha-1}e^{-\alpha/\beta}dx \quad \text{for } x > 0 \qquad (1)$$

where α is the shape parameter, β is the scale parameter, x is the precipitation value and $\tau(\alpha)$ is the gamma function. The gamma distribution is undefined for x = 0, but the precipitation may have zero value, so the cumulative probability distribution given a zero value is derived as follows:

$$H(x) = q + (1-q)\,G(x) \qquad (2)$$

where q is the probability of the zero precipitation value. The cumulative probability distribution is then transformed into the standard normal distribution to calculate SPI. The value of SPI indicates the strength of the anomaly. Mckee *et al.* (1993) suggested a classification system to define the intensity of dry/wet phases (**Table 1**).

Table 1. Dryness/wetness categories according to SPI values

Category	SPI values
Extremely wet	≥ 2.0
Severely wet	1.50 to 1.99
Moderate wet	1.00 to 1.49
Near normal	0.99 to -0.99
Moderately dry	-1.00 to -1.49
Severely dry	-1.50 to -1.99
Extremely dry	≤ -2.0

Penman-Monteith Equation

The standard Penman-Monteith method for estimating evapotranspiration can be mathematically expressed as follows (Allen *et al.*, 1998):

$$E0 = (\Delta/ \gamma H + Ea)/ (\Delta/\gamma) \quad (3)$$

where Δ/ ɣ is an empirical parameter depending on temperatura, H is calculated as H = (1-r)Rin−Ro; where Rin (incoming radiation) is given by the equation:

$$(1\text{-}r)\ Rin = 0.95{*}Ra\ (0.18 + 0.55n/N) \quad (4)$$

where Ra is the solar radiation, Ro is the outgoing radiation, r is the albedo (0.05 for water), and n/N is the ratio between actual sunshine hours and possible sunshine hours. The term n/N can also be estimated using the cloudiness, e.g., a cloudiness of 60 % gives an *n/N* of 40 % (= 100 -60). R is calculated from equation:

$$R = \sigma T\ 4\ (0.56 - 0.09\sqrt{}ed)\ 0\ a\ (0.10+0.90n/N) \quad (5)$$

where ed is the actual vapor pressure and σT is the a theoretical black body radiation. Ea is calculated from the equation:

$$Ea = 0.35\ (0.5 + u2/100)(ea–ed) \quad (6)$$

where *u*2 is the wind speed in m/s and ea is the saturation vapor pressure. Remember that the relative humidity RH = ed/ea.

Artificial Neural Network (ANN) Training and Prediction Experiment

An ANN is the densely interconnected parallel structure and is a collection of mathematical or analytical model that can emulate the observed or given properties of biological neuron systems and draws the analogies of adaptive biological learning system by using the learning rules and hybrid algorithm (Janaki, 2013). Neurons of ANN are in a group forming a layer, it operates in logical parallelism. A network can vary from single to many layers, but the basic structure of a network usually consists of three layers, where data are provided to the network of ANN, the data are processed in hidden layers and the results of input layer are produced in output layer (Janaki, 2013) as shown in **Fig. 2**. There are several ways to use ANN (Janaki, 2013), in the present study, back propagation neural network with several numbers of neurons and hidden layers was used. The following steps were used for modeling drought:

a. Selection of Input and Target data for calibration and validation.
b. Model structure selection and estimation of its parameters.
c. Validation of selected model RStudio along with the ANN package (neuralnet) was used for designing, implementing, visualizing, validating and simulating neural networks.

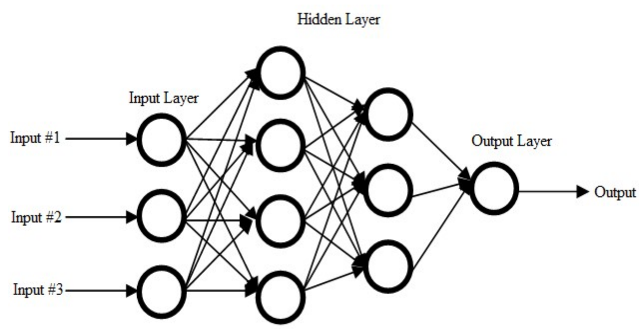

Fig. 2 A typical back propagation network structure.

RESULTS AND DISCUSSION

Dimensions of Extreme Conditions in Ijebu-Ode

The different SPI computed at different time scales are presented in this section. It can be observed that 16 cases of extreme drought (SPI < -2), 24 cases of severe drought (-1.5 to -1.99) and 44 cases of moderate drought (-1.0 to -1.49) occurred in the study period for the different time scales (**Table 2**).

Table 2. Frequency and Intensity of Drought Events in Ijebu Ode

Drought	SPI-3 January	SPI-3 April	SPI-3 June	SPI-3 October	SPI-6 June	SPI-6 December	SPI-12 December	SPI-24 December	Total
Extreme	2	2	2	2	2	2	2	2	16
Severe	3	3	3	3	3	3	3	3	24
Moderate	5	5	6	6	6	6	6	4	44

In the 3 months time scale for the month of January, two extreme drought cases were experienced in 1983 (-2.6) and 1988 (-2.1) as shown in **Fig. 3**. The figure further shows that the extreme drought of 1983 began after a near normal period in 1980, while the 1988 extreme drought subsided in 1990. This was followed by series of undulating curves, which indicates a period of moderate droughts and near normal events. An increase in trend of observed SPI values could be noticed (**Fig. 3**), which implies that drought cases for 3-month time step would be minima in the future.

In the 3 months time scale for April, two extreme drought cases were experienced in 1983 (-2.1) and 1988 (-2.6) as shown in **Fig. 3**, similar to the 3-months time scale for January, higher extreme drought event were experienced in 1988. It can be observed in the figure that majority of the years fell under zero for the observed SPI values, indicating there were more dry events during the study period for the time step. In addition, there was decreasing pattern of the SPI values which implies that drought cases in this time step would increase in the future.

Figure 5 shows the trend of variation in the calculated SPI values for the 3-months time scale while considering the month of June. As observed in **Table 2**, the two cases of extreme drought could be noted in 1986 (-2.1) and 1993 (-2.6). The **Fig. 5** shows that the 1986 extreme drought started in 1983 and subsided in 1988, while 1993 extreme drought, which started in 1990 ended in 1994. The figure also shows that majority of the SPI valued computed for 3-months time step for month of June was within the near normal SPI and moderate drought events. Furthermore, the figure shows an increasing trend toward positive SPI for the time step, indicating that dry event would be minima in consequent years in this time scale.

Figure 6 shows the trend of variation in the calculated SPI values for the 3-months time scale for the month of October. Two extreme drought cases was experienced in 1976 (-2.6) and 2005 (-2.1). The figure further shows that majority of the meteorological conditions experienced within the study period were close to normal. Furthermore, the increasing positive trend observed **Fig. 6** implies that drought will be minimal in this time scale.

Figure 7 shows the trend of variation in the calculated SPI values for the 6-months time scale while considering the month of June. As observed in **Table 2**, the two cases of extreme drought noted in 1986 (-2.1) and 1998 (-2.6) could be seen in **Fig. 7**. The figure also shows that the 1986 extreme drought subsided in 1998 with a SPI value close to normal, on the other hand, the 1998 drought was followed by a period of drought with reduced intensity, which ended in 2004. In addition, it can be observed in the figure that there is an increasing trend in the SPI values computed for this time scale, which shows that drought would be minimal in subsequent years.

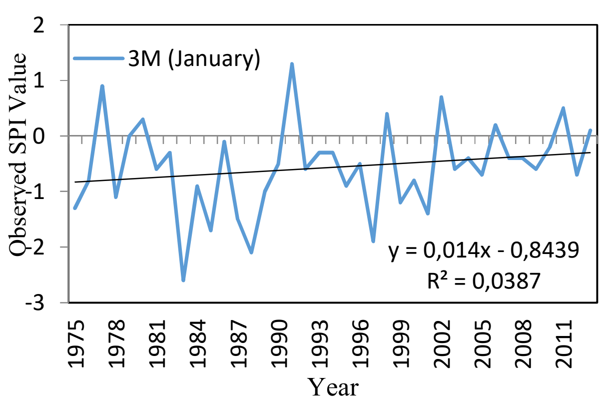

Fig. 3 SPI values based on 3 months time scale (January).

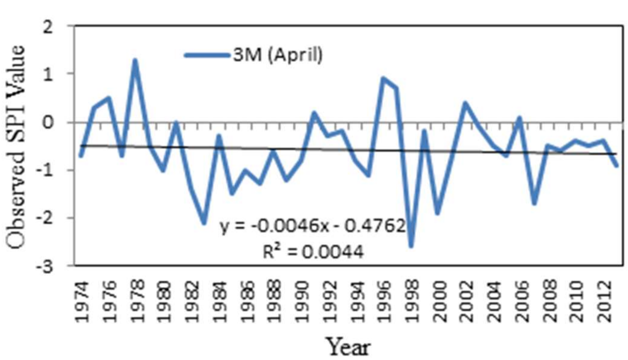

Fig. 4 SPI values based on 3 months time scale (April).

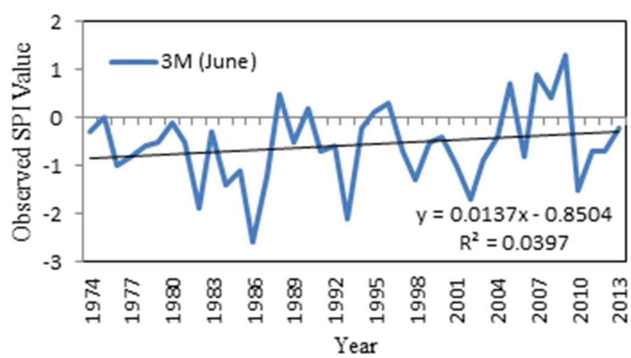

Fig. 5 SPI values based on 3 months time scale (June).

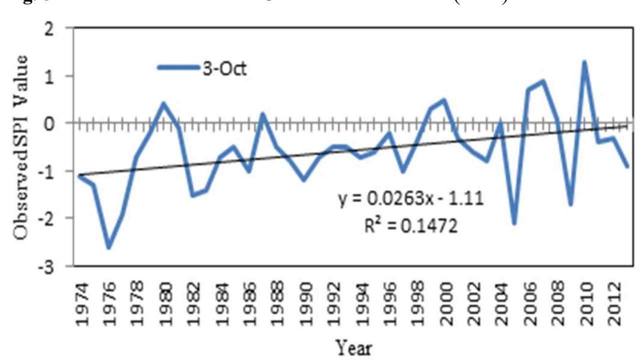

Fig. 6 SPI values based on 3 months time scale (October).

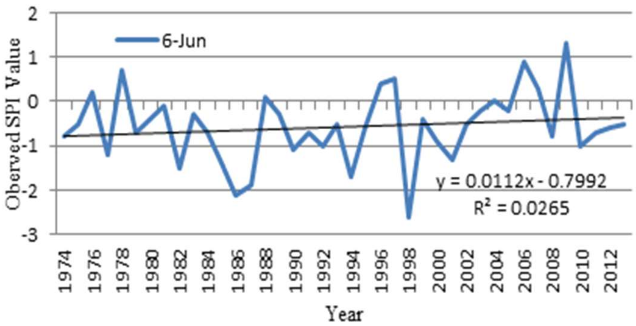

Fig. 7 SPI values based on 6 months time scale (June).

Figure 8 shows the trend of variation in the calculated SPI values for the 6-months time scale while considering the month of December. As observed in **Table 2**, the two cases of extreme drought occurred in 1976 (-2.1) and 1983 (-2.6). The figure shows that the 1976 extreme drought started in 1974 and subsided in 1979, while 1983 extreme drought, which started in 1981 ended in 1985. The figure also shows that majority of the SPI valued computed for this time step was within the near normal SPI and moderate drought events. Furthermore, the figure shows an increasing trend toward positive SPI, indicating that dry event would be minima in subsequent years.

Figure 9 shows the trend of variation in the calculated SPI values for the 12-months time scale while considering the month of December. As observed in **Table 2**, the two cases of extreme drought were noted in 1982 (-2.6) and 1986 (-2.1). The figure shows that the 1982 extreme drought started in 1981 and subsided in 1983 and1984, which later increased in severity up to 1986. The figure also shows that majority of the SPI valued computed for this time step was within the near normal SPI and moderate drought events. Furthermore, the figure shows an increasing trend toward positive SPI, indicating that dry event would be minima in subsequent years in this time scale.

Figure 10 shows the trend of variation in the calculated SPI values for the 24-months time scale while considering the month of December. As observed in **Table 2**, the two cases of extreme drought were noted in 1983 (-2.6) and 1986 (-2.1). The figure shows that the 1983 extreme drought started in 1981 and subsided in 1983 and 1984, which intensifies in 1986. The figure also shows that majority of the SPI valued computed for this time step was within the near normal SPI and moderate drought events. Furthermore, the figure shows an increasing trend toward positive SPI, indicating that dry event would be minima in subsequent years.

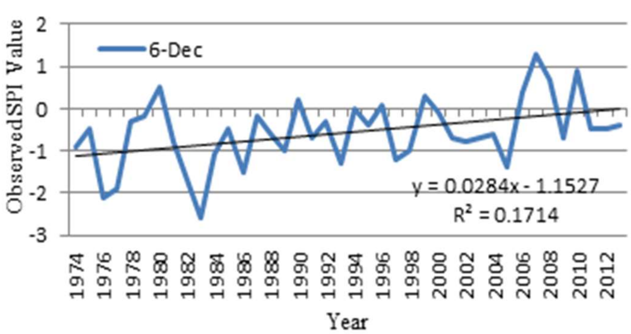

Fig. 8 SPI values based on 6 months time scale (December).

Drought Modeling Using ANN

The result of the SPI analysis in the previous section revealed that meteorological extremes are expected to occur in subsequent years in the study area. Since only the 3-months time scale for the month of April showed trend of increasing drought. It was considered for modeling and prediction. Rainfall, average temperature, relative humidity and potential evapotranspiration were also considered for the simulation in the ANN model since these meteorological indices influence the availability of water.

Table 3 shows that result potential evapotranspiration and other indices for the time scale being considered. The result in **Table 3** was divided into two sets, 75% and 25% of the data were used to train and test the network. After series of trials and errors in the training and testing of the ANN, two models were selected and presented two models in this study. The first ANN model used in this study consists of an input layer with four nodes each for rainfall, temperature, relative humidity

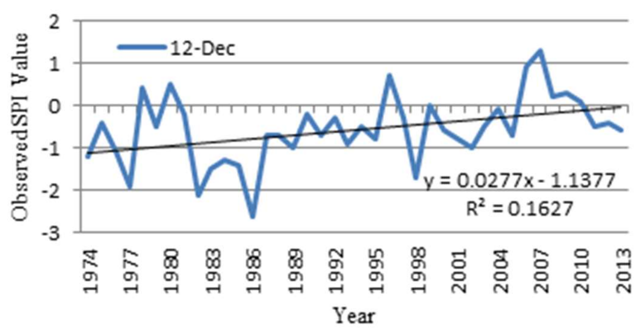

Fig. 9 SPI values based on 12 months time scale (December).

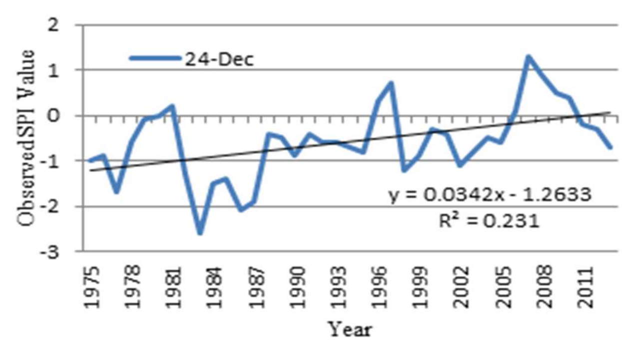

Fig. 10 SPI values based on 24 months time scale (December).

Table 3. Result of Meteorological Indices (3-months time scale, April)

Year	SPI	Rainfall (mm)	Temperature (°C)	RH	EPT (mm)
1991	0.2	341.2	28.5	82.5	339.2
1992	-0.3	278.4	29.0	78.1	116.8
1993	-0.2	314.3	28.6	77.4	308.5
1994	-0.8	196.3	28.7	80.5	323.6
1995	-1.1	186.9	29.1	79.7	326.8
1996	0.9	509.7	28.5	83.6	339.8
1997	0.7	494.4	28.5	73.6	297.5
1998	-2.6	80.8	27.3	86.5	350.3
1999	-0.2	287.2	28.7	81.4	334.5
2000	-1.9	104.3	29.5	70.5	295.1
2001	-0.7	202.1	28.8	73.2	282.5
2002	0.4	358.4	29.3	79.5	331.0
2003	-0.1	317.9	29.4	78.4	328.5
2004	-0.5	263.4	28.8	79.5	324.2
2005	-0.7	237.1	29.4	81.6	338.0
2006	0.1	340.6	28.9	83.0	343.6
2007	-1.7	109.0	29.8	78.3	339.2
2008	-0.5	223.4	28.8	78.0	336.3
2009	-0.6	259.9	28.7	82.3	367.9
2010	-0.4	229.1	29.8	80.3	342.4
2011	-0.5	261.3	29.3	80.0	329.7
2012	-0.4	264.9	30.1	80.6	366.5

and potential evapotranspiration, two hidden layer composed of 5 and 3 nodes, and one output layer consisting of 1 node denoting the predicted drought. **Figure 11** shows the graphical representation of ANN model. The second ANN model is presented in **Fig. 12** below, this model is similar to the first model expect for the single hidden layer. The performance of the two models was investigated using the root mean square error (R.M.S.E). **Table 4** presents the comparison between the two ANN models. As shown the table, the second model with a single hidden layer had a root mean square error of 0.971. This implies that the second ANN model predicted drought well, this model was then used to forecast drought in the study area.

Drought Forecasting

In order to forecast the occurrence of drought in 2015, 2025, 2035 and 2045, the four meteorological indices were fitted in simple least square regression model (LSRM). The summary of the models are presented in **Table 5**, while the forecasted values are presented in the **Table 6**.

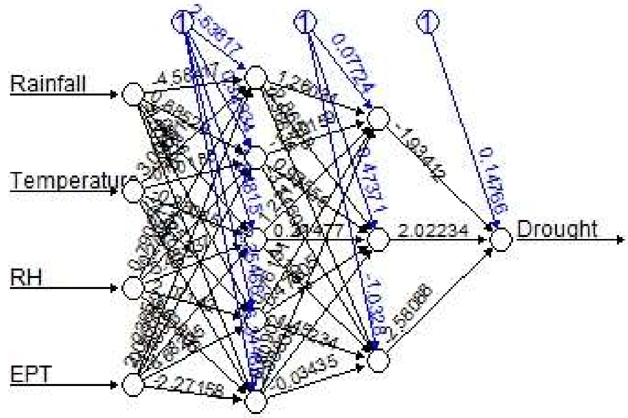

Fig. 11 Graphical Representation of Model I.

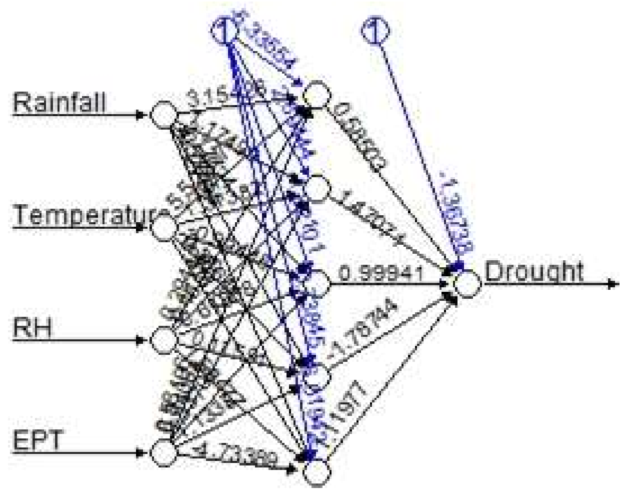

Fig. 12 Graphical Representation of Model II.

Table 4. Comparison of Predicted Result the two ANN Models

Observed Drought	ANN Model 1		ANN Model 2	
	Modeled Drought	Root Mean Square Error	Modeled Drought	Root Mean Square Error
0.857607767	0.428167144	2.126	-0.00795166	0.971
0.364343169	-0.51994802		-0.60060555	
-0.74550218	-1.01408602		-1.0896096	
1.474188514	0.231309251		0.073390275	
-0.25223758	-1.46134169		-1.16782401	
-0.00560528	-1.17851647		-1.03281519	

Table 5. Summary of Least Square Regression Model of Meteorological Indices

	Rainfall (mm)	Tempe-rature (°C)	Relative Humidity (%)	Potential Evapotrans-piration (mm)
Model	y = -3.370x+305.1	y = 0.05x+28.9	y = 0.036+79.1	y = 3.61x+279.4
R^2	0.041	0.304	0.004	0.219

Table 6. Computed value of meteorological indices based on LSRM

Year	Rainfall (mm)	Temperature (°C)	Relative Humidity (%)	Potential Evapotrans-piration (mm)
2015	220.9	29.63	80	369.8
2025	187.2	30.13	80.3	405.9
2035	153.5	30.63	80.7	442.03
2045	119.8	31.13	81.03	478.17

As observed in **Table 6**, rainfall was forecasted to reduce as other meteorological indices increases. **Table 7** shows that predicted conditions of the 3-month time scale meteorological extreme based on ANN modeling. Prediction for the year 2045 shows that there would be periods of severe dryness. The study shows that the hypothesis of increasing rainfall in the tropics due to climate change does not hold for all areas and time steps, since there is indication that drought will persist in few months in years to come.

Discussion of Findings

In this study, the overall meteorological drought variability in Ijebu-Ode was assessed by reconstructing historical occurrences of droughts at varying time steps and drought categories by employing the SPI approach. The long-term record (40 years) of rainfall for different time scales of Ijebu-Ode was fitted to a gamma probability distribution that is then transformed into a normal distribution, which, by definition, has zero mean and unit variance.

It is advantageous to use several time steps when applying the SPI approach (Khadr *et al.*, 2009), this is because drought decisions could be extensively analyzed, and events missed on one time scale might be caught in another time scale. For example, it was observed that drought events in all time scale trends toward positive SPI except the three-month time scale for the month of April. This implies that the general premise of increasing rainfall in Ijebu-Ode situated in the tropics does not hold true for all time steps.

Artificial Neural Network (ANN) models used in this study show the capability to modeling the drought process. Simple regression and multiple linear regression (MLR) are frequently used as hydrologic and meteorological forecasting. Although they are simple and easy to use, they have limitations in that they cannot forecast accurately when data are noisy and have nonlinear relationship. Therefore ANN applicability for drought modeling cannot be over emphasized.

At present, the most common ANN architecture and algorithms being applied are multilayer feed forward, Hopfield networks, radial basis function network, recurrent network, self organization feature maps, and counter propagation networks. However, the multilayer feed forward networks are the most commonly used for hydrological applications (Dawson and Wilby, 2001). In multiple-layer perceptron (MLP) networks, as used in hydrologic investigations, a single hidden layer with a sigmoid transfer function and an output layer with a linear transfer function, are preferred for their simplicity and effectiveness (Anctil and Rat 2005; Hsu *et al.* 1995; Sivakumar *et al.* 2002). In this study, the model with a single hidden layer was found to perform better, hence it can be concluded that a single layer works best when predicting drought.

Table 7. Summary of Predicted Drought Conditions

Year	SPI	Condition
2015	-0.685	Near normal
2025	-0.403	Near normal
2035	-0.809	Near normal
2045	-1.823	Severe Drought

The process from validation to testing was done by using a residual statistics and is known as the root mean square (RMSE), which assisted in selecting the best ANN model for the study. The model with a single hidden layer was found appropriate for predicting drought since its RMSE tends toward zero indicating a more powerful predicting ability.

An increase in drought indicated by three-month time steps of April implies that there is argent need for drought monitoring in Southwest Nigeria and the tropics as a whole. This will involve strict monitoring and measuring of water supply nationwide, adequate planning for irrigation for early planting, reduction of water loss and wastage through efficient measures, and powering programmes to enlighten the public on recycling and reuse of water to meet water needs during drought.

CONCLUSION

Generally, rainfall in on the increase in Southwest Nigeria and the tropics as a whole, this study has revealed that a closer observation based on SPI computation for different time scales, renders this hypothesis to be partial, and cannot be generalized. This study calls for a need into urgent investigation and monitoring of drought in Southwest Nigeria were flooding has gained numerous attention in the past. This could be a guide to the decision makers in Nigeria to develop strategies of water resources management in the context of drought.

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