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MODELS VALIDATION AND FORECASTING FOR DROUGHT RISK REDUCTION IN DEVELOPING COUNTRIES

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ABSTRACT

Drought risk reduction should be based on effective monitoring and early warning systems affordable by both privileged and vulnerable nations and regions. Drought can be pandemic over months and hence, Standardized Precipitation Index (SPI) at time scale of one – month was modelled for drought monitoring and real time forecasting. Developed predictive SPI models were used to forecast droughts in the seven meteorological stations in the region in the year 2009 and the forecast negative SPIs, reflecting droughts, were compared with drought class thresholds to predict and identify drought occurrences at different phases such as emergence watch, warning and emergency. The results showed drought forecasts of emergence phase at most of the stations. This implied that monitoring was necessary so that warning alert could be declared as soon as the drought emergence phase progressed into warning stage. It is recommended that the models should be used to forecast droughts ahead on monthly bases. Also, the simple predictive models should be developed for other less developed regions as the early warning services component of people-centred early warning systems for effective drought risk reduction in developing countries.

Key words: Drought risk reduction, hazard risks, standardized precipitation index

INTRODUCTION

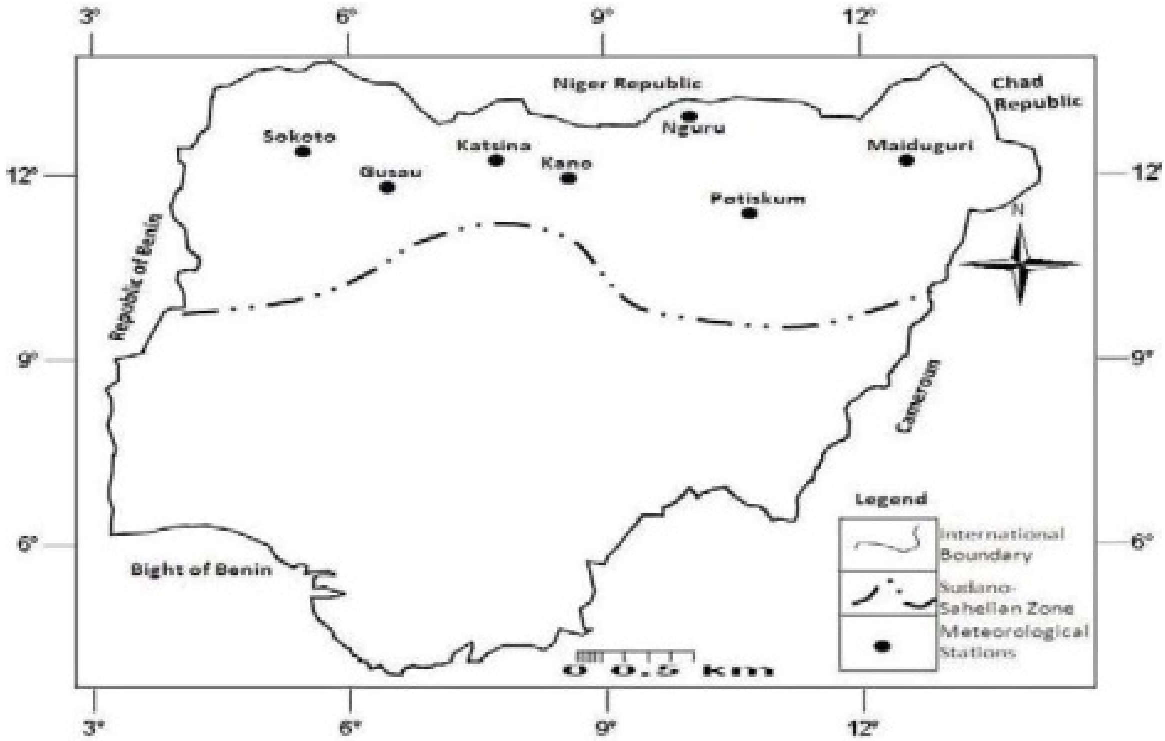
Drought is a natural hazard caused by below normal precipitation and it threatens human race and the environment. During the period 1900-2013, 642 drought episodes were reported globally resulting in the death of 12 million people and affecting more than 2 billion with total economic damages estimated at USD 135 billion (EM-DAT, 2014). The extreme droughts of 1972-1973, 1983-1984 and 1991-1992 adversely affected Nigeria and other vulnerable African and developing countries with less coping capacity (Masih *et al.,* 2014; Adeogun *et al.,* 2014).

Medugu (2007) called for the development of a national drought forecasting and early warning system to manage the frequent droughts in the Nigerian Sudano-Sahelian Region (NSSR). Svoboda (2009) and United Nations International Strategy for Disaster Reduction (ISDR) (2006) identified the components of a drought early warning system to consist monitoring, analysis and forecasting of the hazards (warning service). In response, Adeogun et al., (2014b) applied stochastic approach to develop drought predictive models as drought warning tools for Nigerian Sudano-Sahelian Region. The use of such models will go a long way to reducing drought risk in the region and other developing countries.

This study aimed at applying Adeogun et. al., (2014b) predictive models, based on Standardized Precipitation Index at a time scale of one month (SPI_1) developed for Nigerian Sudano Sahelian Region, to forecast drought occurrence and severity at a short term scale and hence, as drought early warning tools in the region.

MATERIALS AND METHODS

The study area is the Nigerian Sudano Sahelian Region with seven synoptic stations as presented in Fig. 1. Thirty years monthly rainfall data, from 1979 to 2008, were processed to generate SPI_1, using an SPI program for each of the station as described in Adeogun *et al.,* (2014a). The SPI_1 data series were used to develop SPI_1 models for drought forecasting using Auto Regressive Integrated Moving Average (ARIMA) and Seasonal Auto Regressive Integrated Moving Average (SARIMA) as described in the Adeogun *et al.,* (2014b).



Source: Masih *et. al.,* (2014)

Figure 1: Nigerian Sudano Sahelian Region

Structure of ARIMA Models

ARIMA and SARIMA are models in which lags of the differenced series appearing in the forecasting models are called “Auto-Regressive” (AR) term, represented by order p; lags of the forecast errors are called “Moving Average” (MA) term, represented by order q and a time series which needs to be differenced to be made stationary is said to be an “integrated” version of a stationary series (Ghafoor and Hanif, 2005). ARIMA can be non-seasonal or seasonal. A non-seasonal ARIMA model is characterized by the notation ARIMA (p,d,q) model while a seasonal ARIMA model is represented by multiplicative Seasonal ARIMA (p,d,q)x(P,D,Q)s model as reported in Shumway and Stoffer (2000), where p and q are the orders of non-seasonal auto-regressive and moving average parameters, respectively whereas P and Q are that of the seasonal auto-regressive and moving average parameters respectively. Also, d and D denote non-seasonal and seasonal differences, respectively and the values are either 0, 1 or 2 and s is the seasonal parameter (Berthouex and Brown, 2002). The orders of non-seasonal (p,q) and seasonal (P,Q) parameters could be obtained by looking for significant spikes in the Auto Correlation Function (ACF) and Partial Auto Correlation Function (PACF) plots of a given time series. Also, the structure of a time series graph and/or ACF gives a clue to the stationarity of the data series which reflects the necessity for transformation of the data or not. For instance, a graph with a rising trend is not stationary and the variation could be removed by logging to make the data series stationary {Adeogun *et al.,* (2014b); Khadr (2011)}.

Overview of Development of ARIMA Models

The stages of model development as contained in Adeogun *et al.,* (2014b) are briefly described as follows:

Model identification and parameters estimation: This involves identifying suitable models from the families of ARIMA/SARIMA models and selecting the orders of non-seasonality and seasonal parameters, (p,q and P,Q, respectively) of the selected models. The parameters of the models were identified from the ACF and PACF plots using XLSTAT programme.

ACF and PACF generation: Each station's SPI_1 time series, prepared in excel spreadsheet, was entered into the XLSTAT to generate the stations ACF and PACF graphs of the data set. The graphs were then analyzed for trend, seasonality and necessary differencing, and model parameters for the ARIMA modelling. The values of the parameters were set at the maximum limits in the programme; this allows for trials of a number of suitable models, with likely parameters having values less than or equal to this limits, by the software.

ARIMA modelling: Each station's SPI_1 time series in excel format were entered in the XLSTAT programme and maximum values of the model parameters identified from ACF and

PACF above were entered to simulate the series and generate possible models for the station. In addition to each model structure, the respective graph, goodness of fit measures and estimates of the values of the model parameters were also generated by the software.

Model diagnostics: Different models identified can be of various combinations of AR and MA individually and/or collectively. However, the best model was selected with the following diagnostic goodness of fit measures such as Alkaike Information Criteria (AIC) and Schwarz-Bayesian Information Criteria (SBC). Together with the goodness of fit measures stated, Sum of Squares for Errors (SSE) of the series was also evaluated.

The goodness of fit measures were used to select the best model from the various suitable models by selecting the one with the lowest values of fit measures. The goodness of fit of the selected best model for each station was further confirmed by analyzing the model's residuals. This is because if the fitted models are adequate, the plot of residuals' ACF and PACF should be approximately white noise, that is, the residuals should have zero mean and uncorrelated.

Model Forecasting and Validation

The developed models were validated using available data. The models were used to predict corresponding time series data from the computed SPI_1, at a 3-months time step (i.e., short time forecasting) because according to Khadr (2011), short time forecasting is suitable for time series analysis. The forecasted time series were compared with the available actual data series to validate the models. This is to determine the reliability of the selected models for drought forecasting and to see how the models actually simulate the actual observation.

Drought Forecasting and Severity

The models were used to forecast monthly SPI_1 on monthly basis for a period of one year ahead. Negative forecast values implied droughts according to Table 1 and drought severity were determined by comparing the monthly forecasts with the severity classes in the Table. Besides, drought thresholds were selected from Table 1 such that near normal and moderately dry conditions were used as indicators for drought emergence watch and warning as expressed thus:

Drought emergence watch would be declared if:

$$-0.99 \leq SPI\_1 \leq 0.99 \tag{1}$$

Near normal condition is selected as the threshold for drought emergence watch because drought is incessant in the study area and hence, there is need for monitoring right from the incidence stage.

Drought warning would be declared if:

$$-1.00 \leq SPI_1 \leq -1.49\text{-} \tag{2}$$

Drought emergency would be declared if Equation (2) became constant for two consecutive months or more and/or the SPI_1 forecasts become more negative (i.e., severely dry and/or extremely dry conditions).

Table 1: Drought Severity Using Standardized Precipitation Index

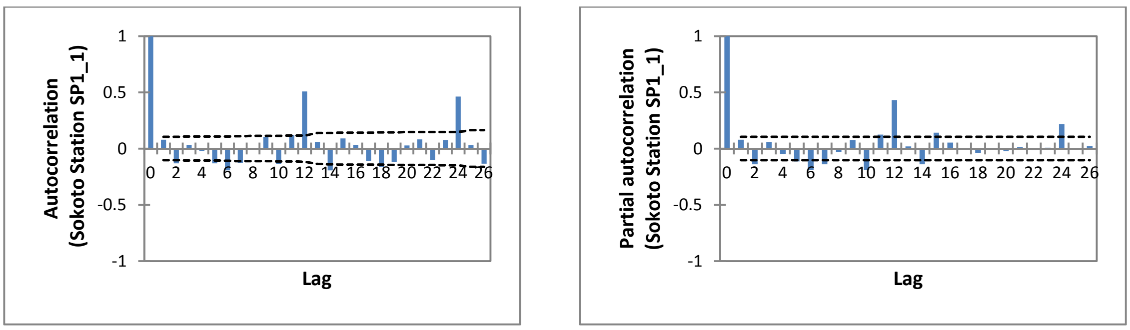
SPI Values	Comment
2.0 +	Extremely wet
1.5 to 1.99	Very wet
1.0 to 1.49	Moderately wet
-0.99 to 0.99	Near Normal
-1.0 to -1.49	Moderately dry
-1.5 to -1.99	Severely dry
-2 and less	Extremely dry

Source: McKee *et al.* (1993)

RESULTS AND DISCUSSION

SPI_1 Model identification and parameters estimation

ACF and PACF: The parameters of ARIMA/SARIMA models of the form (p,d,q), for non seasonal, or (p,d,q)x(P,D,Q)s for seasonal, were identified using ACF and PACF. For instance, Figs. 2 (a and b) show the ACF and PACF plots for selecting suitable model parameters for Sokoto Station SPI_1 time series. The ACF (Fig. 2a) is damping out in sine wave manner with significant spikes at the first lag. This reflects that the series can be modelled with a Moving Average (MA) or q parameter of 1 (maximum limit) (that is, $q \leq 1$). Also, the first spike is significant in the PACF (Fig 2b) which shows that the series can be modelled with an Auto Regressive (AR) or p parameter of 1 (maximum limit) (that is, $p \leq 1$). Hence, the process can be modelled with a combination of AR and MA (Adeogun *et al.*, 2014b.



(a) Autocorrelation function (ACF) (b) Partial Autocorrelation function (PACF)

Figure 2(a and b): ACF and PACF plots for selecting models for Sokoto Station SPI_1 series

Source Adeogun *et al.,* (2014b)

Furthermore, the graphs reflected seasonality, that is, apart from the first significant spike, other significant spikes occurred at lag 12, and 24 which reflected seasonality every 12 months. Therefore, suitable models for the process would be Seasonal ARIMA (SARIMA) process and the form (p,d,q)x(P,D,Q)s can be represented as, for instance, $(1,d,1)x(1,D,1)_{12}$, where s is the seasonal parameter (that is, 12), and differencing terms, d and D, can be 0,1, or 2 which was simulated by XLSTAT.

By entering the limits of the parameters p and q into the XLSTAT, a number of models together with goodness of fit of the statistical parameters were generated as presented in Table 2.

Table 2: Comparison of Goodness of Fit Statistics and Statistical Parameters of SPI_1 Models

Item No	Station	Series/ SARIMA Model	Mean	Standard Deviation	AIC	SBC	SSE
1	Sokoto	SP1_1	0.478	0.978	-	-	-
		$(111)x(111)_{12}$	0.464	0.784	766.703	785.774	171.000
		$(110)x(110)_{12}$	0.486	1.073	982.230	993.672	358.304
		$(011)x(011)_{12}$	**0.465**	**0.778**	**774.314**	**762.872**	**142.581**
2	Katsina	SP1_1	0.168	0.768	-	-	-
		$(111)x(111)_{12}$	**0.125**	**0.481**	**750.794**	**769.865**	**153.599**
		$(110)x(110)_{12}$	0.178	0.864	949.033	960.475	324.352
		$(011)x(011)_{12}$	0.132	0.495	752.012	763.455	171.282
3	Nguru	SP1_1	0.332	0.873	-	-	-
		$(111)x(111)_{12}$	0.295	0.670	753.789	772.860	171.894
		$(110)x(110)_{12}$	0.333	0.907	912.474	923.916	288.396
		$(011)x(011)_{12}$	**0.289**	**0.631**	**760.154**	**771.596**	**130.835**
4	Potiskum	SP1_1	0.276	0.885	-	-	-
		$(111)x(111)_{12}$	0.252	0.576	798.742	817.813	177.748
		$(110)x(110)_{12}$	0.274	0.943	1029.408	1040.851	412.452
		$(011)x(011)_{12}$	**0.251**	**0.575**	**795.257**	**806.699**	**177.945**
5	Maiduguri	SP1_1	0.275	0.895	-	-	-
		$(111)x(111)_{12}$	**0.212**	**0.695**	**767.899**	**786.970**	**172.777**
		$(110)x(110)_{12}$	0.279	0.968	945.855	957.297	321.493
		$(011)x(011)_{12}$	0.239	0.693	771.312	782.454	180.994
6	Kano	SP1_1	0.512	0.958	-	-	-
		$(111)x(111)_{12}$	0.501	0.816	726.041	745.112	150.620
		$(110)x(110)_{12}$	0.510	0.987	857.550	868.992	246.408
		$(011)x(011)_{12}$	**0.505**	**0.807**	**727.253**	**738.695**	**98.408**
7	Gusau	SP1_1	0.516	1.024	-	-	-
		$(111)x(111)_{12}$	0.467	0.770	823.398	842.469	195.099
		$(110)x(110)_{12}$	0.503	1.070	987.165	998.607	362.589
		$(011)x(011)_{12}$	**0.468**	**0.769**	**820.589**	**832.041**	**176.131**

Source: Adeogun *et al.,* (2014b)

Selected Model Diagnostic Goodness of fit: The goodness of fit of models generated were compared to select the best models as highlighted in Table 2 for each station. For example, three out of all the models simulated for Sokoto Station SPI_1 were found suitable by the programme from which a model with the lowest fit measures (AIC =774.314, SBC =762.872) was selected, that is, $(0,1,1)x(0,1,1)_{12}$.

By entering the parameters p,,q,P,Q and s of the model $(110)x(110)_{12}$ for Sokoto Station into XLSTAT to simulate the station's SPI_1 for the study period, 1979 to 2008, that is 360 months, the graph in Figure 3 is obtained which shows that the model closely simulates the computed SPI_1 data. Model graphs for other stations, estimates of model parameters and residual plots were detailed in Adeogun (2014b).

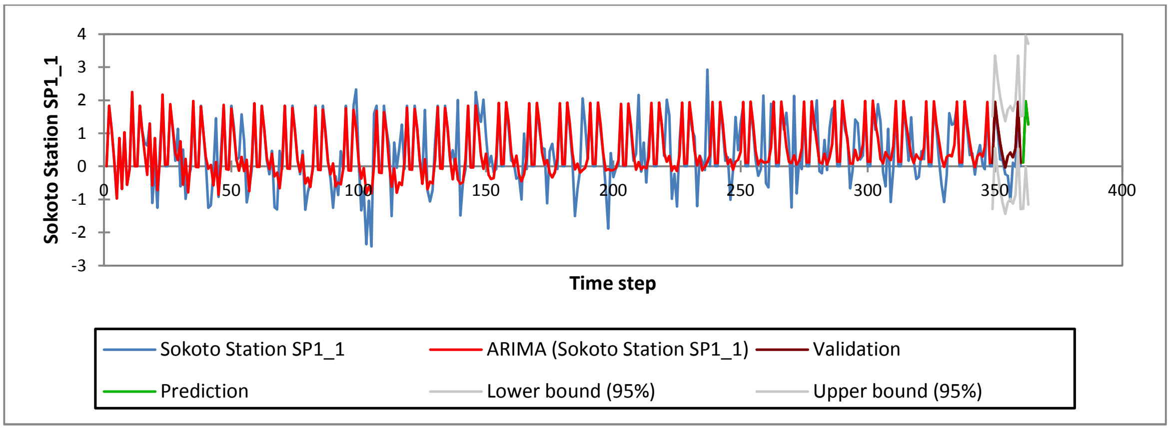


Figure 3: Simulation of computed Sokoto Station SPI_1 with forecasted SPI_1 using SARIMA $(0,1,1)x(0,1,1)_{12}$ (Source: Adeogun et al., 2014b)

The summary of the selected models for the stations were summarised in Table 3. As shown, the suitable SPI_1 model for drought forecast in Sokoto Station was $(110)x(110)_{12}$ while $(111)x(111)_{12}$ model was found suitable for Katsina and Maiduguri. Model $(011)x(011)_{12}$ was found suitable for drought forecast at Nguru, Potiskum, Kano and Gusau Station.

Table 3: Developed Drought Forecasting SPI_1 Models for NSSR Synoptic Stations

Stations	Sokoto	Katsina	Nguru	Potiskum	Maiduguri	Kano	Gusau
SPI_1 Models	$(110)x(110)_{12}$	$(111)x(111)_{12}$	$(011)x(011)_{12}$	$(011)x(011)_{12}$	$(111)x(111)_{12}$	$(011)x(011)_{12}$	$(011)x(011)_{12}$

The models were validated, and then used as drought warning tools to forecast drought in the Nigeria Sudano Sahelian Region in this study.

Model Validation and Forecasting

Tables 4 to 6 show the results of model validation for the selected SPI_1 models using available data. Table 4 – 6 reflected part of the computed SPI_1 and predicted SPI_1, from 357 to 360th months, of the study period. The predictive models were used to forecast SPI_1 three months into the future, that is, from 361st month to 363rd month and the results were as shown. The validation was done by comparing the computed SPI_1 (from observed precipitation) with the forecasted SPI_1 and the results showed fairly good agreement as presented for each of the stations in Tables 4 to 6.

Table 4: Validation of SARIMA Model for Sokoto Station SPI_1

Months	Computed SPI_1	Predicted SPI_1	Computed SPI_1 (for validation)	Forecasted SPI_1
357	0.110	0.602		
358	-0.010	0.543		
359	1.830	1.830		
360	0.000	0.000		
361			0.000	0.000
362			1.850	1.830
363			1.130	1.110

Table 5: Validation of SARIMA Model for Katsina Station SPI_1

Months	Computed SPI_1	Predicted SPI_1	Computed SPI_1 (for validation)	Forecasted SPI_1
357	-0.400	0.996		
358	0.280	0.218		
359	0.000	0.000		
360	0.000	0.000		
361			0.000	0.000
362			0.000	0.000
363			1.130	1.110

Table 6: Validation of SARIMA Model for Gusau Station SPI_1

Months	Computed SPI_1	Predicted SPI_1	Computed SPI_1 (for validation)	Forecasted SPI_1
357	0.040	-0.267		
358	0.760	-0.325		
359	1.500	1.500		
360	2.250	1.830		
361			0.000	0.000
362			1.520	1.500
363			0.990	0.970

Drought Forecasting and Severity

The models were used to forecast drought from one month to one year ahead and the results were presented in Fig. 4 to Fig. 10. The computed thirty years SPI_1 time series and SPI_1 forecast time series records were plotted with respect to months. The total number of months for the 30 years equals 360 months and the forecast for the following year starts from the 361st month to the 372nd month. The two data sets were similar in trend which means that the forecasts closely simulated the actual SPI_1 and for clarity the last three months of the study periods, from 358th to 360th month, were represented as shown in Fig. 4 to 10.

Using the threshold range for near normal condition as expressed by Equation 1, it is clear that the SPI_1 forecasts for the months or periods under the horizontal line set as the upper limit of the threshold range, 0.99, reflected drought emergence watch for each station as shown in Fig 4 to Fig 10. Fig 4, Fig 5 and Fig 7 reflected that there should be more vigilance at Sokoto, Katsina and Potiskum respectively, because there was indication of drought in the 372nd month at each of the stations while Fig. 6, Fig 8, Fig. 9 and Fig 10 reflected moderately wet conditions during the last month of forecast. Moderately dry condition for satisfying Equation 2 was not observed during the forecast but, there would be the need for continuous monitoring as explained before.

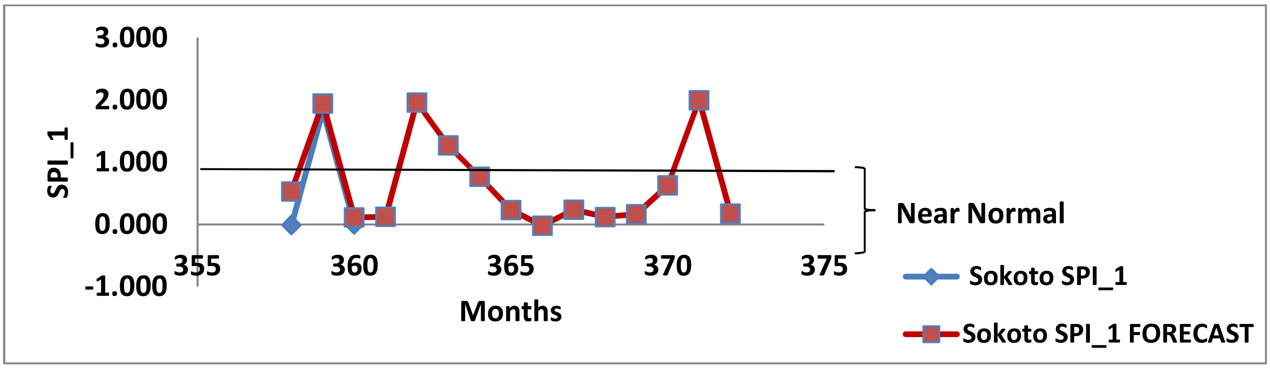


Fig 4: Twelve months forecast for Sokoto Station SPI_1

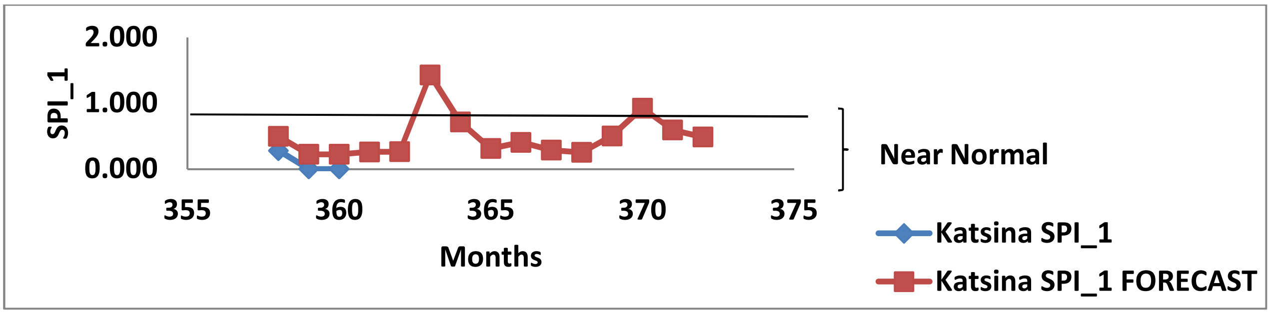


Fig 5: Twelve months forecast forKatsina Station SPI_1

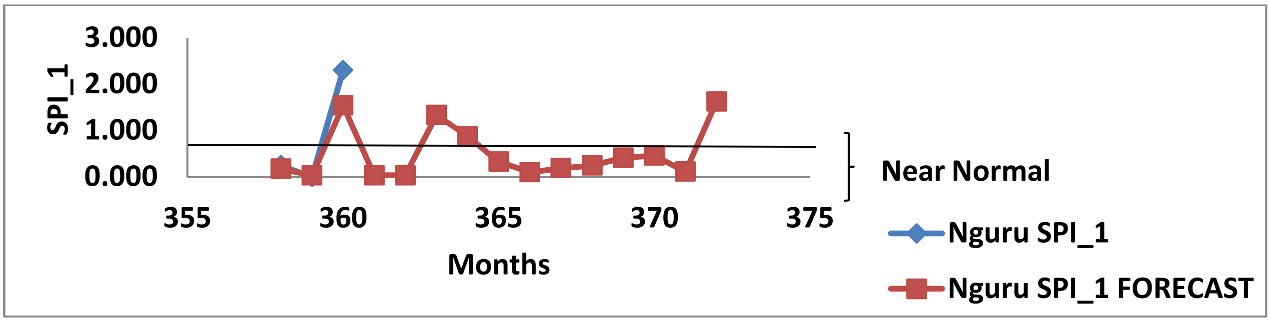


Fig 6: Twelve months forecast for Nguru Station SPI_1

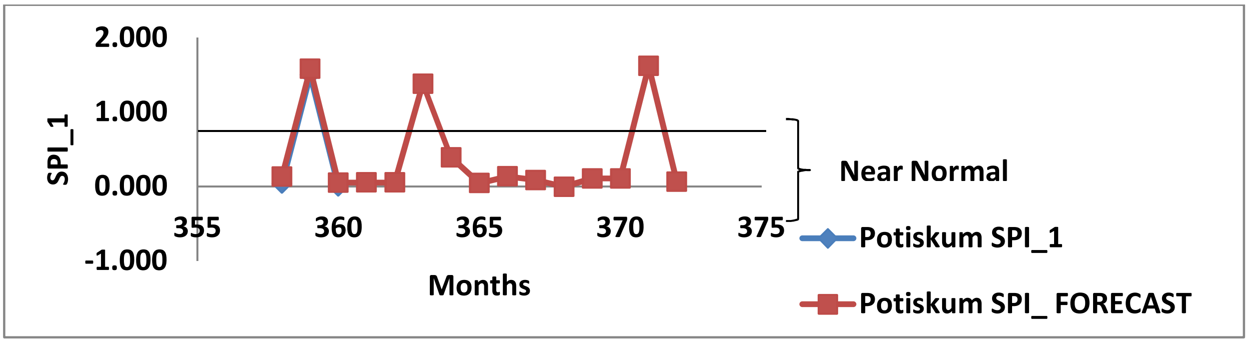


Fig 7: Twelve months forecast for Potiskum Station SPI_1

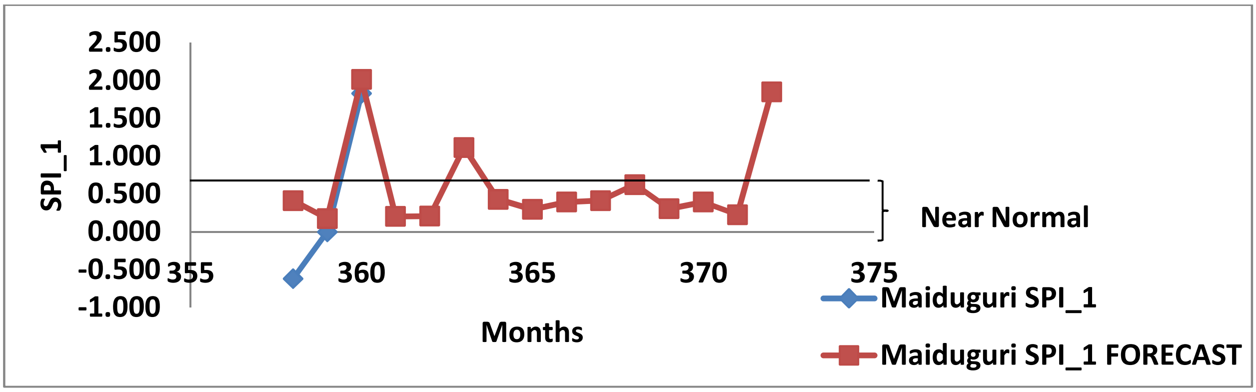


Fig 8: Twelve months forecast for Maiduguri Station SPI_1

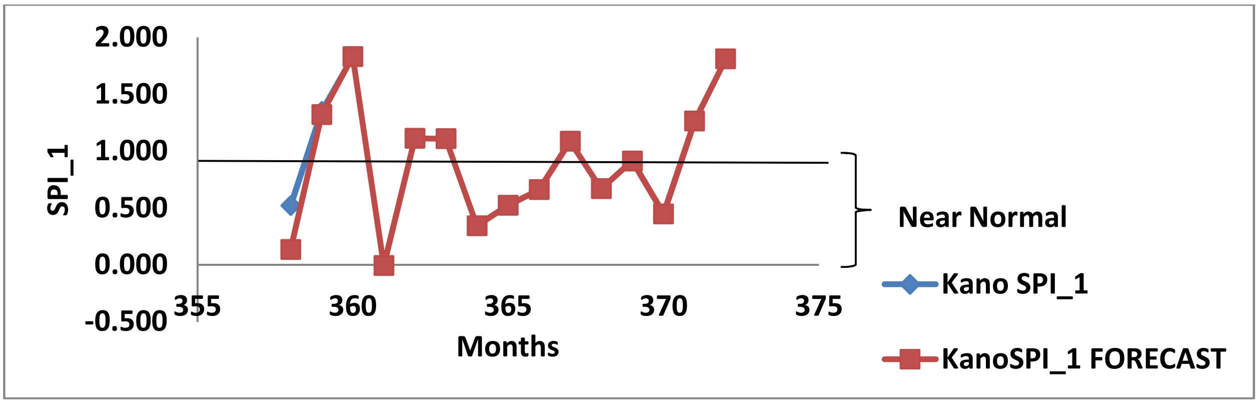


Fig 9: Twelve months forecast for Kano Station SPI_1

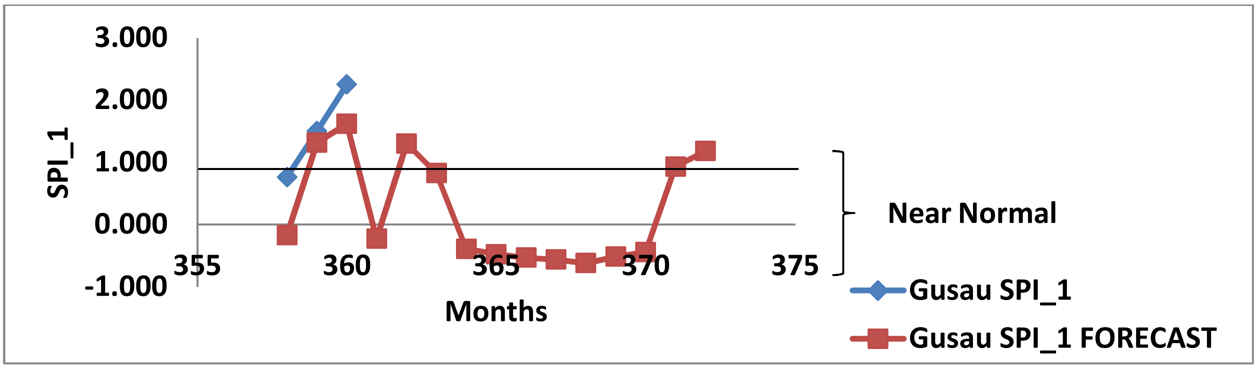


Fig 10: Twelve months forecast for Gusau Station SPI_ 1

CONCLUSION AND RECOMMENDATIONS

This study applied developed SPI_1 models to forecast droughts on monthly bases for Nigerian Sudano Sahelian Region. The models were validated using available data. Drought emergence was observed during the study and this implied that there should be continuous monitoring using the models. Drought warning alert could be declared as soon as the near normal drought situation became worse.

It is recommended that the models should be used to forecast droughts ahead for a period of one month to one year. Also, the simple predictive models should be developed for other less developed regions.

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