RESEARCH ARTICLE

Forecast of Drought Using Statistical Approach for Erode District

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ABSTRACT

Drought plays a crucial role in agriculture, especially in farming and has a significant impact on the environment. The present study focuses on the forecast of drought using one of the hybrid artificial neural network namely the Adaptive Neuro-Fuzzy Inference System (ANFIS). For this study, 39 years of monthly precipitation value of Erode district are used. Firstly, using monthly precipitation values, Standard Precipitation Index (SPI) values are computed at three monthly scale since Erode district mainly depends on North-East Monsoon. Secondly, with computed SPI value and mean precipitation value of North-East Monsoon season, different ANFIS forecasting models are constructed with its precursory time period. Further, the outcome of the anticipated ANFIS model and observed values were collated using Root Mean Square Error and Mean Absolute Error values. The model with minimal RMSE value was termed as the best fit model.

Keywords: *Drought Forecasting; SPI; ANFIS; RMSE; MAE*

INTRODUCTION

Drought is a period with an uncommon difference in the precipitation rate for a protracted time. It is challenging to get through because it is the least accurate and predictable compared to all other natural calamities. It is usually categorized at different stages based on the intensification in the hydrological cycle; among them, agricultural drought is a condition where there will be a deficit in the soil moisture which will lead to a tremendous reduction in agricultural production. (Mishra and Desai, 2005, 2006; Mishra *et al.*, 2007). In this impact, it is necessary to properly quantify and assess drought in the prone areas. The most successful prediction will mitigate the harmful consequences. Thus forecast of drought plays a vital role in indicating of further happening well advance. (Morid *et al*.,2007).

Many researchers have compared Standardized Precipitation Index (SPI)with various indexes and verified that SPI is one of the best methods to monitor the drought. Tirivarombo *et al.,* (2018) compared the SPI and standardized precipitation evapotranspiration index (SPEI) for the drought analysis, they concluded that SPI seems to be more accurate in the case of temperature missing data. Tsakiris and Vangelis (2004) compared SPI with Palmer Drought Severity Index (PDSI) and concluded that SPI was the best method for assessing drought, employing easy interpretation and a simple structure. For forecasting drought, several linear and non-linear methods were developed. Among them, in recent times, the best model being used is the adaptive neuro-fuzzy inference system (ANFIS) which has been an overcoming method for the traditional methods. Shirmohammadi *et al*. 2013 compared artificial neural networks, ANFIS, and support vector machines. Nguyen *et al*. (2015) used SPI values for monitoring and forecasted using Fuzzy logic and ANFIS. and reported that the latter shows the best model even for the long and short-term time scales. In this study, the main aim is to assess the drought using the SPI value for the Erode district of Tamilnadu. Further, identify the best input variables combination using precursor rainfall and SPI value to get a clear-cut and precise outcome for drought forecasting. The best-fitted models will be identified using statistical criteria among the forecasted models.

MATERIAL AND METHODS

Study Location and Data Description

Study area suite

For this study, Erode was taken as the study area. It lies between 10° 36” and 11° 58” North Latitude and between 76° 49” and 77° 58” East Longitude with an elevation of 171.91m above sea level. This area comes under the western zone of Tamilnadu. The average rainfall of Erode from 1981 through 2019 was 52.22mm. Erode district was mainly relying on North-East monsoon (NEM) rainfall which occurs during October, November, and December. The mean rainfall of the period 1981-2019 was 106.45mm.

Data Description

The secondary data of this study was collected from the Agro Climatic Research Centre, Tamilnadu Agricultural University, Coimbatore. Monthly precipitation data were obtained from January 1981 to December 2019 over 39 years.

Methodology

Standardised Precipitation Index(SPI)

McKee *et al*. (1993) introduced this index for assessing drought, which can be acquired by dividing the difference-between the rainfall data and its mean to the standard deviation. It is used for analyzing and assessing the occurrence of drought over a long period. The value obtained from this calculation takes the range of values including the positive and negative value in which a positive value indicates the wet period and a negative value indicates the drought period. This index can be calculated for different time scales like 1, 3, 4,6,12 and 24 months. Different time scales include the different terms of the drought condition. SPI for 1, 3, 4-month time scale indicates the agricultural drought since it relies on short-term duration. SPI for the 6-month scale indicates the meteorological drought. SPI-12 and 24 months imply the hydrological drought since it relies on long-term duration. The SPI categories based on the value are given in Table 1.

SPI is based on the mathematical derivation which is calculated from the cumulative probability of observed rainfall and it has been manifested that it comes under gamma distribution (Thom 1958). This study calculated SPI on the command prompt SPI_SL_6.exe file and the R studio under the 1.4.1717 version. In both the computation process the results obtained are the same.

Adaptive Neuro-Fuzzy Inference System (ANFIS)

Jang *et al*. 1997 was the first person to propose the ANFIS model which is one of the hybrid algorithms (i.e.) a combination of Artificial Neural Network (ANN) and Fuzzy Logic (FL) in a single algorithm. This method is one of the non-linear methods for modeling which covers the benefits and training accuracy of the above two methods and also overcome the drawback of fuzzy logic. Generally, the fuzzy inference system (FIS) consists of two types: Sugeno- Takagi FIS and Mamdani FIS. Mostly in drought forecasting, Sugeno-Takagi FIS is used. Sugeno- Takagi fuzzy inference system is based on IF-THEN rules. In simple, the obtained output of every single rule can be narrated as the direct fusion of all the input variables together with a constant term. Let us presume Sugeno-Takagi type of ANFIS model with two fuzzy as done by Patel and Parekh (2014)

Rule 1: If a1 is X1 and a2 is Y1, then

$$u1 = x1\, a1 + y1\, a2 + z1 \tag{1}$$

Rule 2: If a1 is X2 and a2 is Y2, then

$$u2 = x2\, a1 + y2\, a2 + z2 \tag{2}$$

in (Eqn. 1 & 2) where x1, x2 and y1, y2 are the input variable for the membership function of a and b; u1, u2 are the output parameter function.

The ANFIS architecture contains five-layer namely (Figure 1),

- The first layer is termed as fuzzification layer or fuzzy layer in which every node in this layer identifies the membership function of the input function using fuzzy.
- The second layer is termed the product layer or the rule base layer, here it multiplies its input signal.
- The third layer is named as normalization layer, where normalization of the product layer is done.
- The fourth layer is framed as the defuzzification layer, in which each node becomes an adaptive node so that it proceeds towards the final output layer
- The fifth layer is the output layer which includes the output node that is obtained by the total of all the output of the four layers.

Further details and mathematical derivation for this hybrid algorithm can be obtained from Jang *et al*. (1997), Nayak *et al*. (2004), and Bacanli *et al.* (2008).

In this study, the ANFIS modeling is done in the software MATLAB version R2021a. For the analysis of the data, the total dataset is divided into two subsets, namely Training data and testing data at the percentage of 80 and 20. For the model building with the ANFIS method, the Sugeno-Takagi type of fuzzy inference system is used with 100 epochs size.

Statistical analysis

Further to test the performance of the different models built, the statistical norms used are root mean square error (RMSE), mean absolute error (MAE), and Coefficient of determination (R^2). The model with low RMSE, MAE value, and high R2value are determined as the best-fitted model.

RESULT AND DISCUSSION

Standardized Precipitation Index (SPI)

SPI is calculated at the 3-month scale as an indication of the North-East Monsoon which Erode district abundantly relies upon. A moderate drought occurred once, a severe drought occurred twice and an extreme drought occurred twice from 1981 to 2019. The following table shows the classes of drought from the year 1981-2019 categorized based on the SPI scale.

From table 2, it can be concluded that from 1981 to 2019, the years 1988, 2002, 2009, 2012, 2016 fall under the drought condition.

Figure 2 indicates the schematic view of the SPI-3 month scale from the year 1981 to 2019 obtained from the R studio software. The x-axis label indicates the year from 1981 through 2019 in which 0-10 indicates the year 1981-1990, 10-20 indicates the year 1990-2000, 20- 30 indicates the year 2000-2010, 30-40 indicates the year 2010-2019. From this graph, it can be explained that the blue the condition of near normal to wet period, the red colour indicates the condition of near normal to dry period (i.e. drought condition).

Adaptive Neuro-Fuzzy Inference System (ANFIS)

In ANFIS, the forecasting models are built based on the study done by Bacanli *et al.* (2008). Concerning Bacanli *et al.* (2008) study, the forecasting model for the Erode district is built with input parameter as the series of antecedent rainfall values, SPI values, and the combination of rainfall and SPI values and the output parameter as corresponding year SPI values.

For forecasting drought, the whole datasets are divided into training and testing data with the allocation of 80% and 20% shown in Table 4.

From figure 3, it can be concluded visually that model 4,5,6,10,11,12,15,16,17,18,19,20 seems to be quite accurate compared to the observed values with the predicted values, and model 3 shows much variation in the prediction. In particular, the model with only SPI values and only rainfall values shows the reliable result after the inclusion of t-4 precursor value while in the combination of both SPI and rainfall values they show genuine results after including an equal number of those precursor values.

To get an accurate best-fitted model among these different models, further statistical analysis is done. To check the goodness-of-fit, Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Coefficient of determination (R2) are calculated.

From table 4 and figure 4, it can be concluded that Model 20 has the lowest RMSE, MAE, and highest R square values of 0.5616, 0.1906, and 0.746, indicating the best-fitted model among those twenty different forecasting models. Model 6 has the second-lowest RMSE, MAE (i.e.) 0.58, 0.19, and second-highest R2 value (i.e.) 0.73 which shows the second-best fitted model and it is the best-fitted model among the models with only SPI precursor values as an input combination. Among considering only rainfall precursor values as an input combination, model 12 shows the best-fitted model with 0.71 as RMSE value, 0.26 as MAE value, and 0.59 as R2 value.

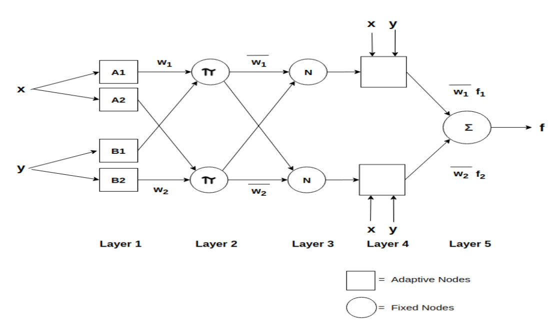


Figure 1. Simplified architectural view of ANFIS structure

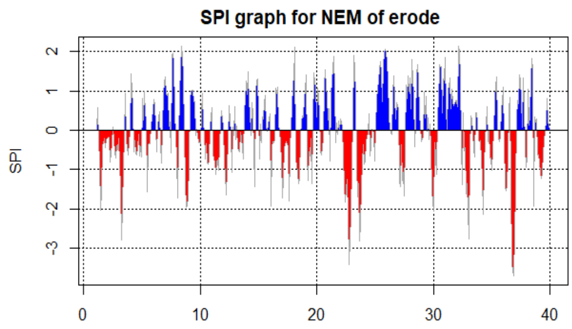


Figure 2. SPI-3 pattern values from 1981-2019 for the district of Erode

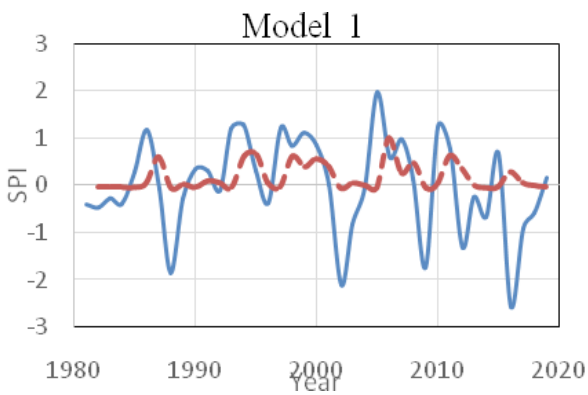


Figure 3a

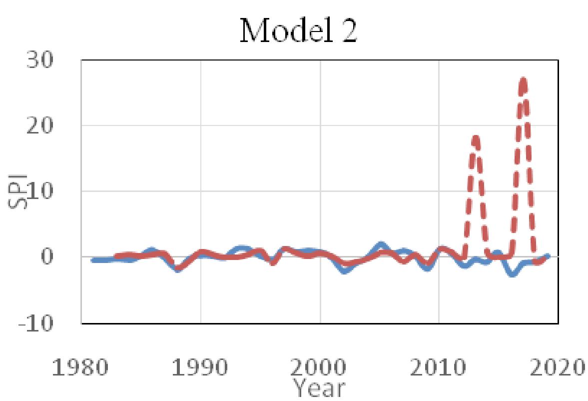


Figure 3b

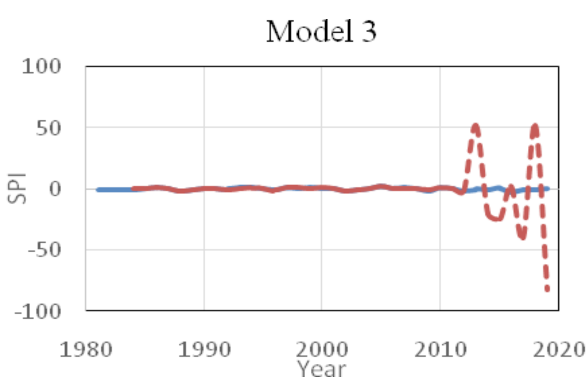
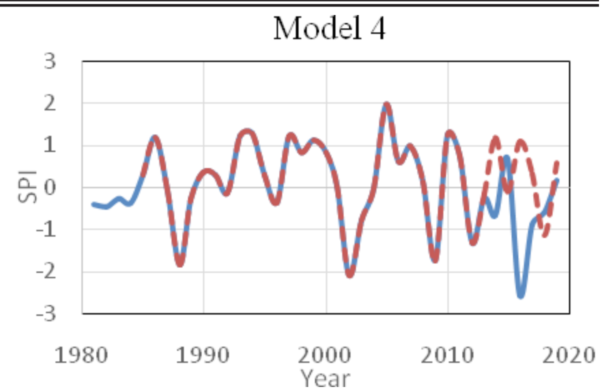


Figure 3c



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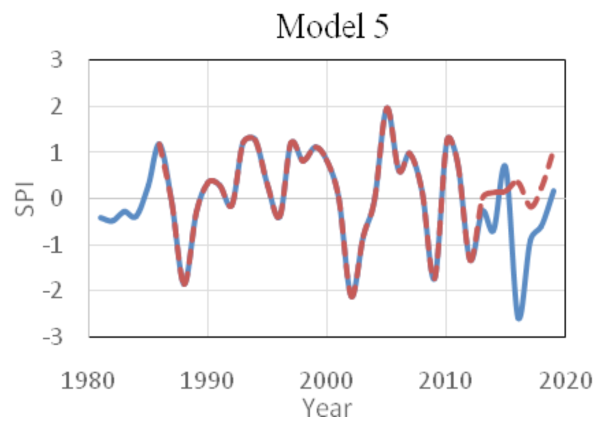

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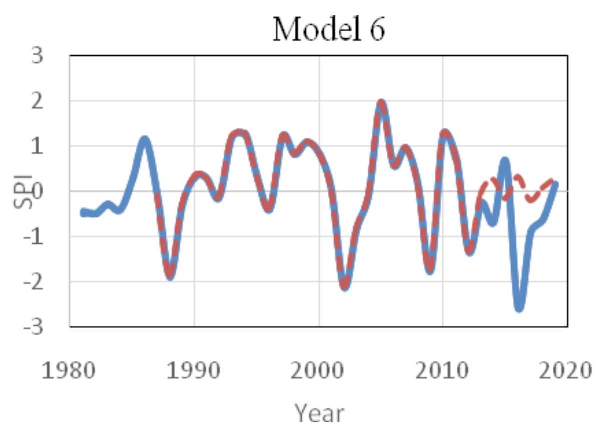

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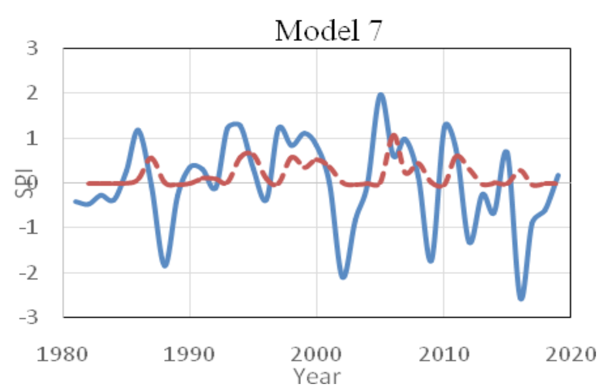
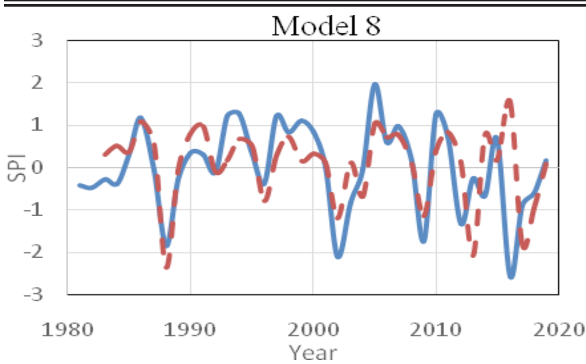


Figure 3g



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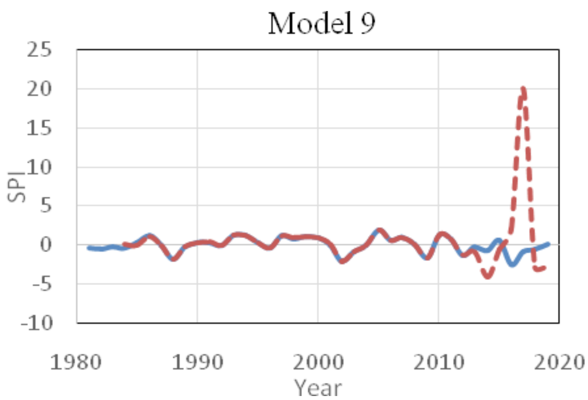


Figure 3i

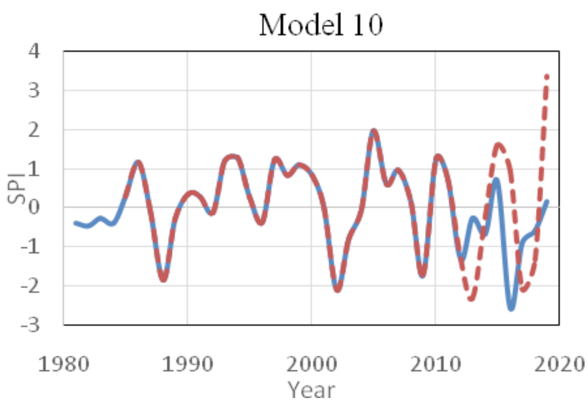
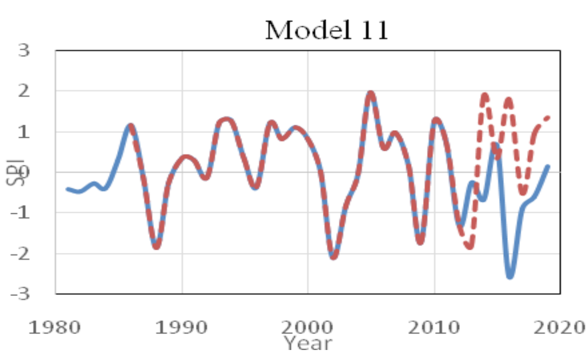


Figure 3j



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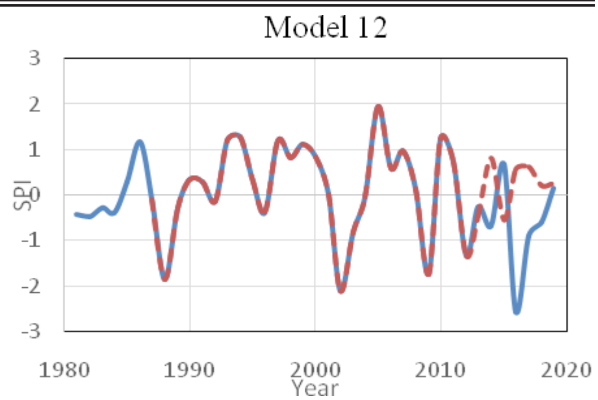

Figure 3l

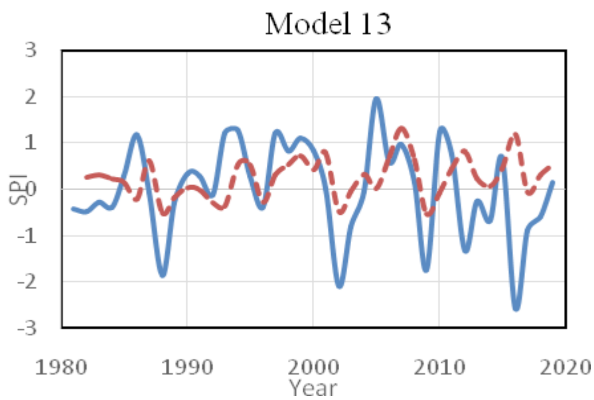

Figure 3m

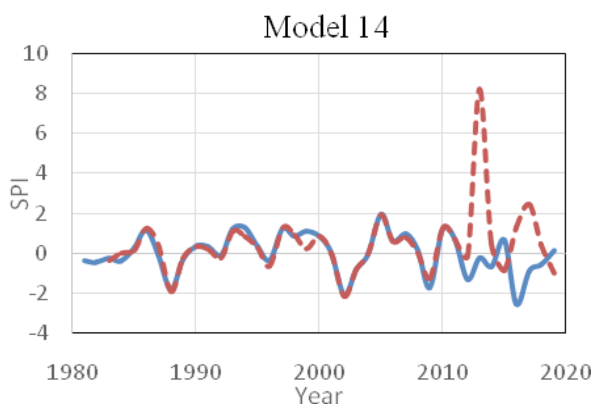

Figure 3n

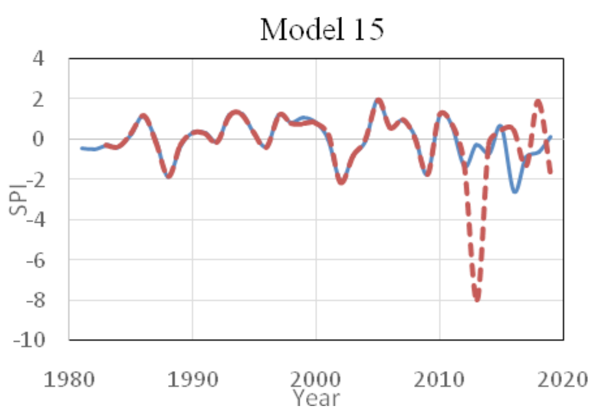

Figure 3o

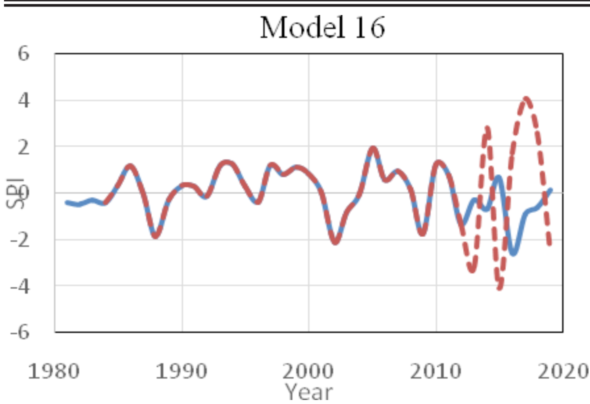

Figure 3p

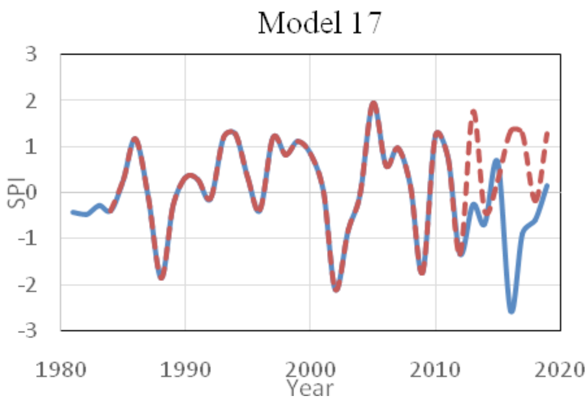

Figure 3q

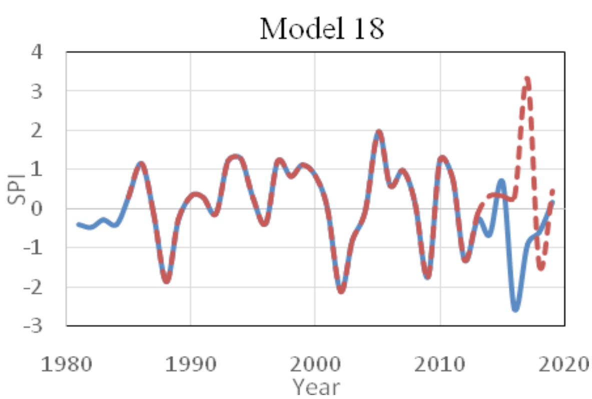

Figure 3r

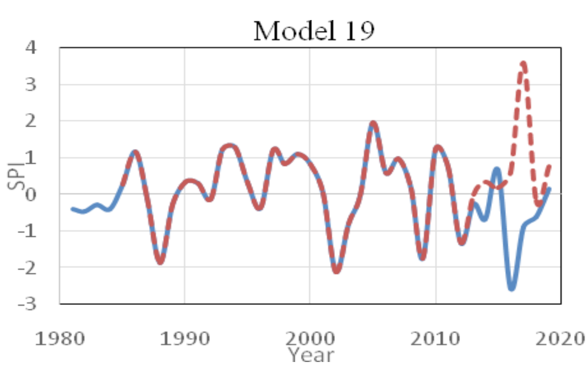

Figure 3s

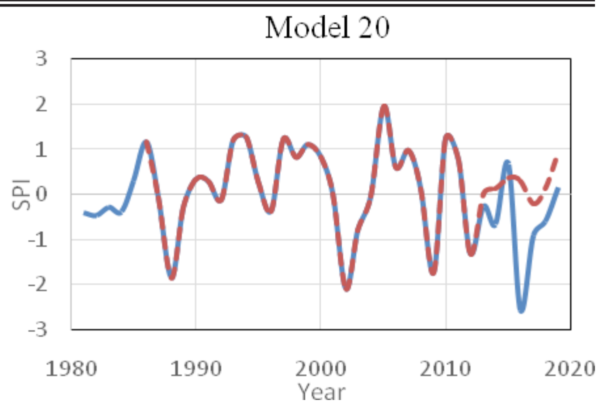

Figure 3t

Figure 3. Graphical representation for the comparison of observed SPI values and Predicted ANFIS model for a different model

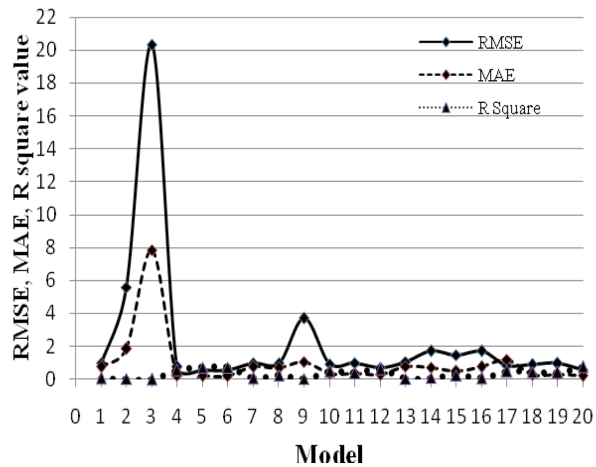

Figure 4. Graphical representation of Statistical Criteria values for all the forecasted model

Table 1. Different Categories based on the SPI values

SPI	Different Category
2.00 ≥ SPI	Extremely Wet
Between 1.99 and 1.50	Very wet
Between 1.49 and 1.00	Moderately wet
Between 0.99 and -0.99	Near Normal
Between -1.00 and -1.49	Moderately dry
Between -1.50 and -1.99	Severely dry
-2.00 ≤ SPI	Extremely dry

Table 2. The drought category for Erode district from 1981 to 2019

	Classes of Drought for NEM						
	Moderate	Severe	Extreme	Normal			Wet
Years based on their SPI categories	2012	1988	2002	1981	1992	2007	1986
		2009	2016	1982	1995	2008	1993
				1983	1996	2011	1994
				1984	1998	2013	1997
				1985	2000	2014	1999
				1987	2001	2015	2005
				1989	2003	2017	2010
				1990	2004	2018	
				1991	2006	2019	

Table 3. Number of training and testing datasets used for forecasting models

S/N	Model Number	Total Number of data used	Number of the training dataset (~80%)	Number of the testing dataset (~20%)
1	M1, M7,M13	38	30	8
2	M2,M8,M14,M15	37	30	7
3	M3,M9,M16,M17	36	29	7
4	M4,M10,M18,M19	35	28	7
5	M5,M11,M20	34	27	7
6	M6,M12	33	26	7

Table 4. Calculated RMSE, MAE and R square value

Model	RMSE	MAE	R2
1	1.00	0.76	0.06
2	5.57	1.84	0.01
3	20.32	7.84	0.00
4	0.74	0.25	0.55
5	0.58	0.21	0.72
6	0.58	0.19	0.73
7	0.99	0.76	0.06
8	0.99	0.68	0.23
9	3.70	1.05	0.01
10	0.93	0.35	0.48
11	0.97	0.35	0.38
12	0.71	0.26	0.59
13	1.06	0.78	0.03
14	1.70	0.71	0.08
15	1.47	0.47	0.23
16	1.70	0.73	0.07
17	0.85	1.19	0.47
18	0.89	0.28	0.45
19	0.96	0.30	0.39
20	0.56	0.19	0.75

CONCLUSION

In this research paper, SPI is used as drought indices for assessing drought for the Erode district since it was one of the recommended methods by the World Meteorological Organization as it requires only precipitation data for monitoring drought. From SPI values, the drought was assessed from 1981 to 2019. From the obtained values, the forecasting models were built. The twenty ANFIS forecasting models were built among these M20 show better performance which was antecedent values of both SPI values and rainfall. Model 6 shows better performance, using only antecedent SPI values where up to (t-6) were used. The best-fitted models are identified using statistical criteria. As model 20 proved as the best model, it can be used to predict future drought years. Further, this study can be utilized to forecast drought in the various districts.

Ethics statement

No specific permits were required for the described field studies because no human or animal subjects were involved in this research.

Originality and plagiarism

Authors should ensure that they have written and submit only entirely original works, and if they have used the work and/or words of others, that this has been appropriately cited. Plagiarism in all its forms constitutes unethical publishing behavior and is unacceptable.

Consent for publication

All the authors agreed to publish the content.

Competing interests

There were no conflict of interest in the publication of this content

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