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Assessment and forecasting of agricultural drought for the district of Tiruppur

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Abstract
Drought is a key factor in agriculture, particularly in farming, as well as having a significant environmental impact. In this aspect, the focus of this research is on drought forecasting utilising the Adaptive Neuro-Fuzzy Inference System (ANFIS), a hybrid artificial neural network. The Tiruppur district's monthly precipitation data for the past 39 years was used in this study as this district is mostly dependent on the North-East Monsoon. SPI values are calculated on a three-month scale using monthly precipitation measurements. Secondly, different ANFIS forecasting models are created with their precursory period using the computed SPI value and mean precipitation value of the North-East Monsoon season. Furthermore, the RMSE, MAE, and coefficient of determination (R^2) values were used to compare predicted values with actual values. The best fit model was defined as one with the lowest RMSE, MAE, and high R^2 values.

Keywords: Drought forecasting, SPI, ANFIS, RMSE, MAE, R^2

1. Introduction

Drought is a condition in which the precipitation rate is unusually low for an extended period of time. It is extremely difficult to navigate since, in comparison to all other natural disasters, it is the least reliable predictor. It is generally divided into stages based on the degree to which the hydrological cycle has become more intense. Drought in agriculture is a state in which there is a lack of moisture in the soil, resulting in a significant decrease in agricultural output. (Mishra and Desai, 2005, 2006; Mishra *et al*., 2007) [10, 11, 12]. In order to mitigate this damage, a comprehensive quantification and assessment of drought in drought-prone areas are required. The most accurate prognosis will lessen the negative effects. As a result, drought forecasting is critical in predicting what will happen next. (Morid *et al*., 2007) [14].

Many studies have compared the Standardized Precipitation Index (SPI) to other indices and found that it is one of the most effective ways to track the drought. Tirivarombo *et al*., (2018) [21] evaluated the SPI with the standardized precipitation evapotranspiration index (SPEI) for drought analysis and found that the SPI is more accurate in the situation of lacking temperature data. Tsakiris and Vangelis (2004) [22] compared the SPI to the Palmer Drought Severity Index (PDSI) and determined that the SPI was the best technique for assessing drought severity because it is easy to comprehend and has a basic structure. Several linear and non-linear techniques for drought forecasting have been developed. The adaptive neuro-fuzzy inference system (ANFIS), which has been a breakthrough approach for traditional methods in recent years, is the best model being utilised among them. Artificial neural networks, ANFIS, and support vector machines were compared by Shirmohammadi *et al*. in 2013 [19]. Nguyen *et al*. (2015) [16] employed SPI values for monitoring and forecasting with Fuzzy logic and ANFIS, finding that the latter is the best model for both long and short term time scales. The major goal of this study is to measure the drought in the Erode region of Tamil Nadu using the SPI value. To achieve a clear and exact result for drought forecasting, choose the optimal input variable combination utilising antecedent rainfall and SPI value. The best-fitting models among the predicted models will be found using statistical criteria.

2. Materials and Methodology

2.1 Study Location and Data Description

2.1.1 Study area suite

Tiruppur was chosen as the research site for this study. With an elevation of 305 metres above sea level, it is located at 11º11" North Latitude and 77º34" East Longitude. This region is located in Tamil Nadu's western zone.

Tiruppur received 54.34 mm of rain on average from 1981 to 2019. Coimbatore district relied heavily on rainfall from the North-East monsoon (NEM), which occurs in October, November, and December. From 1981 to 2019, the average rainfall for those months was 108.3mm.

2.1.2 Data Description
Secondary data from the Agro Climatic Research Centre, Tamil Nadu Agricultural University, Coimbatore, was used in this study. Monthly precipitation data was collected for 39 years, from January 1981 to December 2019.

2.2 Methodology
2.2.1 Standardised Precipitation Index (SPI)
McKee *et al.* (1993) [9] developed this drought indicator, which is calculated by dividing the difference between the rainfall data and its mean by the standard deviation. It's used to investigate and analyse the incidence of drought throughout time. The range of values derived from this computation encompasses positive and negative values, with positive values indicating rainy periods and negative values indicating dry periods. This index may be calculated on a variety of periods, including 1, 3, 4, 6, 12, 24 month. The different parameters of the drought state are included in different time periods. Because it is based on short-term duration, SPI for 1, 3, and 4-month time scales implies agricultural drought. The meteorological drought is shown by the SPI on a 6-month scale. Because it relies on long-term duration, SPI-12 and 24 months suggest a hydrological drought. Table 1 indicates the drought category.
SPI is based on a mathematical calculation derived from the cumulative likelihood of recorded rainfall, and it has been shown to fall within the gamma distribution (Thom 1958) [20]. SPI computed using the command prompt SPI SL 6.exe file and R studio version 1.4.1717 in this research. The results generated from both calculation processes are identical.

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

2.2.2 Adaptive Neuro-Fuzzy Inference System (ANFIS)
Jang *et al.* posited the ANFIS model in 1997 [5], which is one of the hybrid algorithms (i.e., a mix of Artificial Neural Network (ANN) and Fuzzy Logic (FL) in a single algorithm). This approach is one of the non-linear modelling methods that combine the advantages and training accuracy of the previous two methods while avoiding the drawbacks of fuzzy logic. Sugeno - Takagi FIS and Mamdani FIS are the two most common forms of fuzzy inference system (FIS). Sugeno-Takagi FIS is mostly used in drought forecasting. The IF-THEN rules underpin the Sugeno- Takagi fuzzy inference system. Simply, the output of each rule may be described as the direct fusion of all of the input variables plus a constant term. Assume a Sugeno-Takagi type ANFIS model with two fuzzy as like Patel and Parekh (2014) [17].
Rule 1: If a_1 is X_1 and a_2 is Y_1, then

$$u_1 = x_1 a_1 + y_1 a_2 + z_1$$

Rule 2: If a_1 is X_2 and a_2 is Y_2, then

$$u_2 = x_2 a_1 + y_2 a_2 + z_2$$

Where x_1, x_2 and y_1, y_2 are the input variable for the membership function of a and b; u_1, u_2 are the output parameter function.

The ANFIS architecture is made up of five layers:
- The first layer is known as the fuzzification layer or fuzzy layer, and each node in this layer uses fuzzy rules to identify the membership function of the input function.
- The product layer, also known as the rule base layer, multiplies the input signal in the second layer.
- The normalisation layer is the third layer, and it is here that the product layer is normalised.

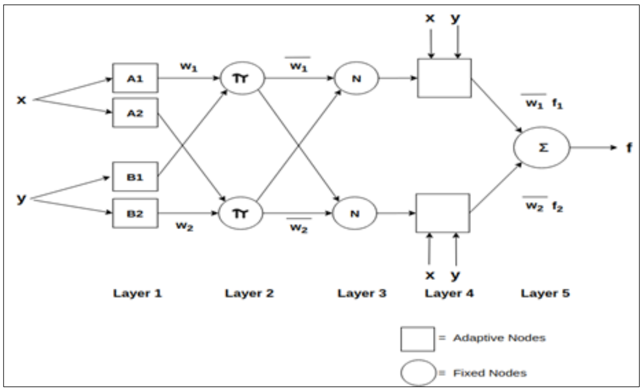


Fig 1: Simplified architectural view of ANFIS structure

- The defuzzification layer is the fourth layer, in which each node becomes an adaptive node and progresses to the final output layer.
- The output layer is the fifth layer, and it contains the output node that is generated by adding all of the outputs from the previous four levels.

Jang *et al.* (1997) [5], Nayak *et al.* (2004) [15], and Bacanli *et al.* (2004) provide further information and mathematical derivation for this hybrid method (2008).
The ANFIS modelling in this work is done with the programme MATLAB version R2021a. The whole dataset is split into three subsets for data analysis, namely training data, testing data, and validation data, with percentages of 80, 10 and 10 respectively. The Sugeno-Takagi kind of fuzzy inference system is utilised for model development with the ANFIS approach.

2.2.3 Analytical statistics
The statistical standards used to assess the performance of the various models constructed are root mean square error (RMSE), mean absolute error (MAE), and coefficient of determination (R^2). The model with the lowest RMSE, MAE, and high R^2 value is considered to be the best-fitted.

3. Result and discussion
3.1 Standardised Precipitation Index (SPI)
SPI is estimated on a three-month period as an indicator of the North-East Monsoon, on which Tiruppur relies heavily. A moderate drought occurred once, a severe drought occurred once and the extreme drought occurred once from 1981 to 2019. The following table shows the classes of drought from the year 1981-2019 categorised based on the SPI scale.

Table 2: The drought category for Tiruppur district from 1981 to 2019

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

From table 2, it can be concluded that from 1981 to 2019, the years 1985, 1988, 1991 falls under the drought condition.

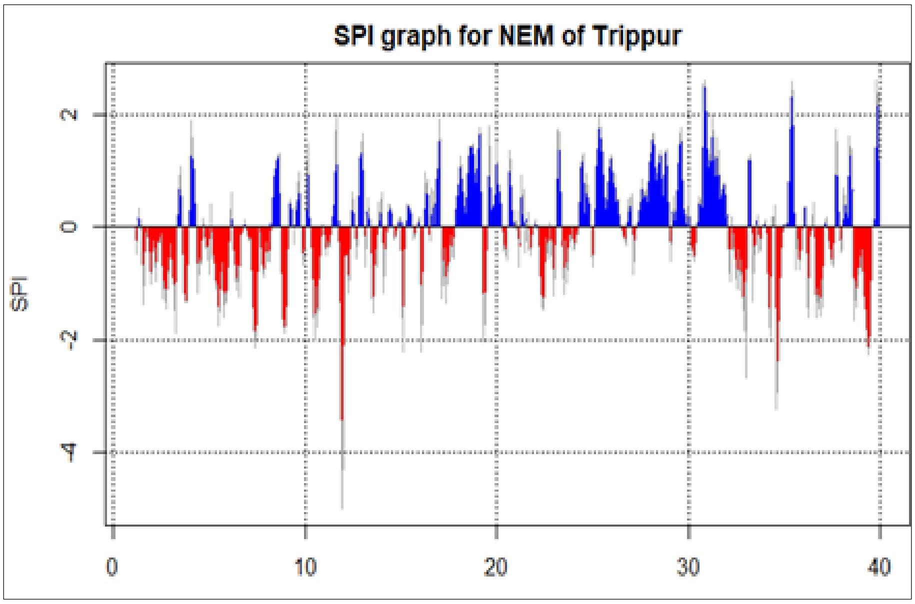


Fig 2: SPI-3 pattern values from 1981-2019 for the district of Tiruppur

The schematic representation of the SPI-3 month scale from 1981 to 2019 generated using the R studio programme is shown in Figure 2. The x-axis label shows the year from 1981 to 2019, with 0-10 representing 1981-1990, 10-20 representing 1990-2000, 20-30 representing 2000-2010, and 30-40 representing 2010-2019. The blue colour indicated the condition of near normal to wet period, and the red colour indicated the condition of near normal to dry period, according to this graph (i.e. drought condition).

3.2 Adaptive Neuro-Fuzzy Inference System (ANFIS)

The forecasting models of ANFIS are built are based on the study by Bacanli *et al.* (2008) [2]. The input parameters for the forecasting model for the Tiruppur district are a series of antecedent rainfall values, SPI values, and a combination of both rainfall and SPI values, with the output parameter being the corresponding year SPI values. In this study, models are created by increasing the number of antecedent values as the input variable, which is similar to Bacanli *et al.* (2008) [2].

Table 3: Different input combinations used for the ANFIS forecasting model

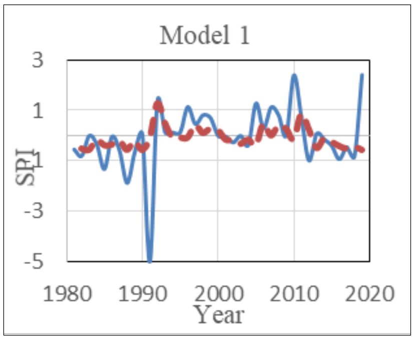
Model	Input Combination	Output
M1	SPI(t-1)	SPI(t)
M2	SPI(t-1),SPI(t-2)	SPI(t)
M3	SPI(t-1),SPI(t-2),SPI(t-3)	SPI(t)
M4	SPI(t-1),SPI(t-2),SPI(t-3),SPI(t-4)	SPI(t)
M5	SPI(t-1),SPI(t-2),SPI(t-3),SPI(t-4),SPI(t-5)	SPI(t)
M6	SPI(t-1),SPI(t-2),SPI(t-3),SPI(t-4),SPI(t-5),SPI(t-6)	SPI(t)
M7	SPI(t-1),SPI(t-2),SPI(t-3),SPI(t-4),SPI(t-5),SPI(t-6),SPI(t-7)	SPI(t)
M8	SPI(t-1),SPI(t-2),SPI(t-3),SPI(t-4),SPI(t-5),SPI(t-6),SPI(t-7),SPI(t-8)	SPI(t)
M9	SPI(t-1),SPI(t-2),SPI(t-3),SPI(t-4),SPI(t-5),SPI(t-6),SPI(t-7),SPI(t-8),SPI(t-9)	SPI(t)

M10	R(t-1)	SPI(t)
M11	R(t-1),R(t-2)	SPI(t)
M12	R(t-1),R(t-2),R(t-3)	SPI(t)
M13	R(t-1),R(t-2),R(t-3),R(t-4)	SPI(t)
M14	R(t-1),R(t-2),R(t-3),R(t-4),R(t-5)	SPI(t)
M15	R(t-1),R(t-2),R(t-3),R(t-4),R(t-5),R(t-6)	SPI(t)
M16	R(t-1),R(t-2),R(t-3),R(t-4),R(t-5),R(t-6),R(t-7)	SPI(t)
M17	R(t-1),R(t-2),R(t-3),R(t-4),R(t-5),R(t-6),R(t-7),R(t-8)	SPI(t)
M18	R(t-1),R(t-2),R(t-3),R(t-4),R(t-5),R(t-6),R(t-7),R(t-8),R(t-9)	SPI(t)
M19	SPI(t-1),R(t-1)	SPI(t)
M20	SPI(t-1),SPI(t-2),R(t-1)	SPI(t)
M21	SPI(t-1),SPI(t-2),R(t-1),R(t-2)	SPI(t)
M22	SPI(t-1),SPI(t-2),SPI(t-3),R(t-1)	SPI(t)
M23	SPI(t-1),SPI(t-2),SPI(t-3),R(t-1),R(t-2)	SPI(t)
M24	SPI(t-1),SPI(t-2),SPI(t-3),R(t-1),R(t-2),R(t-3)	SPI(t)
M25	SPI(t-1),SPI(t-2),SPI(t-3),SPI(t-4),R(t-1)	SPI(t)
M26	SPI(t-1),SPI(t-2),SPI(t-3),SPI(t-4),R(t-1),R(t-2)	SPI(t)
M27	SPI(t-1),SPI(t-2),SPI(t-3),SPI(t-4),R(t-1),R(t-2),R(t-3)	SPI(t)
M28	SPI(t-1),SPI(t-2),SPI(t-3),SPI(t-4),SPI(t-5),R(t-1)	SPI(t)
M29	SPI(t-1),SPI(t-2),SPI(t-3),SPI(t-4),SPI(t-5),R(t-1),R(t-2)	SPI(t)

The entire datasets are separated into training, testing, and validation data for drought forecasting, with allocations of 80%, 10%, and 10% respectively.

Table 4: 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 (~10%)	Number of the validation dataset (~10%)
1	M1, M10, M19	38	30	4	4
2	M2, M11, M20, M21	37	30	4	3
3	M3, M12, M22, M23, M24	36	29	4	3
4	M4, M13, M25, M26, M27	35	28	4	3
5	M5, M14, M28, M29	34	27	4	3
6	M6, M15	33	26	4	3
7	M7, M16	32	26	3	3
8	M8, M17	31	25	3	3
9	M9, M18	30	24	3	3



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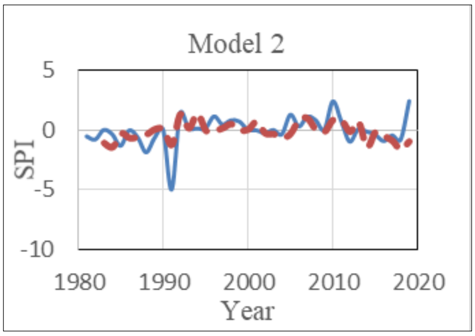

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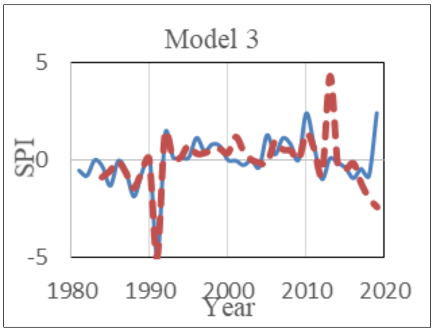

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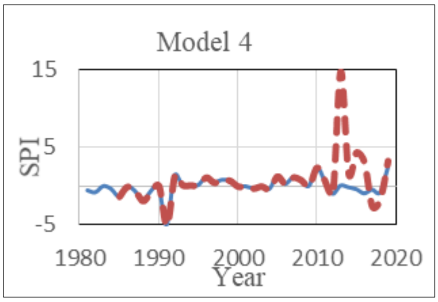

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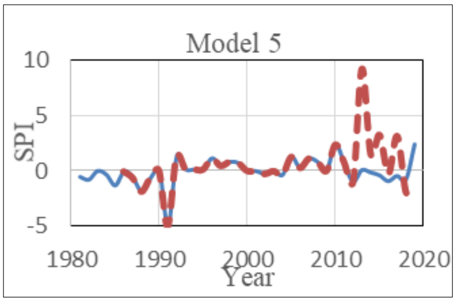

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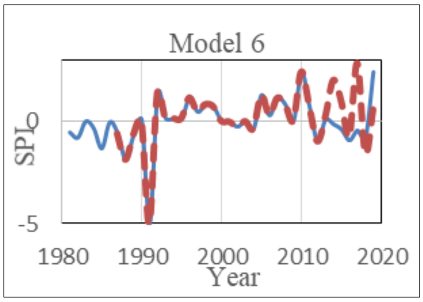

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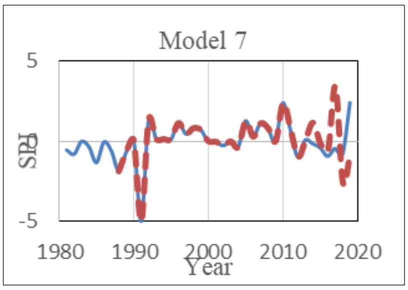

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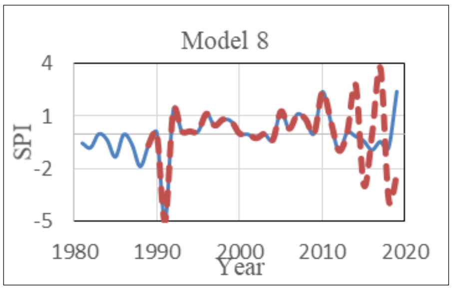

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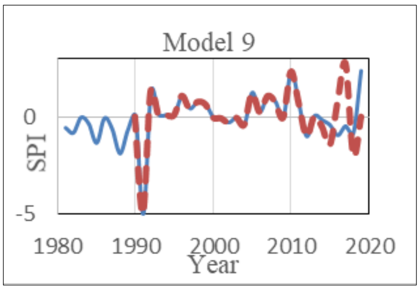

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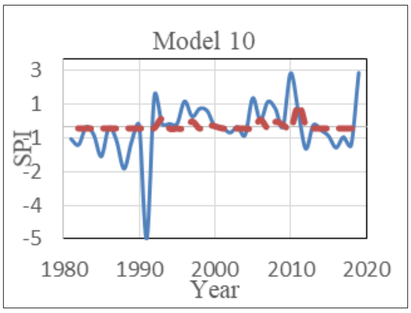

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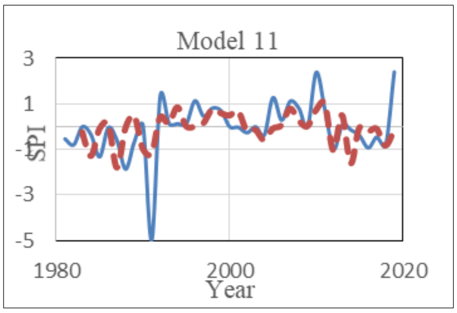

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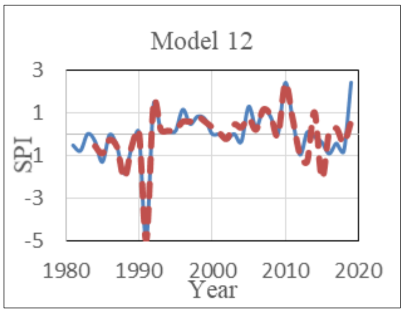

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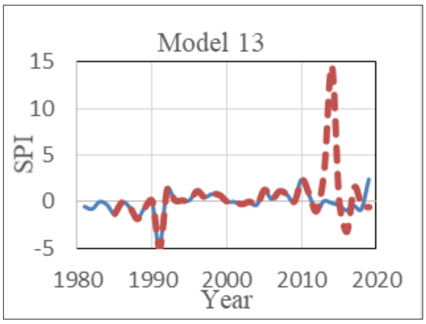

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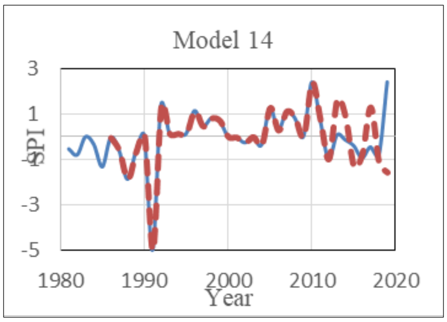

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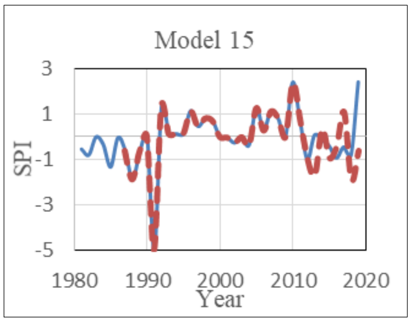

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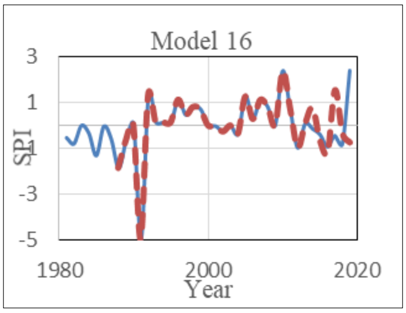

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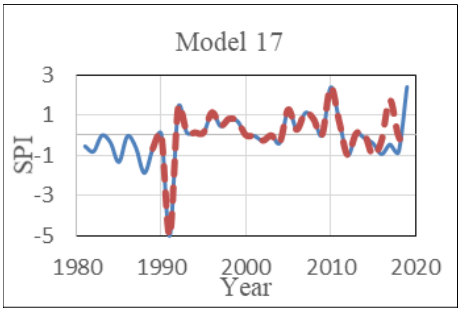

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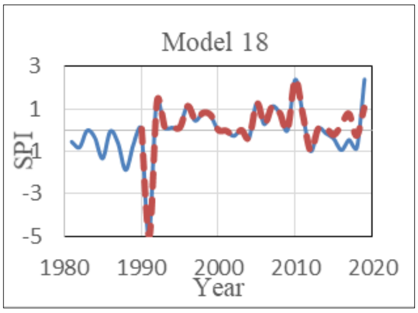

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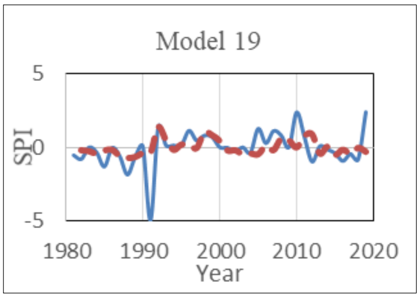

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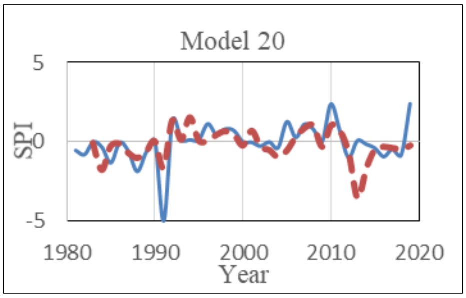

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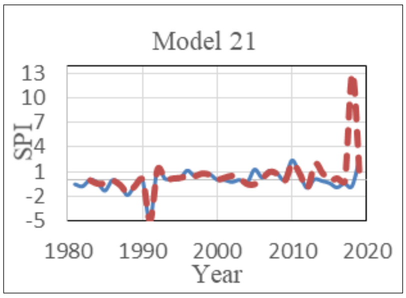

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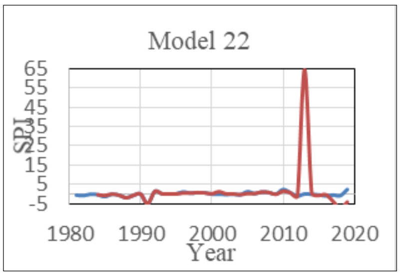

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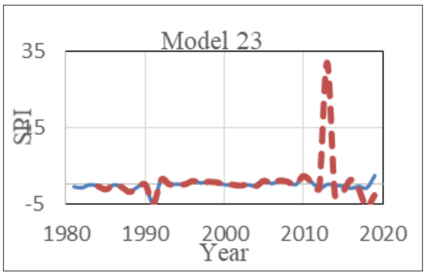

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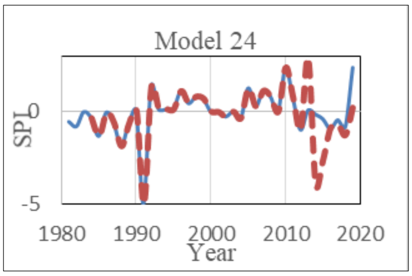

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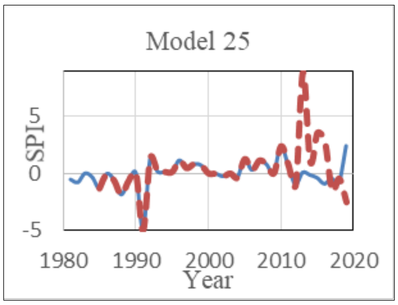

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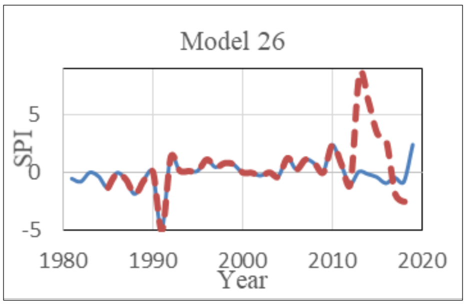

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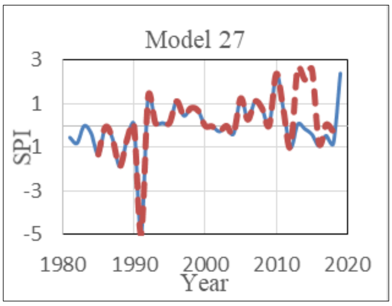

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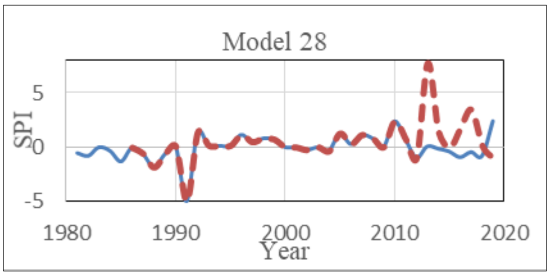

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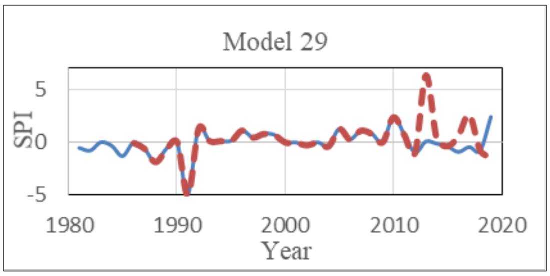

Figure 3(xxix)

Observed Predicted

Fig 3: Graphical depiction of observed SPI values vs predicted ANFIS model for a different model

Models 4, 5, 6, 7, 8, 9, 12, 13, 14, 15, 16, 17, 18, 22, 23, 24, 25, 26, 27, 28, 29 appear to be fairly accurate in comparison to observed values with projected values in the training dataset, indicating that the datasets are well trained. For instance, after incorporating the t-4 precursor value, the model with just SPI values and only rainfall values produce trustworthy findings, but the model with both SPI and rainfall values produces real results after including an equal amount of those precursor values.

Further statistical analysis is performed to obtain an accurate best-fitted model among these many models. Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Coefficient of determination (R2) are used to determine the goodness-of-fit. Results are given in table 5 and the graphical representation is given in figure 4.

Table 5 and Figure 4 show that, out of 29 models, Model 18 has the lowest RMSE, MSE, and R^2 value. This 18^{th} model consists of 9 years of precipitation data as input. The whole 29 models may be divided into three groups. Only SPI values were used as input variables in the first nine models as an increase in the precursor year. And only rainfall value with increasing the antecedent years used as input variables in models 10 to 18. The input variables in the models from 19 to 29 are a mix of SPI and rainfall data.

Model 6 was the best-fitting model in terms of the combination of only SPI values, as it has low RMSE, MAE, and high R^2 values (i.e., 0.796, 0.294, 0.674). There appears to be an increase in the RMSE, MAE values, and a drop in the R^2 after model 6, leading to the conclusion that it is preferable to end at model 6. In terms of rainfall values, adding a variable increases the model's performance, however, when comparing models 17 and 18, the difference between those values is so little that it can be assumed that adding a variable would eventually reach a point of stability, resulting in an increase in error. Model 24 has a low RMSE, MAE and a high R^2 value for the combination of SPI and rainfall values.

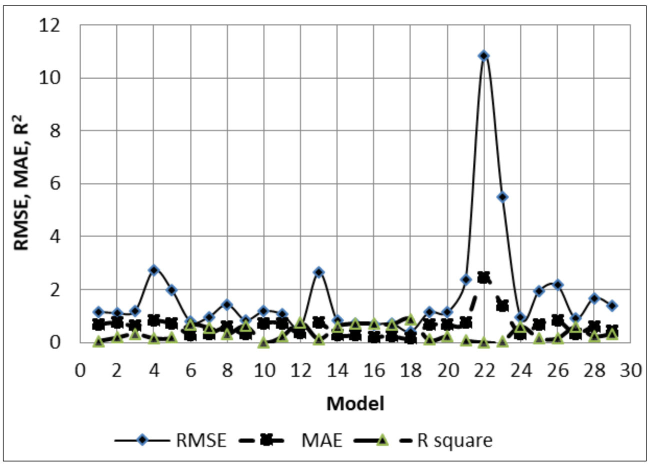

Fig 4: Graphical representation of Statistical Criteria values for all the forecasted model

Table 5: Calculated RMSE, MAE and R^2value

Model	RMSE	MAE	R^2
1	1.168	0.693	0.065
2	1.122	0.767	0.193
3	1.205	0.635	0.333
4	2.728	0.833	0.174
5	1.974	0.711	0.192
6	0.796	0.294	0.674
7	0.964	0.335	0.562
8	1.441	0.591	0.320
9	0.852	0.331	0.620
10	1.187	0.732	0.025
11	1.073	0.730	0.226
12	0.596	0.352	0.776
13	2.660	0.751	0.140
14	0.829	0.289	0.616
15	0.709	0.274	0.719
16	0.687	0.223	0.725
17	0.711	0.244	0.692
18	0.412	0.160	0.896
19	1.139	0.667	0.109
20	1.134	0.675	0.236
21	2.385	0.742	0.078
22	10.844	2.446	0.009
23	5.499	1.394	0.036
24	0.946	0.329	0.608
25	1.958	0.690	0.174
26	2.161	0.855	0.161
27	0.912	0.341	0.588
28	1.684	0.605	0.246
29	1.398	0.454	0.334

4. Conclusion

In this paper, SPI is chosen as a drought indicator for the Tiruppur area since it is one of the recommended methods by the World Meteorological Organization's for drought monitoring because it just requires only precipitation data and is simple to compute. The drought was estimated from 1981 to 2019 using SPI data. The forecasting models were created using the SPI values obtained. The twenty-nine ANFIS forecasting models were created, among these, M18 showing the best performance in terms of antecedent rainfall levels. Model 6 performs better when just antecedent SPI values are utilised, and this model appears to be the best model with the least amount of input variables. Statistical criteria are used to identify the models that fit the best. Models 18 and 6 were found to be the most accurate, thus they may be used to forecast future drought years. This research may also be used to anticipate drought in different regions.

5. Reference

1. Anshuka A, Van Ogtrop FF, Vervoort RW. Drought forecasting through statistical models using standardised precipitation index: a systematic review and meta-regression analysis. Natural Hazards 2019;97(2):955-977.
2. Bacanli UG, Firat M, Dikbas F. Adaptive neuro-fuzzy inference system for drought forecasting. Stochastic Environmental Research and Risk Assessment 2008;23(8):1143-1154.
3. Cancelliere A, Di Mauro G, Bonaccorso B, Rossi G. Drought forecasting using the standardized precipitation index. Water resources management 2007;21(5):801-819.
4. Janapriya S, Bosu SS, Kannan B, Kokilavani S. Spatial and temporal analysis of drought in Manjalar sub-basin of Vaigai in Tamil Nadu using standardized precipitation index. Journal of Applied and Natural Science 2016;8(2):609-615.
5. Jang JSR, Sun CT, Mizutani E. Neuro-fuzzy and soft computing- a computational approach to learning and machine intelligence [Book Review]. IEEE Transactions on automatic control 1997;42(10):1482-1484.
6. Kisi O, Gorgij AD, Zounemat-Kermani M, Mahdavi-Meymand A, Kim S. Drought forecasting using novel heuristic methods in a semi-arid environment. Journal of Hydrology 2019;578:124053.
7. Kokilavani S, Panneerselvam S, Ga D. Centurial rainfall analysis for drought in Coimbatore city of Tamil Nadu, India. Madras Agricultural Journal 2019;106(7/9):484-487.
8. Kyada PM, Kumar P. Daily rainfall forecasting using adaptive neuro-fuzzy inference system (ANFIS) models. Int. J Sci. Nat 2015;6(3):382-388.
9. McKee TB, Doesken NJ, Kleist J. January. The relationship of drought frequency and duration to time scales. In Proceedings of the 8th Conference on Applied Climatology 1993;17(22):179-183.
10. Mishra AK, Desai VR. Drought forecasting using stochastic models. Stochastic environmental research and risk assessment 2005;19(5):326-339.
11. Mishra AK, Desai VR. Drought forecasting using feed-forward recursive neural network. Ecological modelling 2006;198(1-2):127-138.
12. Mishra AK, Desai VR, Singh VP. Drought forecasting using a hybrid stochastic and neural network model. Journal of Hydrologic Engineering 2007;12(6):626-638.
13. Mokhtarzad M, Eskandari F, Vanjani NJ, Arabasadi A. Drought forecasting by ANN, ANFIS, and SVM and comparison of the models. Environmental earth sciences 2017;76(21):1-10.
14. Morid S, Smakhtin V, Bagherzadeh K. Drought forecasting using artificial neural networks and time series of drought indices. International Journal of Climatology: A Journal of the Royal Meteorological Society 2007;27(15):2103-2111.
15. Nayak PC, Sudheer KP, Rangan DM, Ramasastri KS. A neuro-fuzzy computing technique for modelling hydrological time series. Journal of Hydrology 2004;291(1-2):52-66.
16. Nguyen LB, Li QF, Ngoc TA, Hiramatsu K. Adaptive neuro-fuzzy inference system for drought forecasting in the Cai River basin in Vietnam. Journal of the Faculty of Agriculture, Kyushu University 2015;60(2):405-415.
17. Patel J, Parekh F. Forecasting rainfall using adaptive neuro-fuzzy inference system (ANFIS). Ijaiem 2014;3:262-269.
18. Shabri A. A hybrid wavelet analysis and adaptive neuro-fuzzy inference system for drought forecasting. Applied Mathematical Sciences 2014;8(139):6909-6918.
19. Shirmohammadi B, Moradi H, Moosavi V, Semiromi MT, Zeinali A. Forecasting of meteorological drought using Wavelet-ANFIS hybrid model for different time steps (case study: the south eastern part of East Azerbaijan province, Iran). Natural hazards 2013;69(1):389-402.
20. Thom HC. A note on the gamma distribution. Monthly weather review 1958;86(4):117-122.
21. Tirivarombo Sithabile, Osupile D, Eliasson Peter. Drought monitoring and analysis: Standardised Precipitation Evapotranspiration Index (SPEI) and Standardised Precipitation Index (SPI). Physics and Chemistry of the Earth, Parts A/B/C 2018, 106. 10.1016/j.pce.2018.07.001.
22. Tsakiris G, Vangelis H. Towards a drought watch system based on spatial SPI. Water resources management 2004;18(1):1-12.