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Agricultural drought forecast for the district of Coimbatore using adaptive Neuro fuzzy inference system

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Abstract
Drought has a significant influence on both in the environment and in the area of agriculture, particularly farming. In this scenario, the Adaptive Neuro-Fuzzy Inference System (ANFIS), one of the hybrid artificial neural networks, is primarily used in this study to anticipate drought. The Coimbatore district's monthly precipitation values for the previous 39 years are used in this study. First, as the Coimbatore district primarily depends on the North-East Monsoon, SPI values are estimated at a 3-month scale using monthly precipitation values. Second, several ANFIS forecasting models are built employing the North-East Monsoon season's mean precipitation value as inputs. Additionally, Root Mean Sum of Error (RMS, Mean Absoulte Error (MAE) and coefficient of determination value (R^2) were used to combine the results of the projected ANFIS model with the observed values. The best-fitting model was defined as having low RMSE, low MAE, and high R^2.

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

1. Introduction
A drought is a time when there is a persistent, unusual difference in the rate of precipitation. When compared to all other natural disasters, it is the least accurate and foreseeable, making it incredibly challenging to survive. It is typically divided into stages based on how quickly the hydrological cycle intensifies at each stage. Agricultural drought is a state when there is a shortage of soil moisture, which will significantly lower agricultural output. Mishra and Desai (2005) [1], (2006) [2], and Mishra *et al*. (2007) [3]. A correct quantification and evaluation of the drought in the affected areas is required. The most accurate prognosis will lessen the negative effects. As a result, the drought prediction is crucial in providing an early warning of future events. Morid *et al*. (2007) [4].

The Standardised Precipitation Index (SPI) has been compared with many other indices by several academics, who have concluded that SPI is one of the most effective ways to track the drought. After comparing the SPI with the standardised precipitation evapotranspiration index (SPEI) for the drought analysis, Tirivaromboetal., (2018) [5] came to the conclusion that the SPI appears to be more accurate in the situation of lacking temperature data. SPI and Palmer Drought Severity Index (PDSI) were compared by Tsakiris and Vangelis in 2004 [6]. They came to the conclusion that SPI was the best tool for assessing drought since it is straightforward to read and has a straightforward structure. Several linear and non-linear approaches for drought forecasting have been developed. The adaptive neuro-fuzzy inference system (ANFIS), which has replaced older approaches, is now the best model being employed among them. Shirmohammadi *et al*. (2013) [7] examined support vector machines, artificial neural networks, and ANFIS. Nguyen *et al*. (2015) [8] showed that ANFIS exhibits the best model even for the long and short term time scale and that SPI values were utilised for monitoring and forecasting. The primary goal of this study is to evaluate the drought in Tamilnadu's Coimbatore area using the SPI value. In order to produce a clear-cut and accurate result for the drought forecasting, it is also important to determine the ideal input variable combinations utilising antecedent rainfall and SPI values. The predicted models will be sorted according to statistical criteria, and the best-fit models will be chosen.

2. Materials and Methodology
2.1 Study area suite
Coimbatore was chosen as the research location for this investigation. Its latitude and longitude are 11º02" North and 76º96" East, respectively, and its elevation is 411m above sea level. This region is part of Tamilnadu's western zone. From 1981 to 2019, Coimbatore received 61.62mm of rain annually. Rainfall from the North-East Monsoon (NEM), which comes in October, November, and December, was primarily what the Coimbatore area relied on. For the years 1981 to 2019, the months saw an average rainfall of 106.88 mm.

2.2 Data Description
Secondary data from the Agro Climatic Research Centre at the Tamil Nadu Agricultural University in Coimbatore was used for this investigation. Over a 39-year period, statistics on monthly precipitation were collected from January 1981 to December 2019.

2.3 Standardised Precipitation Index (SPI)
This indicator for evaluating drought was developed by McKee *et al*. in 1993 [9] and may be obtained by dividing the difference between rainfall data's mean and standard deviation. It is employed for investigating and evaluating the long-term incidence of drought. The result derived from this computation contains both positive and negative values, where a positive value denotes a period of rain and a negative value denotes a period of drought. This index may be computed over several time periods, including 1, 3, 4, 6,12 and 24 months. The numerous terms of the drought state are included in various time frames. Since SPI focuses on short-term length, it can detect agricultural droughts on a 1, 3, and 4-month time frame. The meteorological drought is shown by SPI during the six-month time period. SPI-12 and 24 months, which depend on long term length, suggest the hydrological drought.

Table 1: Various Categories determined 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 1 is lists the SPI categories based on the value. It has been demonstrated that SPI falls within the gamma distribution and is based on a mathematical derivation that is determined from the cumulative probability of recorded rainfall (Thom 1958) [10]. In this study, SPI was computed using the R studio under the 1.4.1717 version using the command prompt SPI_SL_6.exe file. The outputs of both calculation processes are identical.

2.4 Adaptive Neuro-Fuzzy Inference System (ANFIS): The ANFIS model, one of the hybrid algorithms (i.e., combining Artificial Neural Network (ANN) and Fuzzy Logic (FL) in a single algorithm), was initially proposed by Jang *et al*. in 1997 [11]. This approach, which is non-linear, overcomes the disadvantage of fuzzy logic while combining the advantages and training accuracy of the previous two approaches. The Sugeno- Takagi FIS and the Mamdani FIS are the two main types of fuzzy inference systems (FIS). Sugeno-Takagi FIS is used mostly in drought forecasting. The IF-THEN rule-based Sugeno- Takagi fuzzy inference system is used. The basic explanation for the results of each rule is the direct fusion of all the input variables with a constant term. Let's assume that the Sugeno-Takagi kind of ANFIS model with two fuzzy functions developed by Patel and Parekh (2014) [12].

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 consists of five layers, with

- The first layer being referred to as the fuzzification layer or fuzzy layer. Each node in this layer uses fuzzy rules to identify the membership function of the input function.
- The second layer, which multiplies its input signal, is known as the product layer or the rule basis layer.
- The third layer, known as the normalisation layer, is where the product layer is normalised.
- The fourth layer is the defuzzification layer, where each node transforms into an adaptable node to advance to the ultimate output layer.
- The fifth layer is the output layer, which contains the output node that is produced when the output of the previous four levels are added together.

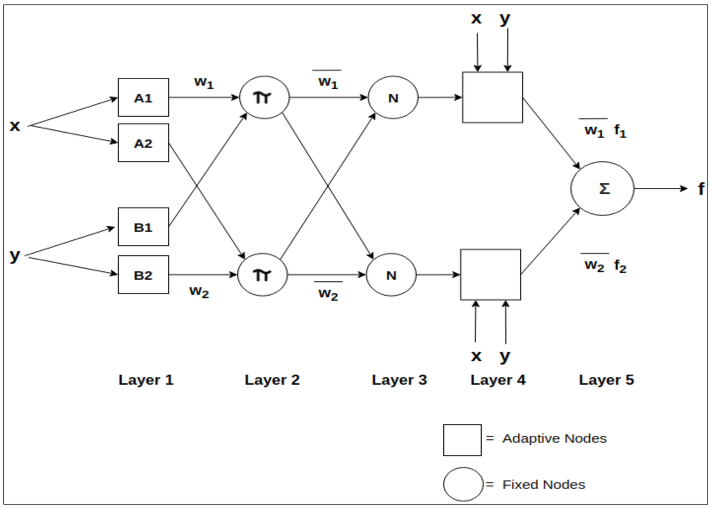


Fig 1: Architecturally straightforward view of the ANFIS structure

From Jang *et al*. (1997) [11], Nayak *et al*. (2004) [13], and Bacanli *et al*. (2008) [14], further information and the mathematical derivation for this hybrid approach may be acquired.

The programme MATLAB version R2021a is used in this work to model the ANFIS. The entire dataset is split into three subgroups for data analysis: training data, testing data, and validation data, with percentages of 80, 10, and 10. A fuzzy inference system of the Sugeno-Takagi type is employed for model construction using the ANFIS approach.

2.5 Statistical analysis

The statistical criteria used to measure the effectiveness of the various models created include root mean square error (RMSE), mean absolute error (MAE), and coefficient of determination (R^2). The model that fits the data the best is the one with the lowest RMSE, MAE value, and highest R^2 value.

3. Result and Discussion

3.1 Standardised Precipitation Index (SPI)

SPI is estimated on a three-month time period as a predictor of the North-East Monsoon, upon which Coimbatore district heavily depends. Between 1981 and 2019, a moderate drought happened twice, a severe one once, and an extreme one twice. According to the SPI scale, the drought classifications from 1981 to 2019 are displayed in the following table.

Table 2: Coimbatore district's drought category from 1981 to 2019

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

From the table 2, it shows that the years 1988, 1991, 2009, 2016, and 2017 are considered drought years.

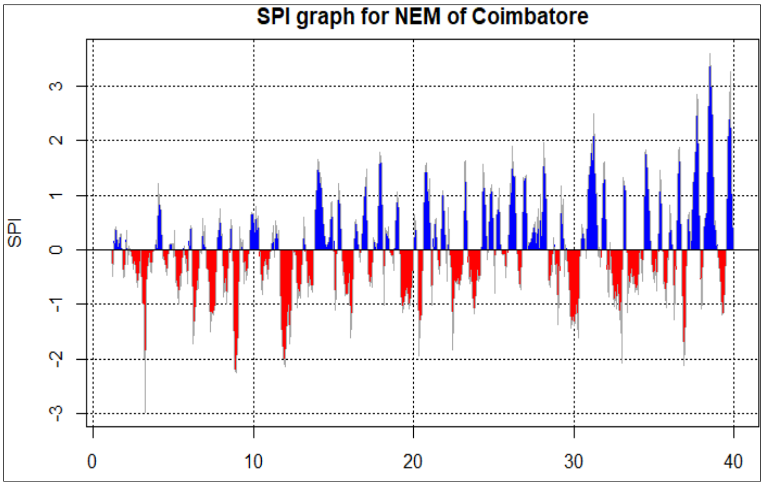


Fig 2: SPI-3 pattern values for the district of Coimbatore from 1981 to 2019

Fig. 2 shows a schematic representation of the SPI-3 month scale from 1981 to 2019 that was generated using the R studio programme. The x-axis label shows the years 1981 through 2019; 0–10 represents the years 1981–1990, 10–20 represents the years 1990–2000, 20–30 represents the years 2000–2010, and 30–40 represents the years 2010–2019. It is clear from this graph that the blue colour denoted a situation that was close to normal to a wet period, while the red colour denoted a condition that was close to normal to a dry period (i.e., a drought condition).

3.2 Adaptive Neuro-Fuzzy Inference System (ANFIS)

The forecasting models of ANFIS were developed based on the research conducted by Bacanli *et al*. (2008) [14]. A series of antecedent rainfall values is used as input parameters in the forecasting model for the Coimbatore district, while matching year SPI values are used as an output parameter. The input variable used to build the models in this study, which is also related to the Bacanli *et al*. (2008) [14] study, is an increase in the number of antecedent values.

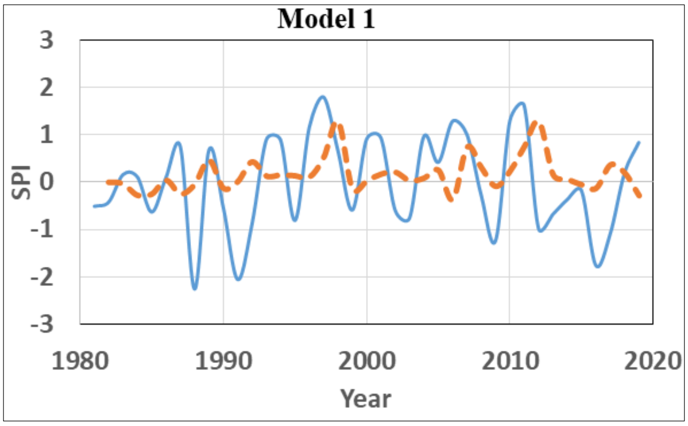
Table 3: For the ANFIS forecasting model, many input combinations were employed.

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

Table 4: Number of datasets used for forecasting models' training and testing

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	38	30	4	4
2	M2	37	30	4	3
3	M3	36	29	4	3
4	M4	35	28	4	3
5	M5	34	27	4	3
6	M6	33	26	4	3
7	M7	32	26	3	3
8	M8	31	25	3	3
9	M9	30	24	3	3

The entire datasets are split into training, testing, and validation data for drought forecasting, with allocations of 80%, 10%, and 10% respectively. Models 3, 4, 5, 6, 7, 8 and 9 appear to be quite accurate in comparison of observed values with the predicted values in particular regarding the training dataset, which indicates that the datasets are well trained. This conclusion can be drawn visually from Figure 3. These model produce valid results after the inclusion of the t-3 precursor value.



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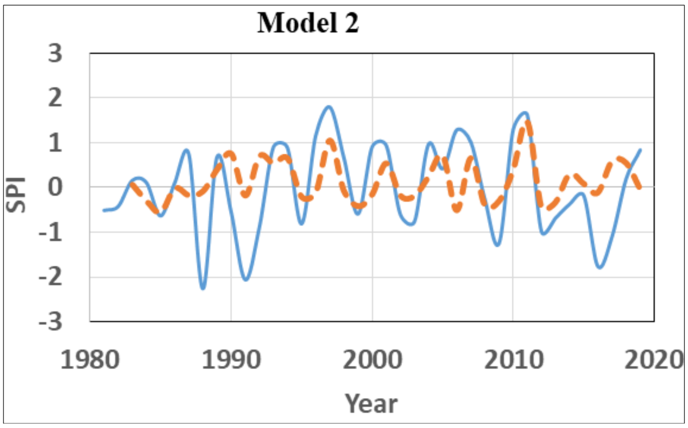

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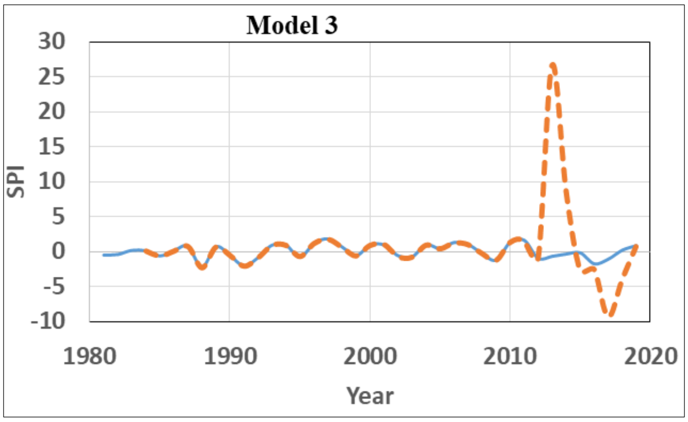

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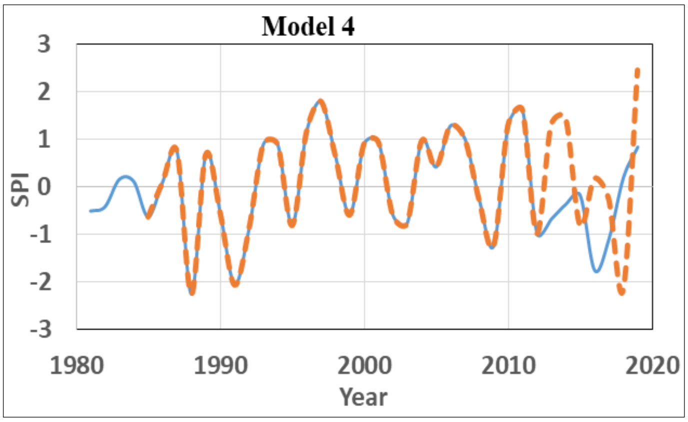

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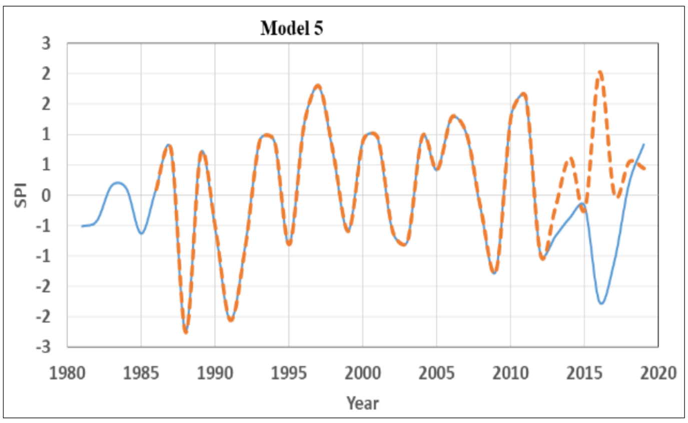

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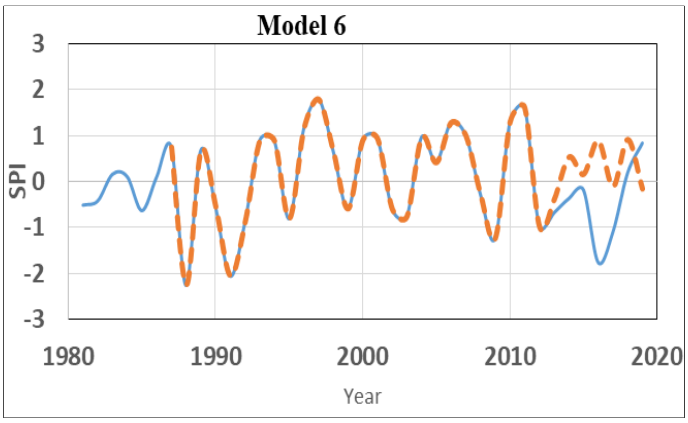

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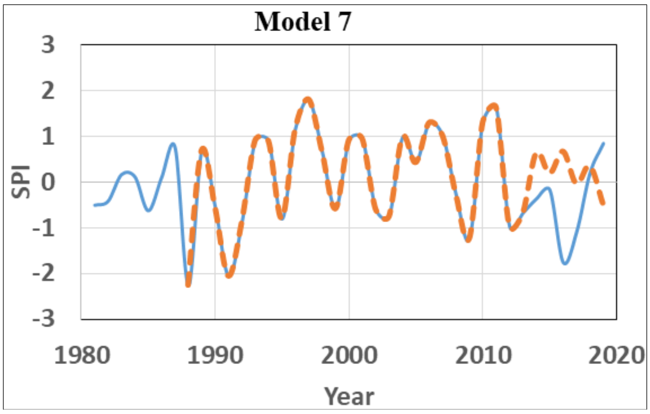

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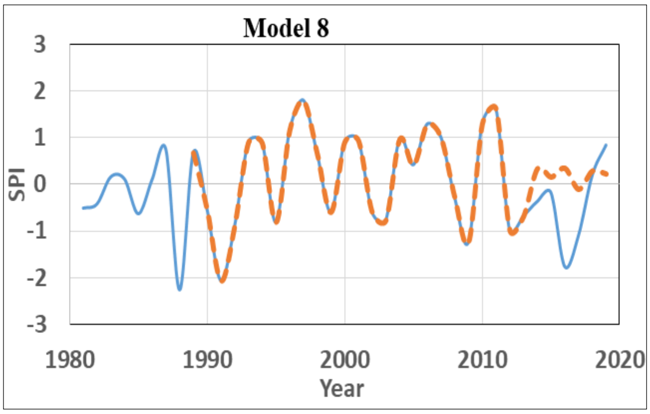

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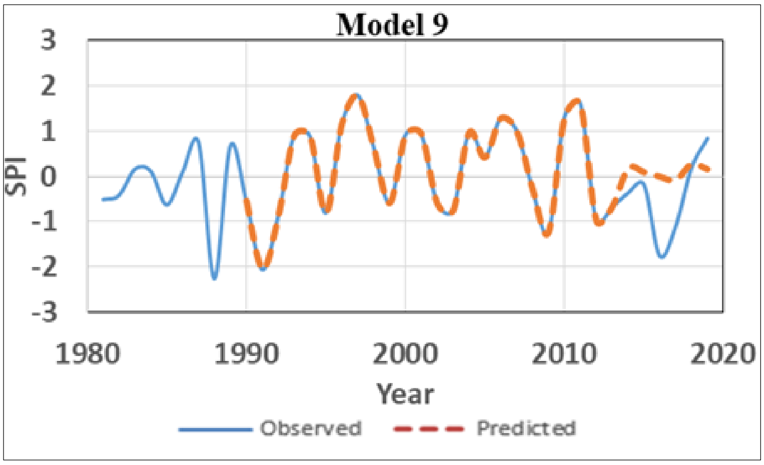

9)

Fig 3: A graphic comparison of predicted ANFIS values and observed SPI values for a different model

Additional statistical analysis is conducted in order to identify the best-fitted model among these many models. Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Coefficient of determination (R2) are calculated to assess the goodness-of-fit.

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

Model	RMSE	MAE	R^2
1	1.026	0.850	0.028
2	0.927	0.732	0.188
3	5.059	1.469	0.019
4	0.762	0.320	0.602
5	0.709	0.211	0.616
6	0.567	0.209	0.746
7	0.557	0.198	0.752
8	0.457	0.157	0.813
9	0.407	0.145	0.854

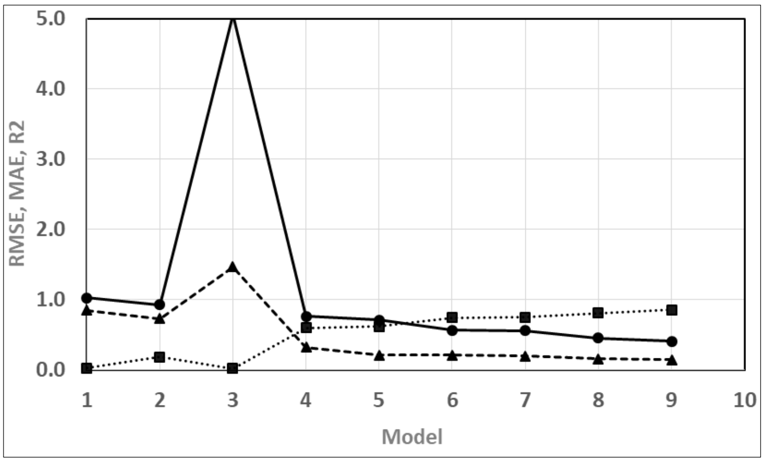

Fig 4: Values for all of the projected model's statistical criteria are represented graphically.

According to table 5 and figure 4, model 9 has the lowest RMSE, MSE, and highest R^2 value out of all 9 models. Nine years' worth of rainfall antecedent values are fed into model 9 in this case. Regarding the rainfall values, the model's performance continues to improve with the addition of the variable, but when models 8 and 9 are compared, there is only a small amount of difference in the values, leading one to the conclusion that adding more variables will eventually reach a point of stability, which will further increase the errors.

4. Conclusion

The Coimbatore district's drought is assessed using SPI in this publication since it was one of the approaches that the World Meteorological Organisation suggested because it just needs precipitation data to monitor drought and is also simple to compute. SPI data were used to estimate the drought from 1981 to 2019. The forecasting models were created using the values that were gathered. The 9 ANFIS forecasting models were developed, and M9 performed the best among them when it came to predicting rainfall antecedent values. Statistical criteria are used to determine which models are the best-fit. Models 9 can be used to forecast upcoming drought years as these were the models that performed the best. This study may be extended with building models using SPI values and combination of both SPI and rainfall and also be used to predict drought in different regions.

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