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Adaptive neuro-fuzzy inference system for drought modeling

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सार – सूखे का पर्यावरण और कृषि क्षेत्रों, खासकर कृषि उत्पादन पर काफी असर पड़ता है। सूखे के असर से निपटना उन सभी स्टेकहोल्डर्स के लिए ज़रूरी है जो प्राकृतिक पानी के सोर्स पर निर्भर हैं। एडेप्टिव न्यूरो-फजी इन्फरेंस सिस्टम (ANFIS), जो हाइब्रिड आर्टिफिशियल न्यूरल नेटवर्क में से एक है, का इस्तेमाल मुख्य रूप से इस स्टडी में सूखे को मॉडल करने के लिए किया गया है। अध्ययन में कोयंबटूर एवं तिरुप्पुर जिलों के लिए पिछले 39 वर्षों के मासिक वर्षा आँकड़ों का प्रयोग किया गया। प्रारंभिक चरण में उत्तर-पूर्व मानसून के प्रभाव को ध्यान में रखते हुए 3 महीने के स्केल पर स्टैंडर्डाइज्ड प्रेसिपिटेशन इंडेक्स (SPI) वैल्यू की गणना की गई।उत्तर-पूर्व मानसून ऋतु की औसत वर्षा एवं गणना किए गए SPI मानों का उपयोग कर कई ANFIS पूर्वानुमान मॉडल विकसित किए गए। इन मॉडलों का मूल्यांकन विभिन्न त्रुटि मानकों–जैसे रूट मीन स्क्वेयर एरर (RMSE), मीन एब्सोल्यूट एरर (MAE) तथा निर्धारण गुणांक (R^2)–के आधार पर किया गया। जिस मॉडल में न्यूनतम RMSE एवं MAE तथा उच्च R^2 पाया गया, उसे आँकड़ों के लिए सर्वाधिक उपयुक्त एवं सुदृढ़ मॉडल माना गया।

ABSTRACT. Drought conditions exerts a pronounced impact across environmental as well as agricultural sectors, particularly in farming. Addressing the impact of drought is essential for all stockholders who depends on natural water sources. This study employs the Adaptive Neuro-Fuzzy Inference System (ANFIS), a hybrid neural-fuzzy modelling approach for drought prediction. The study utilizes the long-term monthly rainfall data spanning covering a 39-year period for the Coimbatore and Tiruppur district. Initial steps involve the estimation of Standardized Precipitation Index (SPI) values at a 3-month scale using monthly precipitation values, considering the impact of North-East Monsoon over the district. Several ANFIS forecasting models are developed using the mean precipitation value of North-East Monsoon season and the computed SPI values. The evaluation of these models incorporates several error metrics such as RMSE, MAE, and the coefficient of determination (R^2), allowing for a comprehensive comparison between the projected ANFIS model and observed values. The model which exhibits the lowest RMSE and MAE, coupled with a high R^2, are considered as robust fit to the data.

Key words – Drought forecasting, ANFIS, SPI, Error metrics.

1. Introduction

Drought refers to a situation in which precipitation consistently deviates from normal levels. Among natural hazards, it is the most difficult to predict, making it particularly challenging to manage. It progresses through multiple stages, each marked by increasing severity in the hydrological cycle. Agricultural drought is a state when there is a shortage of soil moisture, which will significantly lower agricultural output (Mishra and Desai, 2005; Mishra and Desai, 2006; Mishra *et al.*, 2007). Quantification and evaluation of these recurring challenge confronting the water resource is mandatory in order to provide an early warning of future events (Morid *et al.*, 2007). This demand the need of accurate projection which will lessen the impacts of drought. Prior forecasting of drought will help in efficient resource management, particularly in regions where water scarcity can have severe consequences (Shyrokaya *et al.*, 2024). It enables better planning and allocation of water resources for agriculture, industry, and human consumption, helping to mitigate the adverse effects of prolonged dry periods (Poornima *et al.*, 2023; Pekpostalci *et al.*, 2024). For farmers, accurate forecasts allow for informed decisions regarding crop selection, irrigation needs, and planting schedules, minimizing the risk of crop failure.

Several studies have highlighted the importance of Standardised Precipitation Index (SPI) in tracking the drought by comparing it with many other indices. Tirivarombo *et al.*, (2018) proved the effciency of SPI in estimating the drought particularly in the situation of lacking the temperature data. Tsakiris and Vangelis (2004) compared the SPI with the Palmer Drought Severity Index and identified SPI as a more reliable indicator for drought assessment. In recent years, numerous methods inclusing both linear and non-linear for forecasting drought have emerged. Among these, the Adaptive Neuro-Fuzzy Inference System (ANFIS) has replaced older approaches and is now recognized as the most effective model in use. Shirmohammadi et al. (2013) compared the ANFIS with Support Vector Machines (SVR) and Artificial Neural Networks (ANN). Nguyen et al. (2015) showed the supremacy of ANFIS model for the long and short term time scale data in which SPI values were utilised for monitoring and forecasting. Kikon *et al.*, 2023 used ANFIS based soft computing models for predicting the drougt index in india. Navale and Mhaske (2023) forecasted the groundwater level in the Pravara River Basin using ANN and ANFIS model. Jariwala and Agnihotri (2023) used compared different statistical models such as ANN, ANFIS and ARIMAX for modelling the drought in Gujarat. Achite *et al.*, 2023 used an improvised ANFIS for modelling the drought in Algeria.

Thus, the study attempts to report drought conditions in the Coimbatore and Tiruppur districts of Tamil Nadu for the first time using SPI values. By utilizing optimal input sets that include previous rainfall amounts and SPI-derived drought indicators, the study aims to produce optimized and accurate models for drought forecasting. The predicted models are evaluated using various error measures to identify the best-fit models for the data. This research will offer valuable insights for stakeholders who rely heavily on water as a primary resource, aiding them in better managing and preparing for drought conditions.

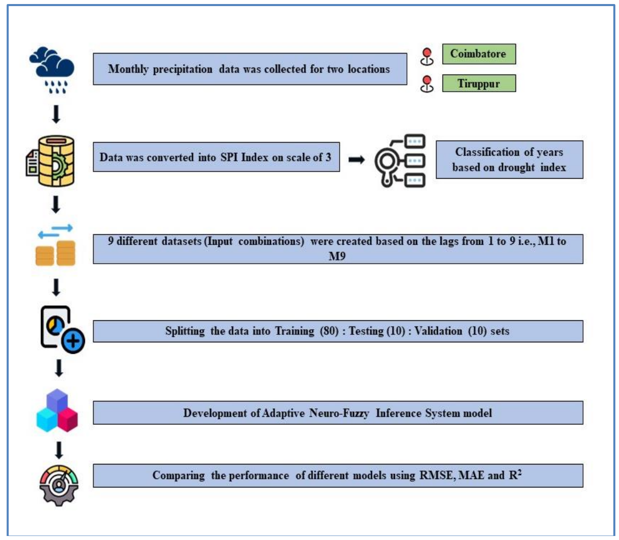

Fig. 1. Workflow of the study

2. Data and methodology

2.1. *Study area*

The selected study area chosen for this research comprises the Coimbatore and Tiruppur districts, which are part of the Western Zone of Tamil Nadu. Geographically, this zone is situated between 10° to 12° north latitude and 76°30´ to 80° east longitude, with standing at an elevation of about 426.7 meters above MSL (Mean Sea Level). These districts experience a higher percentage of rainfall throughout the North-East monsoon season than during the South-West monsoon. The study utilized monthly precipitation data spanning 39 years, spanning January 1981 to December 2019. These secondary rainfall records were sourced from the Agro Climatic Research Centre, AC&RI, Tamil Nadu Agricultural University, Coimbatore. A detailed schematic of the study process is presented in Fig. 1.

2.2. *Standardised precipitation index (SPI)*

Standardised Precipitation Index is an indicator which is highly used for evaluating the drought (Mc Kee *et al.*, 1993). It is highly suitable for examining and evaluating the long-term incidence of drought. SPI is calculated by standardizing rainfall, where the deviation of rainfall from its long-term mean is scaled using the standard deviation. This results in both positive and negative values - positive values indicate wetter-than-normal conditions, while negative values signify drier periods. The index can be computed for durations such as 1, 3, 4, 6, 12, and 24 months, each capturing different drought characteristics. Shorter time scales (1, 3, 4 months) reflect agricultural drought, the 6 - month scale

TABLE 1

Various Categories determined on the SPI values

SPI	Different Category
SPI ≥ 2.00	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
SPI ≤ -2.00	Extremely dry

indicates meteorological drought, while the 12 and 24-month scales represent hydrological drought. Table 1 summarises the SPI categories which typically follows a gamma distribution, derived from cumulative rainfall probability (Thom, 1958). In this study, SPI was generated in R Studio version 1.4.1717 using the SPI_SL_6.exe command file, and both computation methods produced consistent results.

2.3. *Adaptive Neuro-Fuzzy Inference System (ANFIS)*

Adaptive Neuro-Fuzzy Inference System is the hybrid algorithms developed by combining the Artificial Neural Networks (ANN) and Fuzzy Logic (FL), combining the adaptive learning strengths of neural networks with the rule-based reasoning style of fuzzy logic. (Jang *et al.*, in 1997). ANFIS is particularly well-suited for handling problems that involve uncertainty, complexity, and non-linearity, making it a powerful tool for tasks like time series prediction, control systems, and pattern recognition. Among the widely used fuzzy inference systems are the Sugeno - Takagi FIS and the Mamdani FIS, with the Sugeno - Takagi rule-based structure being particularly favored in drought-forecasting applications. The basic idea behinf the algorithm is that each rule is the direct fusion of all the input variables with a constant term. Let's assume that the Sugeno-Takagi based ANFIS model with two fuzzy functions (Patel and Parekh, 2014).

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 represent the input parameters linked to the membership functions of variables a and b, while u_1 and u_2 denote the corresponding output functions.

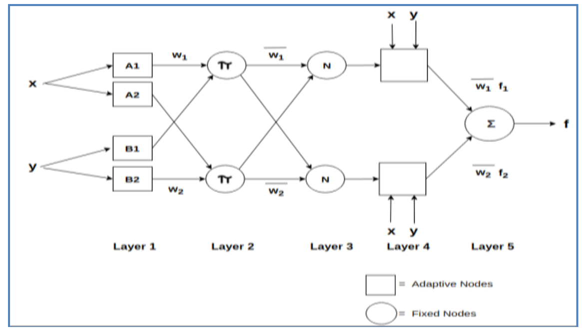

Fig. 2. Architecturally straightforward view of the ANFIS structure

The ANFIS architecture consists of five different layers which was shown in the Fig. 2. The first layer, often called the fuzzification or input layer, or fuzzy layer This layer takes the input values and converts them into membership values using fuzzy membership functions such as Gaussian or triangular functions. This study uses the triangular membership functions. The second layer is called product layer or the rule basis layer where the membership degrees of the inputs are combined to generate firing strengths of fuzzy rules. The third layer, the normalization layer, adjusts the firing strengths of the rules by dividing each value by the total firing strength, ensuring proportional contribution from all rules. The fourth layer is the defuzzification layer or consequent layer. In this layer, the normalized firing strengths are used to calculate the output of each rule using a linear function of the input variables. The fifth and final layer is the output layer, which aggregates the outputs generated by the preceding layers to produce a single predictive value. Further methodological details are available in Jang et al. (1997), Nayak et al. (2004), and Bacanli et al. (2008). MATLAB R2021a was used for ANFIS modelling, with the dataset divided into 80% training, 10% testing, and 10% validation. The Sugeno–Takagi fuzzy inference system was adopted for constructing the forecast models.. A fuzzy inference system of the Sugeno-Takagi type is employed for model construction using the ANFIS approach in this study.

2.4. *Selection criteria*

To evaluate model performance, statistical indicators such as RMSE, MAE, and R^2 were employed. The model with the lowest RMSE and MAE and the highest R^2 was considered the most suitable.

$$\mathbf{RMSE} = \left(\sqrt{\sum_{i=1}^{n} \left\{ \frac{Y_i - \hat{Y}_i}{Y_t} \right\}^2 \Big/ n} \right)$$

$$\mathrm{MAE} = \frac{1}{n} \sum_{t=1}^{n} \left| Y_i - \hat{Y}_i \right|$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2}{\sum_{i=1}^{n}(Y_i - \bar{Y}_i)^2}$$

where Y_t is the observed values, $\hat{Y}_t$ is the predicted values, $\bar{Y}$ is the mean observations and n is the number of data points.

3. Results and discussion

The monthly rainfall data obtained for the Coimbatore and Tiruppur district was converted into SPI index on a time scale of 3. Figs. 3(a & b) illustrates the SPI-3 time series for the period 1981–2019 for both districts. The y-axis represents SPI values, while the x-axis indicates the years in decade intervals: 0–10 corresponds to 1981–1990, 10–20 to 1990–2000, 20–30 to 2000–2010, and 30–40 to 2010–2019. Blue shades indicate near-normal to wet conditions, whereas red shades reflect near-normal to dry or drought conditions. This graphical depiction provides a clear view of drought fluctuations over the study period. The monthly SPI index values were converted into a yearly index by calculating the mean of the monthly SPI values. Based on this yearly index, the years were classified into different drought categories according to the scales provided in Table 1. This classification helps in categorizing the severity of drought conditions over the years, offering insights into long-term drought trends for the study area. Coimbatore district experienced two moderate droughts, one severe drought, and two extreme drought events. The drought years identified for Coimbatore include 1988, 1991, 2009, 2016, and 2017. Similarly for Tiruppur district 1985, 1988 and 1991 were considered to be drought years. The details report on the classifiction of years were given in the Table 2(a&b) for coimbatre and Tiruupur district respectively.

SPI at the three-month scale (Table 3) was used as the primary predictor for the North-East Monsoon, which is crucial for Coimbatore. The ANFIS forecasting framework was designed following Bacanli et al. (2008). A sequence of antecedent SPI values served as input variables, while the corresponding annual SPI values were used as outputs. Increasing the number of past SPI inputs improved model robustness, in line with findings from Bacanli et al. (2008). The dataset was divided into 80% training, 10% testing, and 10% validation, as shown in Table 4.

To ensure the robustness and predictive capability of the developed ANFIS models, a systematic data splitting strategy was adopted, & performance was assessed across training, and testing datasets. A total of 38 years of SPI-3 index data were used for Coimbatore and Tiruppur district, with a rolling lag-based input structure from Model 1 (M1) to Model 9 (M9). Each subsequent model

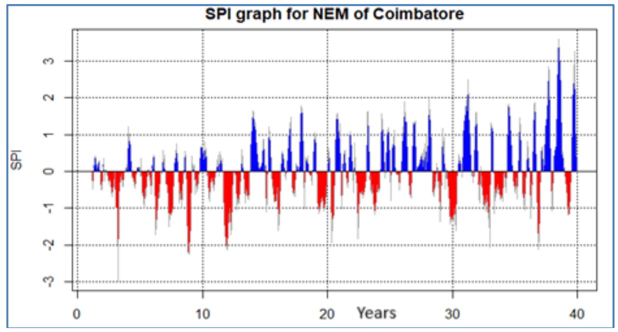

Fig. 3(a). SPI-3 pattern values for the district of Coimbatore from 1981 to 2019

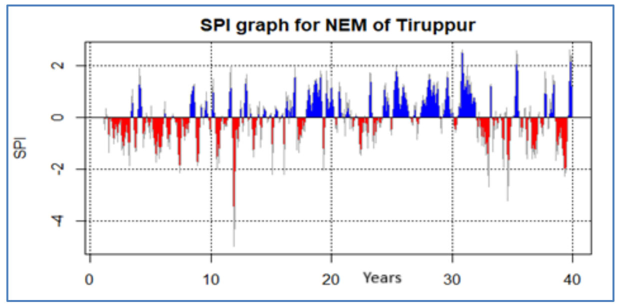

Fig. 3(b). SPI-3 pattern values for the district of Tiruppur from 1981 to 2019

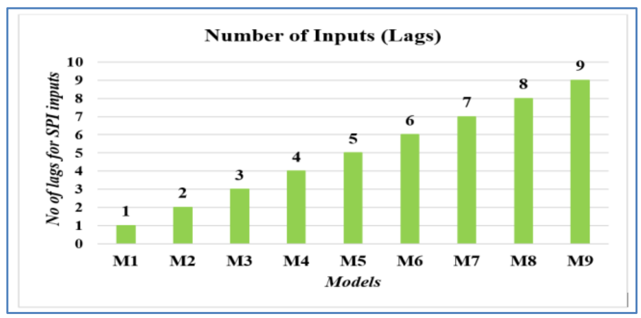

Fig. 4. Lag selection idea for different models

incorporate one additional lagged SPI term as an input i.e., from SPI(t−1) to SPI(t−9) (Table 3). Accordingly, the effective dataset size decreased by one year with each additional lag, resulting in a progressive reduction in sample size from M1 to M9. The dataset for each model was split in the ratio of approximately 80% for training, and 10% each for testing and validation. Table 4 presents the distribution of data points across the models. Fig. 4 shows the graphical view of lag selection criteria for different ANFIS models.

The ANFIS models were developed and fitted for all input–output combinations using the selected dependent and independent variables. Figs. 5 and 6 present the graphical comparison between the predicted ANFIS outputs and the observed SPI values for the Coimbatore and Tiruppur districts, respectively. For both districts, Models 3, 4, 5, 6, 7, 8 & 9 closely matched the observed

TABLE 2(a)

Classification of years based on drough index for Coimbatore district

Moderate Drought	Severe Drought	Extreme drought	Near Normal				Very Wet
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	

TABLE 2(b)

Classification of years based on drough index for Tiruppur district

Moderate Drought	Severe Drought	Extreme drought	Near Normal					Very Wet	Extreme Wet
1985	1988	1991	1981	1990	2000	2008	2016	1992	2010
			1982	1993	2001	2009	2017	1996	2019
			1983	1994	2002	2011	2018	2005	
			1984	1995	2003	2012			
			1986	1997	2004	2013			
			1987	1998	2006	2014			
			1989	1999	2007	2015			

TABLE 3

For the ANFIS forecasting model, many input combinations were employed

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)

TABLE 4

Number of datasets used for model training and testing

S.No	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

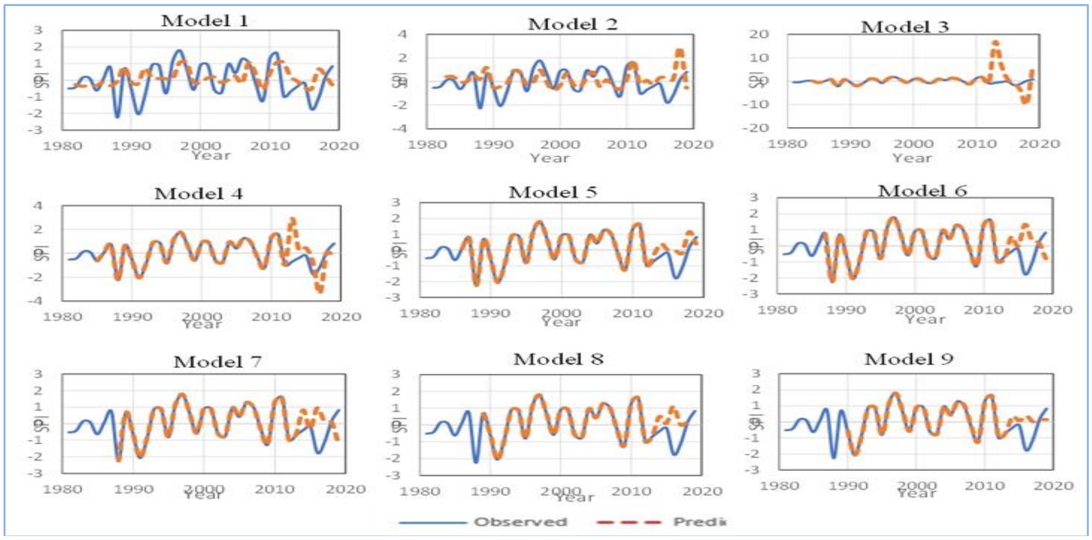

Fig. 5. Comparison of predicted ANFIS values and observed SPI values for different model in Coimbatore district

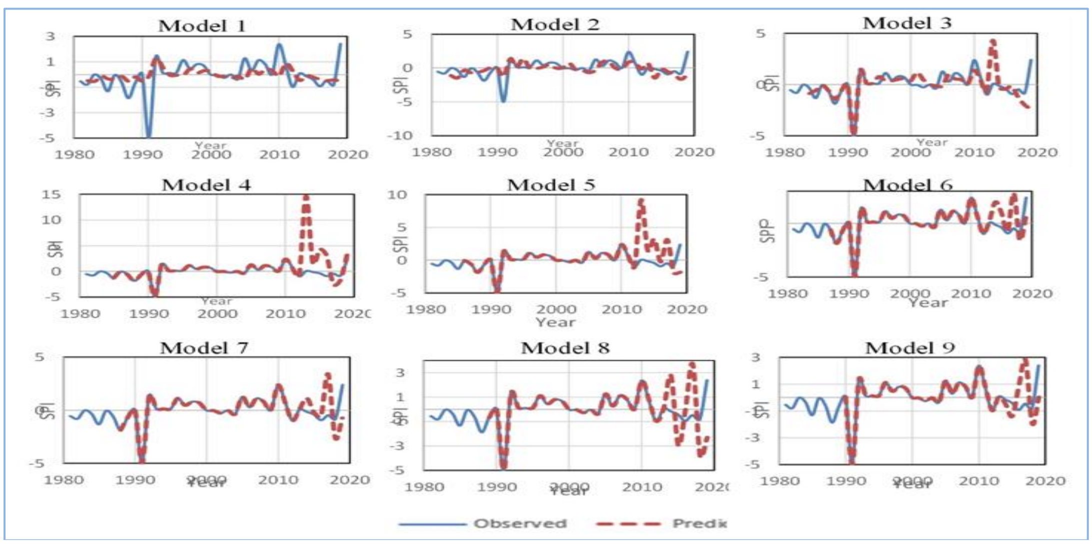

Fig. 6. Comparison of predicted ANFIS values and observed SPI values for different model in Tiruppu district

TABLE 5

Results of model performance

Model	**Coimbatore**		**Trippur**	
	RMSE	**MAE**	**RMSE**	**MAE**
M1	0.97	0.80	1.17	0.69
M2	1.01	0.75	1.12	0.77
M3	3.74	1.26	1.21	0.64
M4	0.78	0.27	2.73	0.83
M5	0.41	0.16	1.97	0.71
M6	0.68	0.23	0.80	0.29
M7	0.68	0.23	0.96	0.34
M8	0.59	0.19	1.44	0.59
M9	0.48	0.17	0.85	0.33

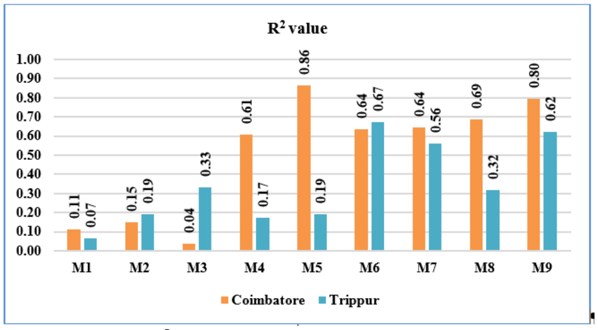

Fig. 7. R^2 values for all the projected models

data, particularly within the training set, indicating that the models were effectively trained. Performance assessment using error indicators such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2) (Fig. 7) helped to identify the most suitable model. For the Coimbatore district, Model 5 emerged as the best-fitting model, exhibiting a low RMSE (0.412), low MAE (0.158), and a high R^2 value (0.863). For Tiruppur distrct, Model 6 was identified as best-fitting model with lowest RMSE of 0.80, lowest MAE of 0.29 and highest R^2 value of 0.67 (Table 5).

Since the study utilizes the SPI-3 index, which reflects short-term drought conditions, forecasting within a 3 to 6-month lead time will be significant and meaningful. This forecast horizon aligns with agricultural and water resource planning cycles, providing stakeholders such as farmers and irrigation managers, an adequate time to implement mitigation strategies for upcoming droughts (Elbeltagi *et al.*, 2023; Poornima *et al.*, 2023). Extending the forecast beyond this range, especially with a limited number of antecedent SPI inputs, may compromise model accuracy and reduce its operational relevance. The ANFIS models developed in this study demonstrated strong predictive performance as evidenced by the low RMSE, MAE and high R^2 values. These results confirm that the selected forecast period is not only statistically sound but also suitable for real-world drought early warning and response systems. Tamil Nadu's Western Zone is heavily dependent on the North-East Monsoon, and timely drought forecasts are crucial to ensure food security and reduce farmer vulnerability (Pazhanivelan *et al.*, 2023). The SPI-based forecast serves as a drought early warning system to advise farmers on critical decisions such as crop selection, irrigation scheduling, and fertigation. Forecasts can support water management for irrigation, especially in semi-arid regions like Coimbatore and Tiruppur where water resources are limited. It can make the district-level contingency plans more efficient. Thus, the study helps in implementing climate-resilient agriculture programs in vulnerable areas.

4. Conclusions

The study focuses on assessing the drought conditions in Coimbatore and Tiruppur districts using the Standardized Precipitation Index (SPI) data which was on par with the procedure suggested by World Meteorological, recommending the usage of precipitation data to monitor the drought. SPI data derived from the monthly precipitation, collected from 1981 to 2019 were used to estimate the drought occurrences. Nine distinct ANFIS forecasting models were developed with varying input variables based on antecedent SPI values. For Coimbatore district, Model 5: utilizing SPI values up to time lag (t-5), and for Tiruppur district, Model 6: utilizing SPI values up to (t-6), exhibited improved performance with fewer input variables. The above results were confirmed using statistical error criteria such as RMSE, MAE, and R^2, and the best-performing models were recommended to forecast future drought years in the respective regions.

In future, the study could be enhanced by integrating additional climatic variables such as temperature, evapotranspiration and soil moisture which may provide a more comprehensive understanding of drought dynamics and improve the model's accuracy. Moreover, investigating seasonal variations and their influence on drought prediction could lead to more robust forecasts. Future studies could also test other machine learning models like Support Vector Regression (SVR), Random Forest (RF), XGBoost or deep learning approachesto compare and potentially outperform the ANFIS model in terms of prediction accuracy and generalization. Thus the drought forecasting also helps stabilize economies dependent on agriculture and protects ecosystems & bio-diversity, reducing the long-term damage caused by drought.

Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Authors' Contributions

M. Radha: Research framework, Methodology, Formal analysis & analytical work, Investigation**,** Review. (*email- radhamyilsamy@gmail.com*).
S. Vishnu Shankar: Methodology, Investigation, Validation, Review & editing.
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