Development of A Meteorological Drought Index Using Fuzzy Logic

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Abstract - *Drought is a natural disaster which impact lives in various ways and leads to great harm. Droughts are of four categories namely agricultural, hydrological, socioeconomic, and meteorological droughts. There are various types of indices that are being used worldwide to effectively monitor and assess droughts. The study addresses the difficulties posed by droughts through the development of a meteorological drought index using fuzzy logic and adaptive neuro-fuzzy inference model. Various combinations of input variables, including maximum temperature, mean temperature, precipitation, and potential evapotranspiration, for the Ramanagara district of Karnataka state was used for model development. Results revealed that the Rainfall Anomaly Index (RAI) performed best among traditional indices, showing the highest correlation (0.862) with upper soil moisture, a key drought indicator. On the other hand, the average of the top-performing fuzzy logic (FL3) model surpassed all traditional indices, exhibiting a correlation of 0.983 with upper soil moisture. Notably, when the average output of the top-performing FL models has been utilized for training, the optimal ANFIS model achieved a correlation of 0.926 with upper soil moisture. To determine the developed models, drought assessments were conducted in four taluks across different seasons. The validation results indicated that the developed models performed comparably to the best-performing traditional drought index (RAI) in most cases. In summary, the soft computing drought indices developed in this study, on the basis of fuzzy logic and ANFIS, outperformed traditional techniques, contributing significantly to more accurate drought prediction and mitigation actions.*

Key Words: Drought, Fuzzy logic, ANFIS, Pearson correlation, meteorological drought, conventional drought incices, soft-computing models.

1.INTRODUCTION

In recent years, the impact of climate change has gained a huge need for more sophisticated tools and methodologies to assess and manage water resources. One of the critical effects of the climate change is drought, which pose a significant threat to agriculture, ecosystems, and human populations worldwide. Traditional meteorological drought indices have proven valuable, yet there remains a compelling need for innovative approaches which enhances the capacity to characterize and give response to drought conditions with greater precision.

The study was to develop a Meteorological Drought Index (MDI) utilizing the fuzzy logic. Fuzzy logic, a computational paradigm inspired by human reasoning, has gained interest in various scientific domains for its ability to handle uncertainty and imprecision inherent in real-world data. By incorporating fuzzy logic into the realm of meteorological drought assessment, this research aims to offer a more nuanced perspective on the complex interactions between atmospheric variables that contribute to drought monitoring, assessment, and forecasting.

Conventional drought indices, including PDSI (Palmer Drought Severity Index) and SPI (Standardized Precipitation Index), have played crucial roles in drought monitoring and prediction (Mhamd Saifaldeen Oyounalsoud et.al. 2022). However, these indices often have limitations in capturing the multifaceted nature of meteorological droughts, especially when faced with irregularities and uncertainties in climatic data. The proposed MDI seeks to overcome these challenges by harnessing the flexibility and adaptability of fuzzy logic, enabling a more dynamic representation of drought conditions that considers the inherent vagueness and ambiguity within meteorological data.

2. Literature Survey

Numerous researches have embraced soft computing techniques for drought monitoring and forecasting. For example, Abbasi et al. (2019) used the GEP (Gene Expression Programming) model in conjunction with the Standardized Precipitation Evapotranspiration Index (SPEI) to forecast drought over a range of periods. The findings revealed an improvement in accuracy of model from 60.1% at SPEI1 (one-month scale) to 92.3 percent at SPEI48 (48-month scale), underscoring the enhancement in overall accuracy with increasing SPEI scale. Similarly, Keskin et al. (2009) employed the Standardized Precipitation Index (SPI) alongside an advanced drought analysis model incorporating FL (Fuzzy Logic) and Adaptive neuro fuzzy inference system (ANFIS) techniques for meteorological drought assessment across nine stations in Turkey at varying time scales. Their findings highlighted the high efficacy of ANFIS in assessment of drought. Furthermore, Malik et al. (2020) presented the CANFIS (Co-active Neuro-Fuzzy Inference System), a contemporary FL model designed to forecast SPI at six sites in the Indian state of Uttarakhand over several time scales. Conventional artificial intelligence models and regression were compared, and the outcomes demonstrated that the

CANFIS model performed better in SPI prediction as comapred to other 2 models. Rezaeian-Zadeh and Tabari (2012) discovered that heuristic techniques offer accurate prediction and can capture the fluctuations of SPIs irrespective of time scales, as Kuriqi et al. (2023) have reported in their research. Salloom (2022) suggested a PID (Proportional-Integral-Derivative) control strategy to improve the neural network models' multi-step-ahead periodic time series prediction performance.

However, the study's focus was restricted to modeling conventional drought indexes. The newly developed AI models could only match the performance of the conventional indices employed in their formation, given their training data comprised of actual outputs from conventional drought indices. Furthermore, there was not much association observed between the performance of AI models and other indices of environmental and hydrological drought. In the study, a meteorological drought index based on FL rules that describe drought and major meteorological features relations was established. This approach aims to address the limitations from previous studies by incorporating a broader range of environmental and hydrological drought indicators into the modeling framework.

3. STUDY AREA AND DATA

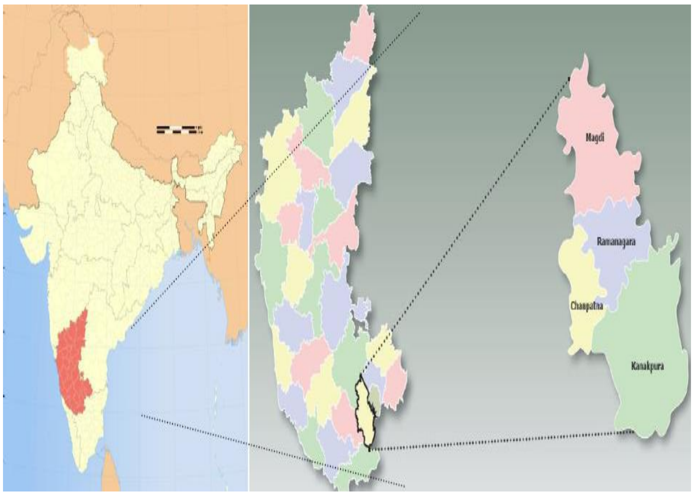


Fig-1: Location Map and District Map of Ramnagara

Ramanagara district in the southern part of Karnataka covers 3,410 square kilometers, belongs to semi-arid region which is prone to drought due to poor percolation of rainfall through the soil. The location map of the study region is displayed in Fig. 1 (Srinivasareddy, 2018). In present research the four taluks of Ramanagara district were selected which have the rain gauge stations located within the coordinates listed in table.1.

The Karnataka State Natural Disaster Monitoring Center provided the data. For every taluk, statistics on mean temperatures, maximum and monthly precipitation, and years 1992 to 2022 were available. In addition to the data previously provided, the indicators of drought included data on root zone soil moisture, deep soil moisture, and top soil moisture. For every taluk under study, once-a-month drought indicator data from 1992 to 2022 was obtained from NASA Power Acess.

Table-1: Latitude and Longitude of the Taluks of Ramanagara district.

Sl.No	Taluk	Latitude	Longitude
1.	Channapatna	12°39’	77°12’
2.	Kanakapura	12°33’	77°25’
3.	Magadi	12°57’	77°13’
4.	Ramanagara	12°43’	77°16’

4. METHODOLOGY

The goal of the study was to establish an ANFIS and fuzzy logic model for monitoring of drought and assessment. Fig. 2 gives the summary of the methodology followed. The input data like precipitation, maximum/mean temperature and PET were used. Three levels of soil moistures data were taken as drought indictors, these were upper soil moisture, root zone soil moisture as well as lower/deep soil moisture for the selected taluks. PET was estimated employing the hargreaves method using Drinc using data like maximum and minimum temperature and latitude

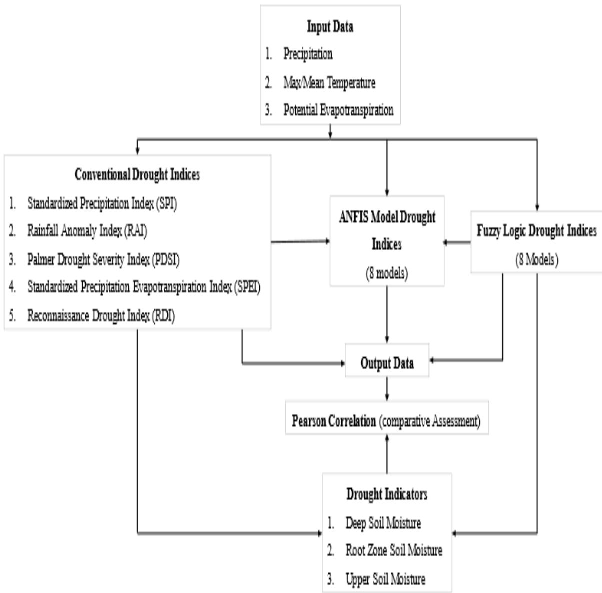


Fig-2: Flowchart of the methodology.

The Drinc software as well as R program were used in the study to calculate five conventional drought indices: the PDSI, RDI (Reconnaissance Drought Index), RAI (Rainfall Anomaly Index), SPI, and SPEI. A comparative assessment between the conventional drought index values and drought indicators (like deep soil moisture, root zone soil moisture and upper soil moisture) was done using Pearson correlation. Ultimately, the correlation was utilized to develop and assess the ANFIS and FL models, two soft computing models. The ANFIS model was developed to improve the capabilities of the FL model using training and testing data during the selected periods.

4.1. CONVENTIONAL DROUGHT INDICES

From 1992 to 2022, four taluks in the study area received conventional drought indices, as stated in the section above. In order to evaluate the extent and duration of the drought in the research region, this step was required. For each index, a different set of input data was employed. The study's usage of drought indices is summarized in Table 2.

Table-2: Summarized list of the conventional drought indices.

Conventional Drought Indices	Input	Range
Standardized Precipitation (SPI)	P	-3.00 to 3.00
Reconnaissance Drought Index (RDI)	P, T, and PET	-2.00 to 2.00
Rainfall Anomaly Index (RAI)	P	-3.00 to 3.00
Standardized Precipitation Evapotranspiration Index (SPEI)	P, T, and PET	-2.00 to 2.00
Palmer Drought Severity Index (PDSI)	P, T, AWC, and L	-4.00 to 4.00

4.2. FUZZY LOGIC MODEL

Many applications requiring time-series data systems for control, classification, and prediction are examined in relation to FL algorithms (Wilbik et al., 2012). FL is frequently utilized in the literature's drought investigations (Ozger et al., 2012; Sobhani et al., 2019). These research have demonstrated that FL is a suitable tool for analyzing and evaluating drought. The fuzzy inference engine, output, database, fuzzy inference engine, rule base, defuzzifier unit, and input unit are among the various FL structure components depicted in Fig. 3. The linguistic variables and terms are initially defined by the algorithm. To translate the measurement into fuzzy terms, for example, if the variable to be measured is precipitation, a range of degrees must be set [0,1]. For the processes of fuzzification and defuzzification, membership functions must be developed. The non-fuzzy input values are converted to fuzzy linguistic terms with the membership function, and vice versa. The output variable is controlled by the fuzzy rules that are written, A simple IF-THEN rule with a condition and a consequence is called a fuzzy rule. The inference engine creates MFs and rules, then combines them to produce the fuzzy output. According to the membership function, the defuzzification procedure yields a quantitative result. After that, the output data is converted into nonfuzzy values and a table is produced to assess every input with respect to its corresponding output (Bai and Wang, 2006).

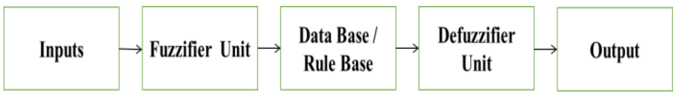


Fig -3: Fuzzy Logic Controller

Eight FL models were created in the study with different input parameters combinations. Table.3 gives the list of these eight developed FL models.

Table-3: List of Developed Fuzzy Logic Models.

Model	Inputs	Number of MFs	Number of Rules
FL1	Rainfall, Maximum temperature	3,3	9
FL2	Rainfall, Maximum temperature	5,5	25
FL3	Rainfall, Maximum temperature, PET	3,3,3	27
FL4	Rainfall, Maximum temperature, PET	5,5,3	75
FL5	Rainfall, Mean temperature	3,3	9
FL6	Rainfall, Mean temperature	5,5	25
FL7	Rainfall, Mean temperature, PET	3,3,3	27
FL8	Rainfall, Mean temperature, PET	5,5,3	75

The table shows that FL 3 had 27 rules to define the model also these rules help in the working of these models in different operating scenarios. The constructed fuzzy rule base statement is exemplified by the following rule: The FL index is highly wet, indicating the wet conditions, if precipitation is high and the maximum temperature is low. MATLAB R2017a was used to create each and every FL model. The FL1 model's rules are displayed in a table 4.

4.3. ADPTIVE NEURO FUZZY INFERENCE MODEL

Modeling and forecasting hydrologic systems and processes has been shown to be an efficient use of ANFIS (Mokhtarzad et al., 2017). The FL models' inference system and the learning powers of ANNs are combined in the ANFIS model (Tagliabue et al., 2021). By using ANNs to automatically generate fuzzy rules and optimise parameters, it addresses the fundamental issues with fuzzy modeling, including defining membership function parameters and creating fuzzy IF-THEN rules (Mokhtarzad et al., 2017). A fuzzy inference system had been utilized in the study to apply the Takagi-Sugeno technique. Although the Sugeno output membership functions are linear or constant, these functions are compatible with adaptive methods such as artificial neural networks (ANNs) and also computationally efficient. Using the ANN learning technique, the membership function parameters were adjusted throughout the training phase. The ANFIS model created for the study consists of 9 input membership functions, twenty-seven output membership functions, and twenty-seven fuzzy rules.

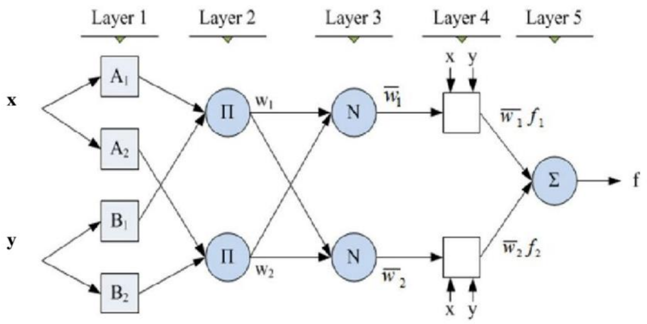


Fig-4: ANFIS configuration used in this study.

Figure 4 illustrates the streamlined adaptive neuro-fuzzy inference system that results from the extensive interactions between all of the system's components. This is a simplified version of the ANFIS model that consists of one output (f) and two inputs (x & y). The five layers of the ANFIS model that Jang (1993) suggested include the calculations that are outlined by Eqs. (1) to (5) (Jang, 1993):

Layer 1: In this layer, each node is adaptive, and its node function is determined as

$$O_i^1 = \mu_{Ai}(T) \quad \text{--------------(1)}$$

Here T is denoted as the input to node i, and Ai is the linguistic label set associated with associated node.

Layer 2: The nodes of this layers are fixed node labelled (Π), which represents the firing strength (W) of a fuzzy rule. The output of every node is the product of the incoming signals.

$$O_i^2 = W_1 = \mu_{Ai}(T)\mu_{Hi}(P) \quad \text{---------------(2)}$$

Layer 3: The fixed nodes (N) in this layer compute the ratio of the firing strengths of each rule to the total firing strengths of all the rules. The outputs from this layer are called the normalised firing strengths and can be computed as follows:

$$O_i^3 = \overline{W}_i = \frac{W_1}{W_1+W_2}, i = 1, 2 \quad \text{----------------(3)}$$

Layer 4: With a node function—a linear combination of input variables—every node in this layer is adaptive. If {pi, qi, ri} is the parameter set, then

$$O_i^4 = \overline{W}_i f_i = \overline{W}_i(p_i x + q_i y + r_i \quad \text{---------------(4)}$$

Layer 5: The single node in this layer, that is fixed, computes the total output, or the sum of all incoming signals.

$$O_i^5 = \sum_i \overline{W}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \quad \text{----------------(5)}$$

To construct and train the ANFIS model, MATLAB R2017a's fuzzy-logic toolbox was used. The prime techniques and properties of the created ANFIS models are listed in Table 5. 3 inputs (potential evapotranspiration, maximum temperature, * rainfall) and 2 types of outputs (as previously described) were tested using these models. In the initial four models (ANFIS1 to ANFIS4), the output was the average performance of the top-performing FL models. And for the subsequent four ANFIS models (ANFIS5 to ANFIS8) utilized the mean normalization of the top-performing conventional drought indices as their output. The training set size remained consistent at 70 percent of the total dataset, with the remaining 30% allocated for testing purposes. Each model underwent 1000 training epochs, employing a hybrid optimization method. Furthermore, the type of membership function for the output remained constant among all models that were developed.

Table- 5: Techniques and features of the created ANFIS model.

Parameter	Type/Method
Fuzzy inference system type	Takagi-Sugeno
AND method	Min
OR method	Max
Defuzzification method	Weighted average
Optimization method	Hybrid
Output parameter	ANFIS1 – ANFIS4: predicted data of the average top-performing FL models ANFIS5 – ANFIS8: top performing conventional indices
Output membership function type	Constant
Input membership function type	ANFIS1: Triangular ANFIS2: Trapezoidal ANFIS3: Generalized Bell-Shaped

	ANFIS4: Gaussian ANFIS5: Two Gaussian ANFIS6: Pi-Shaped ANFIS7: Difference Between Two Sigmoidal ANFIS8: Product of Two Sigmoidal
Input parameters	Rainfall, Maximum Temperature, PET

4.4. PEARSON CORRELATION

A statistical measure called the Pearson correlation coefficient is utilized to determine the strength and direction of a linear relationship among 2 random variables. Due to its versatility, it has been widely utilized in a variety of applications, like noise reduction, data processing, and time-delay estimation (Benesty et al., 2008). Notably, research has shown that the Pearson coefficient is effective in precisely matching indicators of drought, including soil moisture, with drought indices (Tian et al., 2020). Thus, the Pearson correlation coefficient has been utilized in this research as a comparative assessing tool for validating the the generated models output with the drought indicators and results obtained from conventional models.

4.5. MODEL VALIDATION

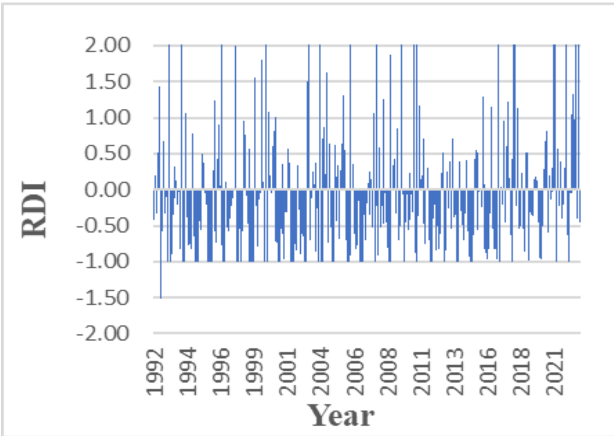
The proposed classification of drought for the recently created FL & ANFIS models is shown in Table 6. The selected scales and ranges have been chosen in order to be compatible with conventional drought indexes. The scale represents severely dry and moist conditions, correspondingly, and it is from -3.0 to 3.0 with 0.5 increments. Using the four taluks that had been selected, the developed FL and ANFIS drought indices were validated. The beginning of January, April, July, & October in 2023 is the middle month of each season. PET, mean temperature, soil moisture, maximum temperature, and precipitation data have been collected during this period.

Table-6: classification of Drought index for indices.

Range	Classification
-3 and less	Extremely Dry
-2.99 to -2.00	Very Dry
-1.99 to -1.00	Moderately Dry
-0.99 to -0.50	Slightly Dry
-0.49 to 0.49	Near Normal
0.50 to 0.99	Slightly Wet
1.00 to 1.99	Moderately Wet
2.00 to 2.99	Very Wet
3.00 and more	Extremely Wet

5. RESULTS AND DISCUSSIONS

This research was conducted to evaluate drought utilizing a variety of drought indices and correlate every index's output with three distinct drought indicators, explained in the methodology section. The research developed a new meteorological drought index which might be used for monitoring of drought in the future by developing and validating various FL models using correlations with drought indicators. According to Benesty et al. (2008) and Tian et al. (2020), the correlation has been conducted using the Pearson coefficient, which is regarded as the finest statistical tool for this investigation. This correlates with the correlation measures utilized by earlier researches in the reviewed literature.



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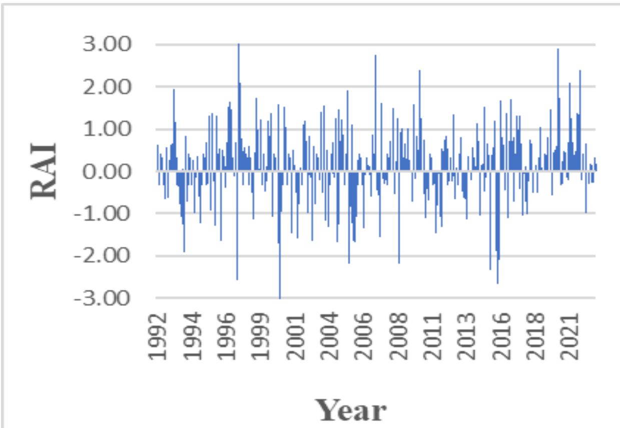

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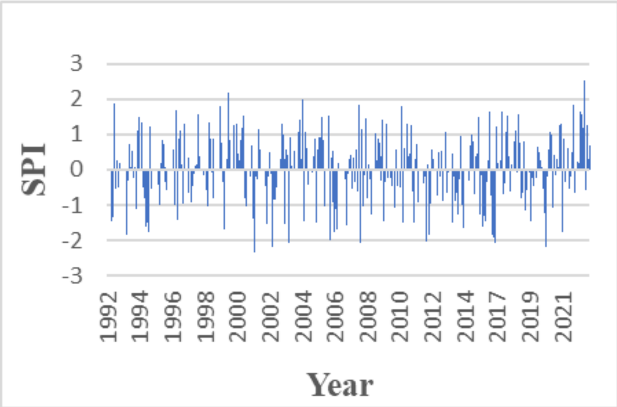

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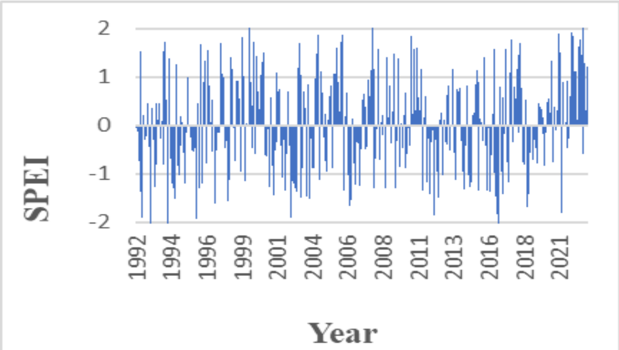

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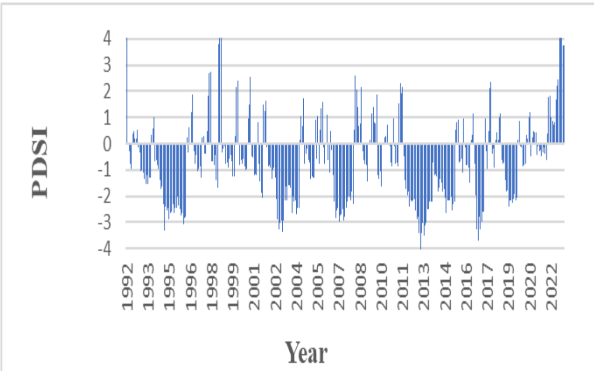


(e)

Fig- 5: Temporal variations of all the five conventional drought indices in the Channapatna between 1992 and 2022: a) Reconnaissance Drought Index, b) Rainfall Anamoly Index, c) SPI, d) SPEI, e) Palmer Drought Severity Index

5.1. CONVENTIONAL DROUGHT INDICES

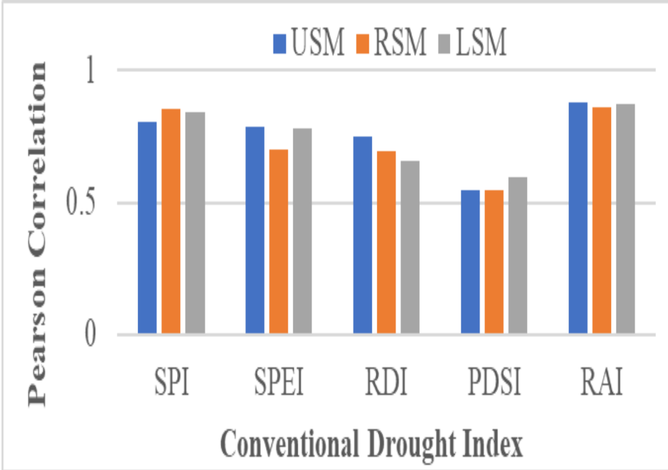


Fig-6: Pearson correlation between drought indices and drought indicators.

For four taluks in the Ramanagara district, five conventional drought indices (SPI, SPEI, PDSI, RDI and RAI) have been calculated. Graphs representing the calculated conventional drought indices are shown. For instance, from 1992 to 2022, the temporal variations in SPI readings for every station is displayed in Fig. 5. The SPI readings varied a lot during the research period, suggesting variations in the drought. With a few minor variations, the SPI values were comparable for each station. Table 7 presents the highest and least SPI readings for every station in the research area to demonstrate the variation in SPI values. According to the SPI classification, a climate that is moist is indicated by positive values, and a dry climate is indicated by negative values.

The Channapatna Taluk station recorded the greatest SPI value of 2.56 in August 2022 (an exceptionally wet climate), while the Magadi station had the lowest SPI value of -3.6 in 2001 (an exceptionally dry climate). During the dry season, all indexes displayed exceptional values, particularly between 2001 and 2009. The SPI readings varied a lot during the research period, suggesting variations in the drought. Similar to the SPI other four drought indices also were similar for all the four taluks with slight variations. SPI and SPEI and RDI were similar since the drought level computed by every index was ranged from -2.0 to 2.0. According to Tefera et al. (2019) and Haied et al. (2017), the results in the literature, PDSI and RAI were similar to each other since the drought level indicated by every index remained within the identical range of -3.0 to 3.0. 19.

Table-7: Minimum and Maximum SPI value for four taluks

Taluk	Minimum SPI Value		Maximum SPI Value	
	Value	Month, Year	Value	Month, Year
Ramanagara	-2.2818	August, 2001	2.4808	August, 2022
Kanakapura	-3.3018	August, 2002	2.2041	August, 2022
Channapatna	-2.7806	June, 2001	2.5506	August, 2022
Magadi	-3.6192	May, 2001	2.3152	December, 2022

By computing the Pearson correlation coefficient among the conventional index values and 3 drought indicators and utilizing it as a comparative assessment tool, the optimal conventional drought index for the research area was determined. Figure 6 depicts the correlation among every conventional drought score and drought indicators. PDSI, having a coefficient value of 0.596, showed the strongest association with lower soil moisture. The strong correlation between accessible water content and deep soil moisture can be attributed to the fact that PDSI estimates take this into consideration. Among the three soil moisture levels, RAI showed the strongest association, with coefficient values of 0.603, 0.620 & 0.718, correspondingly. As a result, it was determined that the RAI had the greatest correlation among traditional drought index and drought indicators. These results were consistent with those of another study that employed a comparable evaluation method.

5.2. FUZZY LOGIC INDICES

Eight different FL models were created using the MATLAB R2017a software. Table 8 presents the results of the calculation of the Pearson correlation among the monthly FL index values and the monthly conventional index values across 1440 data points (4 taluks×12months×30years).

The highest connection has been observed among the FL1 and RDI (0.861), while the lowest correlation has been noted among FL8 and PDSI (0.207). A high correlation shows that the created FL index and the conventional drought indices have a strong association.

Table-8: Correlation of FL Models with Conventional Drought Indices.

Model	Correlation with the Conventional Drought Indices				
Name	SPI	SPEI	RDI	PDSI	RAI
FL1	0.798	0.772	0.861	0.583	0.783
FL2	0.722	0.731	0.835	0.426	0.658
FL3	0.682	0.709	0.794	0.408	0.539
FL4	0.467	0.360	0.455	0.304	0.255
FL5	0.763	0.752	0.799	0.595	0.802
FL6	0.792	0.663	0.770	0.547	0.761
FL7	0.698	0.705	0.765	0.542	0.662
FL8	0.392	0.273	0.366	0.207	0.254

Three inputs (potential evapotranspiration, mean temperature, and rainfall), 3 membership functions for potential evapotranspiration, and 5 membership functions for the rainfall & mean temperature, and seventy-five fuzzy rules were present in the least-performing model (FL8). Rainfall and the highest temperature were the two inputs in the best-performing model (FL1), which also included nine fuzzy rules and three membership functions for each input.The model's overfitting due to the extra inputs and fuzzy rules may have contributed to its low output. These findings also demonstrate the impact of temperature and rainfall as drought index inputs in contrast to evapotranspiration. An illustration of the association among the FL & conventional indices is shown in Figure 7, which depicts the correlation between FL1 and RDI. Fig. 7's trend line, with R2 = 0.8064, indicates a linear relationship.

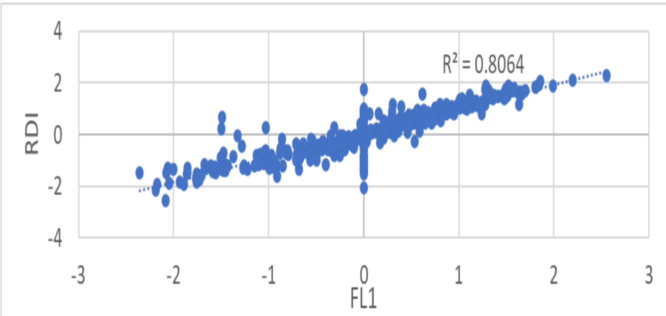


Fig-7: Scatter plot depicting the relationship between the FL1 and RDI drought indices.

By calculating Pearson correlation coefficients along with drought indicators, the FL models were further validated. The association between the selected drought indicators and FL models is displayed in Fig. 8. FL3 and upper soil moisture showed the highest correlation coefficient (0.983), whereas

FL8 and higher soil moisture showed the lowest correlation coefficient (0.321). Furthermore, FL4 showed low correlations with each of the three drought indicators. These findings recommend that FL4 and FL8 have been the least accurate drought forecasting models among the eight models created. The best-performing models, on the other hand, were FL1, FL3, and FL7, which showed the highest correlation coefficients (0.875, 0.983, and 0.814, respectively) with the drought indicator (upper soil moisture). The findings support the FL-based drought index created by Nasab et al. (2018), and they also demonstrate a strong correlation among the calculated conventional drought indices and produced FL-based index.

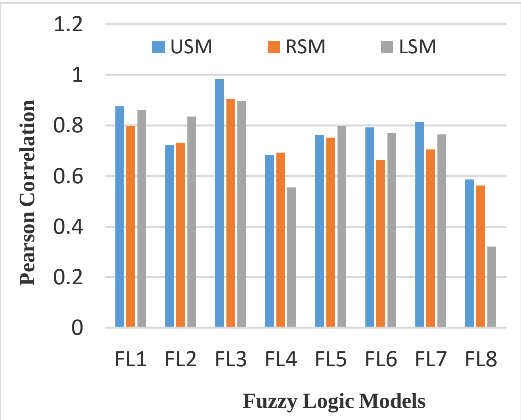


Fig-8: Correlation of FL Models with Drought Indicators.

5.3. ANFIS DROUGHT INDICES

ANFIS models were created with the aim to improve the predictive capabilities of FL models through the refinement of fuzzy parameters using a training dataset with multiple inputs and a single output. Eight models with 2 forms of output were created: 1) the mean values of the most effective conventional indices, and 2) the mean values of the most effective FL models (Mhamd Saifaldeen Oyounalsoud, 2022).

A Pearson correlation was computed across 1440 data points (4 taluks × 12 months × 30 years) between the monthly values of the ANFIS index and the monthly values of the conventional index. Table 9 presents the findings. The connection between ANFIS1 and RAI was found to be the highest at 0.942, while the correlation between ANFIS6 and PDSI was the lowest at 0.529.

The Pearson correlation between the drought indicators and the ANFIS models was employed to further validate the models. The association between the eight ANFIS models and the three drought indicators is displayed in Fig. 9. ANFIS1 and higher soil moisture showed the strongest relationship (0.926), whereas ANFIS4 and lower soil moisture showed the lowest correlation (0.413). Furthermore, there was a lower association found between ANFIS6 and the majority of the drought indicatorsANFIS6, the lowest correlated model, and ANFIS1, the model with the highest correlation, while the number of inputs, membership functions, and rules are same; Despite this, the output was the triangle membership functions of the average top-performing FL model in ANFIS1. Due to these variations, the correlation coefficient between the upper soil moisture and the value increased from the lowest to the greatest. The outcomes of the presented study were compared with previous research by Mishra and Desai (2006).

Tabe-9: ANFIS Model Correlation with Conventional Drought Indices.

Model	Correlation with the Conventional Drought Indices				
Name	**SPI**	**SPEI**	**RDI**	**PDSI**	**RAI**
ANFIS1	0.879	0.862	0.895	0.584	0.942
ANFIS2	0.792	0.739	0.806	0.573	0.830
ANFIS3	0.883	0.856	0.893	0.587	0.941
ANFIS4	0.866	0.822	0.876	0.578	0.916
ANFIS5	0.835	0.783	0.846	0.581	0.884
ANFIS6	0.749	0.692	0.765	0.564	0.787
ANFIS7	0.885	0.862	0.895	0.582	0.940
ANFIS8	0.885	0.863	0.895	0.582	0.932

5.$. MODEL VALIDATION

Data from four selected stations in the Ramanagara district (Ramanagara taluk, Kanakapura taluk, Magadi taluk, and Channapatna taluk) were collected during the midpoint of each season in 2023 in order to validate the developed models, and the drought index has been calculated using the developed models. By utilizing the drought classifications displayed in Table 6, the top-performing models, FL3 and ANFIS1, have been utilized to evaluate drought in the areas of the chosen stations.

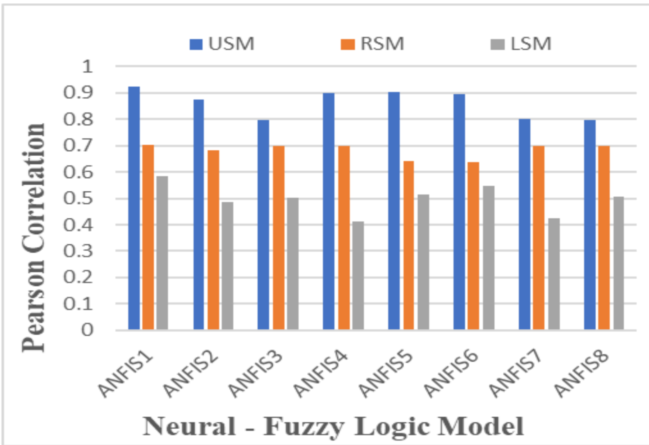
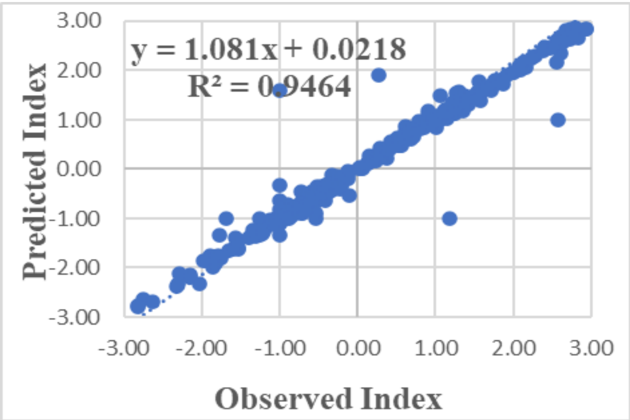
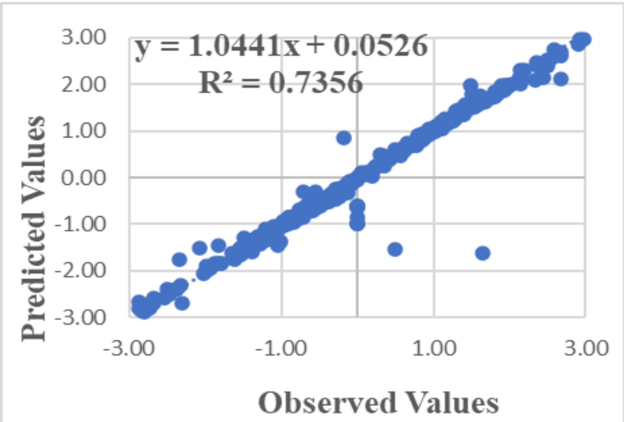


Fig-9: Correlation of the neuro-fuzzy models with the drought indicators.

The performance of these models was tested by drawing the graphs of the ANFIS model that was performing best for both the training and testing phases as shown in Fig. 10(a) and (b). The slope for both the phases was more than one which indicates that the overestimation can be neglected. The linear relationship between observed and predicted datasets are positively strong.



(a)



(b)

Fig-10: (a) training and (b) testing scatter plots for datasets of the best ANFIS model.

The conventional drought index (RAI), which was used to compare the indices, showed the strongest association with the soil moisture indicator. Additionally, the average precipitation in 2023 was lower than in previous years, which raised the risk of drought, as per the IMD (India Meteorological Department). The generated models performed similarly in drought prediction overall, according to the validation results, and they generally matched the results of the best associated RAI. In the Kanakapura taluk, the developed models outperformed the conventional index, particularly in July while the area received a lot of rainfall (113 mm). Near-normal to slightly wet conditions have been projected by the drought index that was developed employing FL and ANFIS. The RAI index, however, revealed an extremely dry condition. FL and ANFIS models did not predict well at Ramanagara Taluk during April with near-normal conditions, where the actual rainfall was 33 mm. Using multiple climate features can result in the inaccuracies in the model that were not incorporated in the development. These findings were consistent with the research conducted by Nguyen et al. (2017), who examined into the quantitative values of the SPEI and SPI drought indices as well as the usage of ANFIS for drought forecasting. The results demonstrated the potential for the ANFIS model to be successfully employed for drought forecasting with high reliability and accuracy. Table 10 shows the validation results of the models created.

Table-10: FL3, ANFIS1 and RAI Drought index.

Taluk & Year	Month	Rainfall	FL3	ANFIS1	RAI
Ramanagara, 2023	Jan	29.70	-1.90	-1.87	-2.72
	April	33.00	-1.18	-1.83	-0.24
	July	33.20	-1.69	-1.60	-1.57
	Oct	362.00	3.29	3.14	3.00
Kanakapura, 2023	Jan	2.09	-1.11	-1.20	-1.83
	April	2.20	-2.67	-2.51	-2.99
	July	10.40	-1.83	-1.67	-2.54
	Oct	113.00	0.72	0.96	-0.07
Channapatna, 2023	Jan	15.34	-2.36	-2.11	-2.95
	April	2.00	-2.93	-2.98	-3.00
	July	28.15	-1.79	-1.48	-1.33
	Oct	163.20	2.34	2.40	2.61
Magad, 2023	Jan	14.20	-1.35	-1.26	-1.65
	April	2.60	-2.95	-2.94	-1.61
	July	0.00	-3.07	-3.05	-3.00
	Oct	150.50	2.94	2.54	2.58

6. CONCLUSIONS

Five conventional drought indices (SPI, SPEI, RAI, RDI and PDSI) were calculated for the study area with four taluks (Ramanagara, Channapatna, Magadi and Kanakapura), and the results revealed that due to its strong association with other drought indicators, like soil moisture, RAI has been the most effective conventional drought index. The results of the conventional drought indicators also suggest that Magadi taluk as the driest of the four taluks whereas Channapatna with the least dry conditions. 8 FL models were created utilizing the fuzzy logic toolbox in MATLAB with different combinations of the inputs (potential evapotranspiration maximum/mean temperature, and rainfall). With a value of 0.984, the strongest correlation among the studied FL models was found between FL3 and upper soil moisture.

The least correlated FL index is the maximum FL8 with three inputs and seventy-five fuzzy rules. It is evident that the fuzzy rules and extra inputs led to poorer performance, most likely as a result of the model becoming overfit. The ANFIS1 model and root zone soil moisture showed a stronger association (0.906). The FL and ANFIS models created also were in relation with the conventional drought indices with respect to the wet and dry conditions of the four taluks suggesting that the created models were best performing. Evapotranspiration has minimal impact on drought indices results. To validate the highest-performing models (FL3 and ANFIS1), four taluks that were utilized in the FL model's rule creation or the ANFIS model's training have been selected. Overall, the new indices which were selected as the best performing models presented accurate drought assessment over the 4 taluks as well as the drought levels with an acceptable efficiency in contrast to RAI conventional index.

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