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ANFIS and RBFNN Efficacy and Timescale Dependence in SPEI-Based Drought Prediction using Meteorological Inputs

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Abstract – Drought is a slow-onset natural disaster that has far-reaching effects on agriculture, water security, and socio-economic systems, especially in climate-vulnerable countries such as Malaysia. It is imperative to predict droughts for prompt mitigation efforts. In this paper, the influence of temporal scale on drought modelling has been put into discussion by analyzing a comparison between two machine learning (ML) models: Adaptive Neuro-Fuzzy Inference System (ANFIS); Radial Basis Function Neural Network (RBFNN) based on Standardized Precipitation Evapotranspiration Index (SPEI) as depicting drought. The SPEI of four timescale categories (SPEI-3, SPEI-6, SPEI-9, and SPEI-12) were calculated weekly and monthly (two different temporal scales) from a 15-year (5,844 observations) set of meteorological records (including precipitation, minimum and maximum temperature, humidity, and mean sea level pressure). Model performance was assessed using the Mean Absolute Error (MAE), Pearson correlation coefficient (r), and Nash-Sutcliffe efficiency (NSE). It is shown that RBFNN surpassed ANFIS at short-, medium-, and long-term timescales in terms of MAE values irrespective of temporal scale, with weekly having the highest accuracy for longer time intervals (especially SPEI-12). It was observed that, in terms of dealing with complex non-linear relationships as well as temporal granularity, RBFNN outperformed ANFIS where ANFIS showed poor performance because of its rule base expansion and input dimensionality. This research provides evidence that integrating RBFNN with weekly temporal scale data and long-term drought indices would be a more robust apparatus for predicting severe drought in Malaysia. These results also highlight the relevance of properly choosing the temporal granularity to develop data-driven forecasting systems for hydrometeorology applications.

Keywords—Drought Prediction, Standardized Precipitation Evapotranspiration Index, Temporal Scale, Meteorology, Machine Learning, Radial Basis Function Neural Network, Adaptive Neuro-Fuzzy Inference System

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1. INTRODUCTION

Water is essential in Earth's system and makes up almost 70% of the surface area, containing approximately 97% of Earth's water stored mainly in the global ocean, with down averages of ~4 km depth [1]. This gigantic reservoir is

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dynamically linked to the Earth's system, especially the atmosphere, to sustain the hydrological cycle governing water storage on Earth [1]. A substantial decline in water supply interrupts this cycle, triggering drought, which leads to ecosystems, agriculture, and human communities at risk [2]. Droughts persistently reduce the amount of precipitation over a long period, causing impaired water levels in rivers, lakes, and groundwater, which results in scarcity of water and socio-environmental consequences [3].

Malaysia depends on water for household, agricultural, and industrial uses, including palm oil production, and more frequent and severe droughts are putting pressure on the country's economic and resource stability[4]. While the country has relatively small temperature variations, an increased severity of extreme events (droughts, floods, and increasing sea levels) is expected because of climate change [5]. The adoption of effective measures to counteract drought events is vital for reducing the negative effects of these climate hazards and securing sustainable water management in Malaysia. Measures to build resilience, including developing water-storage infrastructure, encouraging rainwater harvesting programs, and having drought monitoring for early warning mechanisms, are recognized as the key initiatives [6].

Accurate drought prediction models are required to implement these measures for the development of proactive plans, reduction in risk, and long-term management of environmental resources based on scientific knowledge. Early drought studies primarily consisted of traditional modelling techniques that depend on statistical computations to understand drought dynamics. However, conventional statistical methods and physical models frequently do not extract non-linear properties that are well embedded in meteorological data; thus, it is difficult to simulate drought [7]. In this regard, ML models present a data-driven approach for handling complicated relationships and large datasets and are therefore able to achieve greater pattern recognition and prediction accuracy [8].

Over the past few years, ML techniques such as the ANFIS, RBFNN, Long Short-Term Memory (LSTM) networks, Autoregressive Integrated Moving Average (ARIMA), and Support Vector Regression (SVR) have been widely used in various studies related to hydrology and drought [9], [10], [11]. Moreover, the key to improving ML accuracy lies in its tuning ability, as proven by [12] comparing SVR, Random Forest Regression (RFR), and Linear Regression (LR) with LR peaks as the best-performing model after tuning. The adaptive characteristics have enabled it to understand data and automatically adjust its hyperparameters, thus making it a highly tuneable model.

ANFIS combines neural networks and fuzzy inference systems to handle uncertainty and approximate reasoning, whereas RBFNN stands out for its simplicity, faster training, and robust generalization in modelling non-linear functions, making it particularly effective in drought forecasting tasks. The present work applies both models for SPEI-based drought prediction on different temporal scales and their ability to predict short- or long-term drought phenomena.

2. LITERATURE REVIEW

2.1 Droughts Occurrences over the Years

Globally, there has been growing concern in recent years over the possibility that droughts are becoming more frequent, severe, and prolonged, given the changing climatic conditions and proven increases in extreme climate events[13]. According to[2], drought is the prolonged absence of precipitation. The general sequences for the various types of droughts are shown in Figure 1. There are three distinct type or drought, meteorological, agricultural and hydrological. The effects of drought are also categorized from its impacts on economic, social and environmental. From Figure 1, the change in natural climate is shown as the start of drought, but typically the time (duration) needed to transition from upper to lower conditions would take a long period. Thus, this emphasize the needs to prepare early countermeasure as droughts is a prolonged conditions and can be unrealised until the symptom shows.

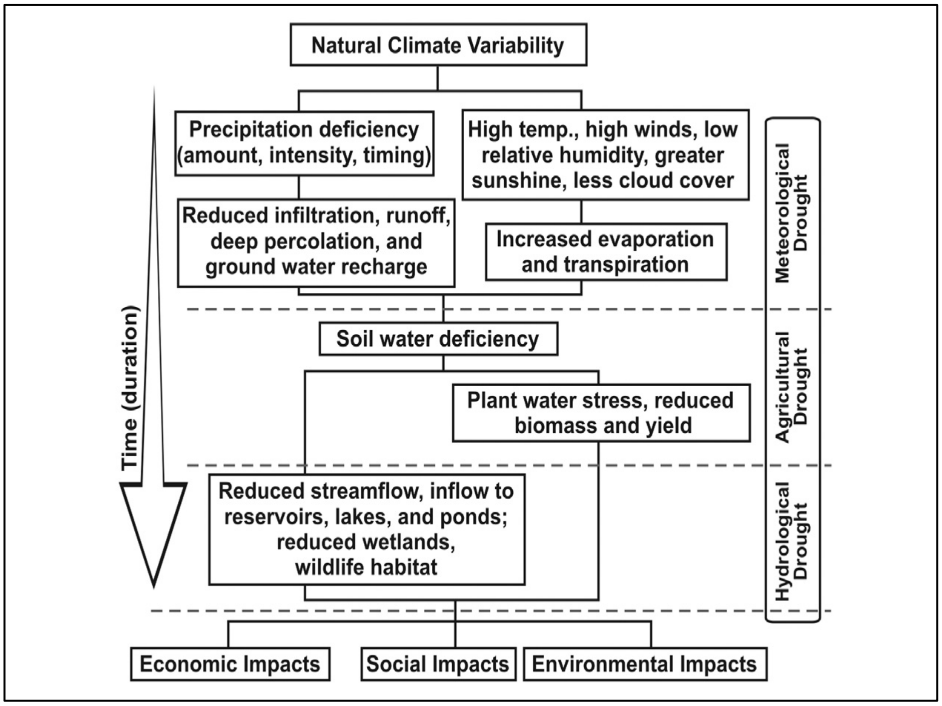


Figure 1. Drought Types, Causal Factors and Their Usual Sequence of Occurrence [13]

Numerous other drought indices can demonstrate drought conditions more accurately than others. The criteria for choosing these intricate drought indices also varied according to the researchers' needs. Table 1 summarizes the forms of a few famously used drought indices. The variables required for the calculation of droughts are precipitation (P), temperature (T), and available water content (AWC). Furthermore, these drought indices are most suited for use with either meteorological or hydrological variables. According to[14], Standardized Precipitation Index (SPI), SPEI, Weighted Anomaly Standardized Precipitation (WASP) index, and Palmer Drought Severity index (PDSI), drought indices used meteorological variables, while Palmer Hydrological Drought Index (PHDI) used hydrological variables.

Table 1. Easy-to-Use Drought Indices

Drought Index	SPI	SPEI	WASP	PDSI	PHDI
Variables used to calculate index	P	P, T	P, T	P, T, AWC	P, T, AWC

Evidently, it would be impossible for such drought indices or indicators to exist, which can be accounted for in all types of droughts. Thus, a researcher's needs are indicators of which indices are best to use. Indices such as the PDSI, SPEI, and SPI are widely recognized for their robustness and interpretability. One major advantage is their ability to deliver a consistent framework for analysing long-term drought trends across diverse climatic regions[14]. Regarding the suitability of the dataset used for this research, only SPI, SPEI, and WASP can be applied to demonstrate drought dynamics because the available data do not have values for AWC. This study employs SPEI calculation as one of the parameters in the model.

This is because SPI is unable to consider the position of temperature variation in upcoming drought possibilities, excluding its role in any global warming scenario. However, temperature is a paramount variable in global warming that ultimately contributes to droughts. On the other hand, the SPEI can accommodate the potential effects of temperature variations and extremes beyond the context of global warming[14]. WASP, on the other hand, is suited for gridded data for tropical regions within 30° latitude of the equator, which conflicts with Malaysia's geographic location, which is located at a latitude of ~7°. Thus, owing to the minimal additional data requirements and ability to address these factors, the SPEI index is preferable for the identification, analysis, and monitoring of droughts.

2.2 RBFNN

RBFNNs are special cases of feedforward neural networks with a three-layer structure, including an input layer, a hidden layer with a radial basis activation function (typically Gaussian), and an output layer with linear weights[15]. This allows a powerful non-linear function approximation because the hidden units transform the input into a high-dimensional space centred around the learned prototypes. RBFNNs have been suggested for their fast convergence and enhanced interpolation and can also offer dimensionality reduction as an alternative to deep multilayer perceptrons (MLPs)[15].

In recent studies on environmental applications, the good performance and efficiency of RBFNN have been demonstrated. For instance, Wang *et al.* [16]used RBFNN to predict soil moisture based on multiple drought indices extracted from remotely sensed images and achieved high forecast accuracy after optimizing Gaussian centres and widths. In addition, Sofian *et al.* [17] in monthly rainfall prediction, proved that RBFNN surpassed backpropagation neural network models and with test R^2 of 0.86 nad very small Mean Squared Error (MSE). In drought simulation, the RBFNN has been demonstrated to provide excellent capabilities for representing both short-term fluctuations and long-term tendencies for SPEI and SPI indices[18].

Its quick training is particularly beneficial for real-time implementation; however, the choice of radial centre and spread (σ) is still an important tweaking requirement. Recent extensions such as RBF-DiffNet [19] embed differential equations in the hidden layer and gain robustness against noise under the transparency and efficiency of RBFNNs. As proven by previous research, this study develops a framework for RBFNNs to identify the best approach to work with meteorological data.

2.3 ANFIS

ANFIS was first introduced in 1993 by Jang. It is[20] a fusion intelligent model of a human-like reasoning style called fuzzy logic, with the learning capabilities of a neural network. ANFIS implements a Sugeno-type fuzzy inference system and is structured into five layers: fuzzification, rule, normalization, defuzzification, and output. This hybrid structure allows ANFIS to handle imprecise data, learn from historical patterns, and incorporate expert knowledge through fuzzy if-then rules. Since 2020, enhanced versions of ANFIS have been applied across diverse environmental and hydrological modelling tasks.

A noteworthy example is the creation of ANFIS-WCA and ANFIS using the Water Cycle Algorithm (WCA) to improve drought prediction based on Runoff Index computation in Algeria (SRI-3, sSRI-6, SRI-9, SRI-12). This hybrid showed superiority over the conventional type of ANFIS when tested for several sub-basins [21]. In the same context, other hybrid ANFIS models with Particle Swarm Optimization (PSO) or Gene Expression Programming (GEP) were found to perform better for predicting the Surface Water Quality Index with higher R^2 values and lower RMSE compared to classical ANFIS architectures.

Moreover, studies [22] showed the potential of ANFIS for mid-term forecasting of SPEI values; however, high fluctuations or statistical outliers negatively affected the model. However, ANFIS suffers from the following: the curse of dimensionality problem in that it has an exponential increase in its rules base owing to the number of features and membership function[20], leading to computational inefficiency or overfitting. To combat this, recent implementations have incorporated dimensionality reduction and optimization methods, such as ANFIS-WCA, to simplify rule sets or ensemble techniques that can combine ANFIS with wavelet transform or evolutionary strategy to achieve improved robustness[21].

ANFIS is an interpretable and flexible model for environmental prediction that incorporates fuzzy logic into adaptive learning. Recent developments have improved its computational efficiency and forecasting using hybrid optimization techniques; thus, optimized ANFIS can be considered as a competitive choice in drought and water quality modelling. Even so, this study employs the standard ANFIS to compare with the RBFNN, with a similar framework design for fair evaluations.

2.4 Research Gaps

A study that [23] emphasized the idea of drought severity relates strongly to spatial and temporal differences in both natural and anthropogenic factors, supporting this research study to focus on understanding temporal granularity and scale-dependent behaviour in data-driven drought prediction models. Similarly, [24] revealed a comprehensive study of the transition phase of meteorological to agricultural drought in Pakistan and pointed out that it exhibits varying time lags significantly affected by temporal scale and local climatic factors, making the focus on optimizing the temporal scale in ML-based drought prediction models necessary. Consistent with the review in, [25] which highlights ML models, particularly in hybrid and deep learning, could enhance drought forecasting accuracy by capturing non-linear and long-term dependencies.

Thus, this study presents extensive knowledge by optimizing the temporal granularities and timescales for drought prediction using adaptive neuro-fuzzy and neural network approaches.

3. RESEARCH METHODOLOGY

This section will discuss methodologies for this study.

3.1 Data Collection

The study was based on 15 years of data from January 1, 2005, to December 31, 2020, in Subang Jaya. Meteorological data were obtained from the Malaysian Meteorological Department (MET Malaysia) and included 5,844 observations of eight weather variables (year, month, day, daily maximum and minimum temperatures (in °C), daily relative humidity percentage (%), daily rainfall amount (mm), and daily mean sea level (MSL) pressure (hPa). The SPEI index with different weekly and monthly temporal granularities, with different timescales for each temporal scale, was also calculated using R Language, from three of the original variables (daily maximum temperature, daily minimum temperature, and total daily precipitation).

3.2 Feature Engineering

This study employed a relatively deep data-processing pipeline, starting from the process of cleaning to detect correct missing values, anomaly detection, and duplicated entries. Subsequently, feature engineering was carried out to create eight new factors based on the SPEI classified by two types of temporal granularities (week- and month-level) and four different time spans: SPEI-3, SPEI-6, SPEI-9, and SPEI-12, commonly known as timescales. Temporal granularity describes the level at which time-series data are aggregated or sampled; here, this differentiates between weekly and monthly scales. To achieve uniform scaling and improve the learning efficiency of the model, all input features were standardized to have zero mean and unit variance, which could further reduce the influence of outliers and enable equivalent treatment for different variables during training.

SPEI was chosen over the SPI because it includes temperature components, which are not available in the latter index. Such inclusion allows the SPEI to account for evapotranspiration, which is of high importance under increasingly warm conditions, overcoming SPI weaknesses in terms of assessing drought intensity under warming trends. SPEI computation relies on a water balance model that considers precipitation with potential evapotranspiration (PET), which provides a more robust drought analysis[22]. The formula for obtaining SPEI is as follows:

$$\mathrm{SPEI} = \mathrm{D_i} = P_i - PET_i \tag{1}$$

where D_i is the water balance at time i, which corresponds to the SPEI value for that period. P_i indicates the precipitation at time i and PET_i is the potential evapotranspiration occurring in the same period. In this study, i represents the two temporal granularities (weekly and monthly) applied to evaluate the impact of time aggregation on drought estimates. SPEI is calculated for four timescales of accumulation: 3- (SPEI-3), 6- (SPEI-6), 9- (SPEI-9), and 12- (SPEI-12). For example, a SPEI-3 on a weekly scale means that the index is calculated considering a 3-weeks cumulated sum of precipitation and evapotranspiration data (2 availabilities), whereas a SPEI-12 on a monthly scale stands for one-year cumulative drought. Such multiple timescales enable the investigation of not only short-term agricultural droughts, but also long-term hydrological droughts.

Table 2 describes the SPEI values for both wet and dry conditions. Although the resemblance to SPI categories is uncanny, the only difference lies in the middle values (-0.99 to 0.99), where SPEI indicates this category as a near-normal condition. In SPI, there is relatively no normal condition, as positive and negative values indicate only dry or wet conditions, respectively. Here, wet conditions would indicate a flood, whereas dry conditions would indicate a drought.

Table 2. Table Type Style

SPEI Value	Category
≥ 2.00	Extremely wet
$1.50 - 1.99$	Severely wet
$1.00 - 1.49$	Moderately wet
$-0.99 - 0.99$	Near normal
$-1.49 - -1.00$	Moderately dry
$-1.99 - -1.50$	Severely dry
≤ -2.00	Extremely dry

3.3 Data Splitting

The dataset, originally comprising 5,844 daily observations, was resampled for the SPEI calculation at two temporal granularities: weekly and monthly. This transformation resulted in 833 weekly and 190 monthly data points. A 70:30 split ratio was applied to separate data into training and testing subsets. Accordingly, 583 weekly samples and 133 monthly samples were allocated for model training, whereas 250 weekly and 57 monthly samples were reserved for testing.

3.4 Study Framework

The entire arrangement of the research is depicted in the flowchart below in Figure 2, where the methodological progress from data collection to model performance assessment is described. It begins with a set of meteorological data comprising five primary meteorological parameters: precipitation, maximum temperature, minimum temperature, relative humidity, and mean sea level (MSL) pressure. Among these, three (precipitation, maximum temperature, and minimum temperature) were used to calculate SPEI, a widely used drought index. Two temporal scales, weekly and monthly, were considered in the computation of SPEI to evaluate how aggregation affects model performance. Four timescales were studied for each temporal scale, which corresponded to short- to long-term drought durations.

These timescales are crucial for discriminating between ephemeral and long-lasting drought events, allowing different modes of drought to be simulated. This dataset, constituted by the five meteorological variables and their respective SPEI values, was provided as input to two ML models: RBFNN and ANFIS. Both models were set up and trained independently with the same input structures, such that a qualitative comparison of their predictive power was possible. The last phase consists of the model performance assessment using three statistical criteria: MAE, Pearson correlation coefficient (r), and NSE.

These criteria were selected for their strength in measuring predictive accuracy, error magnitude, and linear correlation strength. The flow diagram illustrates the methodological steps used to determine the optimum temporal scale, timescales, and ML model for SPEI-based drought forecasting in Malaysia.

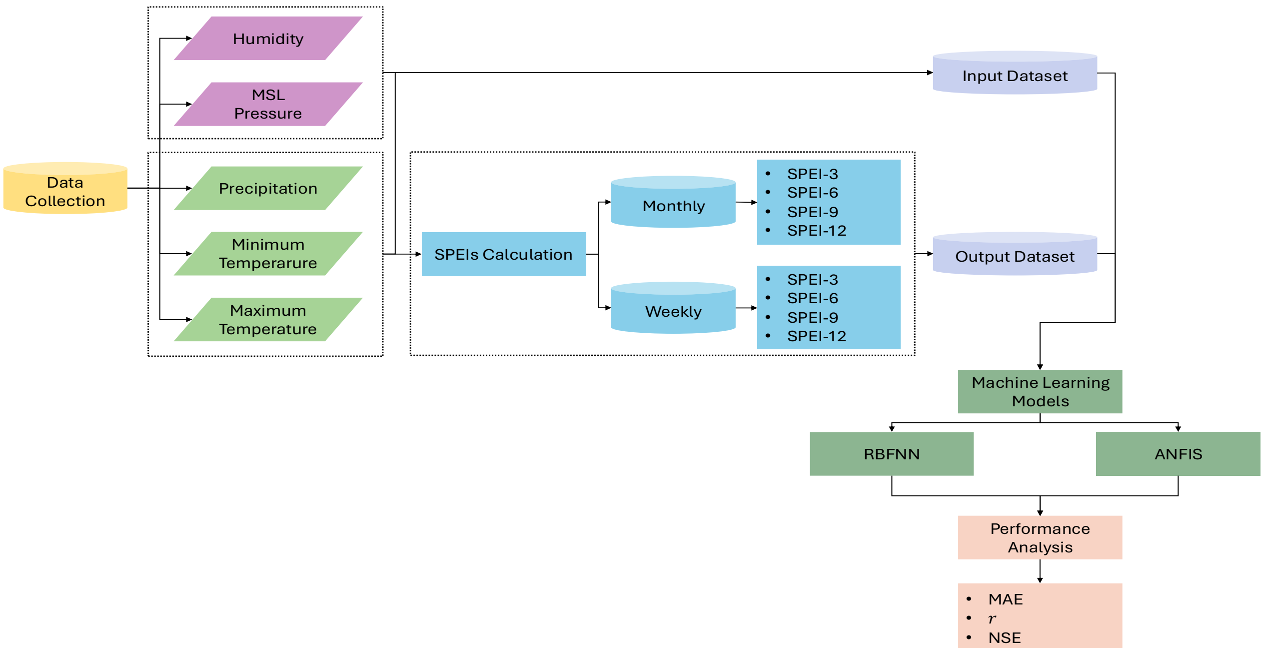


Figure 2. Architectural Pipeline for Data Preprocessing and Model Deployment in Predictive Modelling

The RBFNN settings in this work were developed to guarantee fair and equal comparison with ANFIS in relation to structural simplicity and training setting. Both models were set up with a hidden layer architecture and an output layer with the same input features (five meteorological variables) to ensure comparability. The Gaussian-type membership function was chosen as the activation function of the RBFNN because of its smoothness and locality, which are consistent with the Gaussian-shaped membership functions applied in ANFIS. Training was conducted using a fixed epoch increment from 100 to 500 to observe the convergence behaviour under equivalent computational effort. This parallel configuration was essential to objectively assess the models' performance and to isolate the learning architecture's effect, that is, neural versus neuro-fuzzy, on the drought prediction outcome.

3.5 Models Setting

3.5.1 RBFNN

The RBFNN comprises three layers: an input layer, a single hidden layer with radial basis function activation, and a linear output layer (Figure 3). Each hidden neuron computes a Gaussian response based on the Euclidean distance between input vector $\boldsymbol{x}$ and its center $\boldsymbol{c_i}$, using

$$\rho\left(||x - c_i||\right) = \exp\left(-\beta_i||x - c_i||^2\right) \tag{2}$$

The network output formula is given by

$$\varphi(x) = \sum_{i=1}^{N} a_i \cdot \rho\left(||x - c_i||\right) \tag{3}$$

where N is the number of neurons in the hidden layer, c_i is the center vector of neuron i, and a_i is the weight of neuron i in the linear neuron output [24].

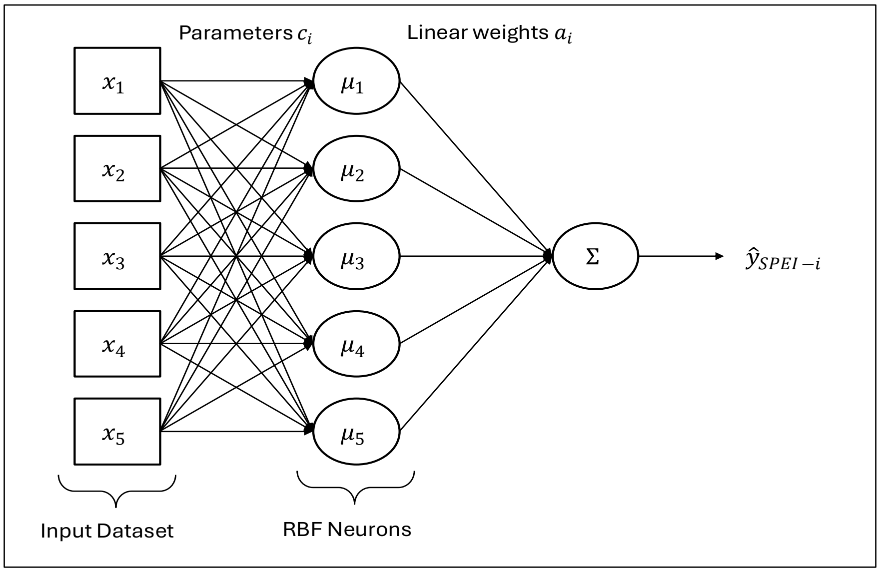


Figure 3. RBFNN Structure for Predictive Model

The input vector of the model comprises the selected meteorological variables (precipitation, minimum and maximum temperature, humidity, and MSL pressure). The target output was the SPEI index for a designated timescale (SPEI-3, SPEI-6, etc.).

The input and target variables were standardized (between 0 and 1) to improve the learning stability and convergence. The dataset was then partitioned (70% for training and 30% for testing) to evaluate the model performance on unseen data and prevent overfitting.

Hyperparameters, such as the number of centres, spread width, and regularization strength, were optimized via cross-validation. Model performance was quantified using metrics such as the MAE, Nash–Sutcliffe Efficiency (NSE), and correlation coefficient (*r*). Comparative evaluation of the ANFIS offers insight into relative predictive proficiency.

3.5.2 ANFIS

The architecture in Figure 4 illustrates a standard Sugeno-type ANFIS with five inputs (five meteorological variables), each passing through a fuzzification layer with five membership functions μ_{ij}, where i represents the input and j is the membership function. In layer 1 (fuzzification layer), each input x_i is transformed into a degree of membership using Gaussian membership functions as follows:

$$\mu_{ij}(x_i) = \exp\left(-\frac{\left(x_i - c_{ij}\right)^2}{2\sigma_{ij}^2}\right) \tag{4}$$

where c and σ are the center and width of the Gaussian, respectively. Layer 2 (rule layer) computes the firing strength of each fuzzy rule using the product operators.

$$\pi = \prod_{i=1}^{n} \mu_{ij}(x_i) \tag{5}$$

Layer 3 (normalization layer) normalizes the firing strength,

$$N_i = \frac{w_i}{\sum_j w_j} \tag{6}$$

Layer 4 (consequent layer) computes the rule output,

$$f_i = w_i(a_1x_1 + \dots + a_nx_n + r) \tag{7}$$

where $a_1, \dots, a_n$ and r are the linear consequent parameters. Layer 5 (output layer) aggregates all the outputs through weighted summation to produce a single crisp output.

$$\hat{y}_{SPEI-i} = \sum N_i f_i \tag{8}$$

This structure allows ANFIS to model non-linear relationships and approximate functions effectively.

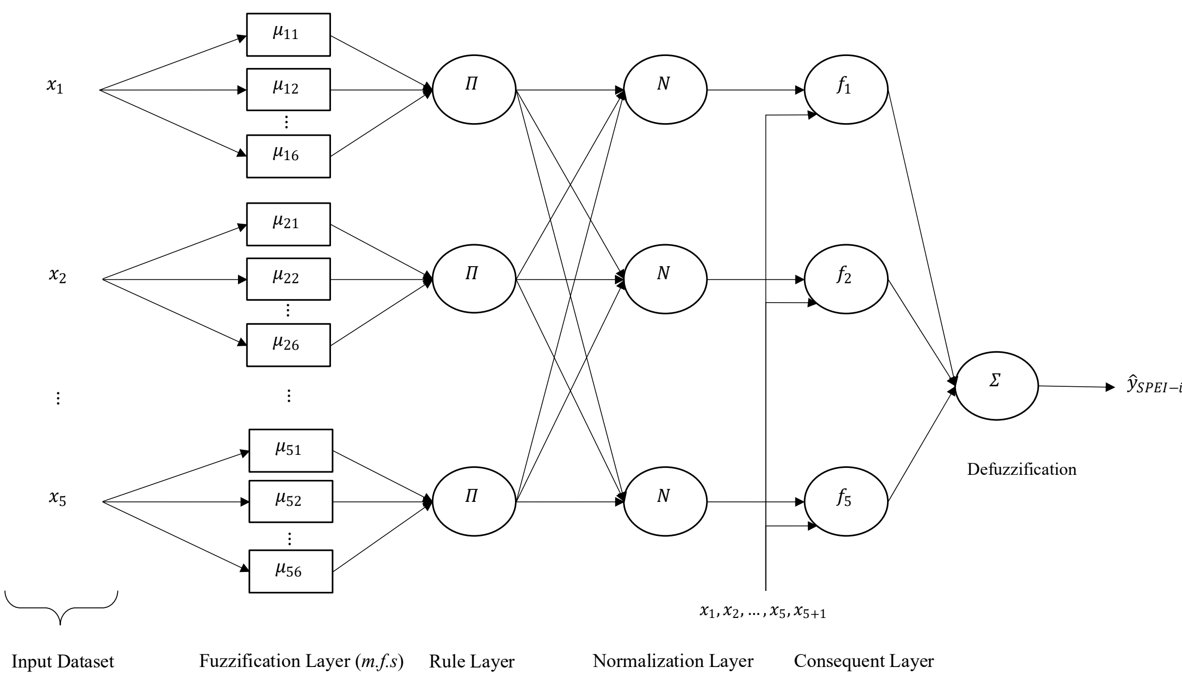


Figure 4. Simplified ANFIS Structure for Predictive Model

Like the RBFNN, ANFIS inputs are five meteorological variables (precipitation, minimum and maximum temperature, humidity, and MSL pressure) with a target output of one (SPEI-3, SPEI-6, SPEI-9, SPEI-12) at a time. Here, the inputs are standardized and split with a 70%–30% ratio on training and testing.

Unfortunately, ANFIS has an explosion rule on membership functions, in which the number of fuzzy rules increases exponentially with the number of inputs. Thus, a more complex model is generated with a higher number of inputs. The model is trained using a hybrid learning algorithm that combines least-squares estimation for the consequent parameters and gradient descent to tune the premise parameters.

To maintain consistency with the comparative RBFNN model, ANFIS was trained for 100–500 epochs with increments of 100, and a 70:30 data split was applied for training and testing. This architecture is known for its interpretability, ability to incorporate expert knowledge, and adaptability to learning non-linear patterns in time-series datasets, particularly in hydrology and drought forecasting [25].

4. RESULTS AND DISCUSSIONS

The actual versus predicted SPEI time series was graphically compared for both the ANFIS and RBFNN models at four timescales: SPEI-3, SPEI-6, SPEI-9, and SPEI-12. These visuals allow for the assessment of how well the predictions made by each model correspond to the actual drought conditions at various temporal aggregation levels.

The performance metrics used were MAE, r and NSE. A lower MAE and higher in r and NSE indicate a good model. However, a negative NSE value indicates a very poor model performance that is unacceptable beyond the mean baseline.

4.1 Monthly

The results of the performance analysis are presented in Table 3 across monthly timescales of the SPEI, where we find that RBFNN outperforms ANFIS in MAE, r and NSE for all SPEI timescales. The RBFNN presents evident improvements in predictive performance with an increase in timescale length, and its minimum MAE (0.53), maximum r (0.69), and maximum NSE (0.36) occur at SPEI-12. In contrast, ANFIS has poorer performance with larger MAE and low correlation, especially at shorter temporal scales where the NSE value can even be negative, which represents failure in predicting as good as using average.

Table 3. Monthly Evaluation

Performance Metric	RBFNN				ANFIS			
	SPEI-3	SPEI-6	SPEI-9	SPEI-12	SPEI-3	SPEI-6	SPEI-9	SPEI-12
MAE	0.76	0.67	0.57	**0.53**	1.05	0.79	0.65	0.65
r	0.42	0.52	0.66	**0.69**	0.28	0.42	0.65	0.61
NSE	0.04	0.06	0.18	**0.36**	-0.85	-0.56	0.03	-0.02

Table 4 shows that the comparison of over-prediction, under-prediction in RBFNN and ANFIS models for four monthly timescales of SPEI (SPEI-3, SPEI-6, SPEI-9, and SPEI-12). Over-prediction values indicate the amount of time for every observation that the prediction values are higher than the actual value, while on the contrary the under-prediction is values for every observation that the prediction is lower than the actual value. In general, the findings indicate that in terms of prediction behaviour both models exhibit almost same balance training and testing phase, but RBFNN has shown a little more consistency at this point. The over-prediction is slightly smaller than the under-prediction for RBFNN at all timescales. The range between the over- and under-prediction numbers decreases in magnitude with growing timescale, from an 18 differences at SPEI-3 (86 over cases and 104 under) to a difference of only 11 at SPEI-12 scale (85 over vs. 96 under). This tendency indicates that RBFNN may underestimate drought intensity slightly and increase as drought length increases.

However, for ANFIS, there is a similar trend in the distribution gap between over- and under-estimations. Nevertheless, ANFIS shows more overpredictions at longer timescales: 90 over vs. 91 under at SPEI-12, suggesting that it starts to slightly overestimate for the longest duration. It is observed that, compared with RBFNN, ANFIS tends to have more variance in timescales, which indicates that its capability is less stable. Although both models have well-behaved prediction biases, those for the RBFNN are relatively more stable and consistent on a monthly scale, especially over longer lead times, which reconfirms its applicability to long-lead drought forecasting.

Table 4. Monthly Over-and Under-Prediction

	RBFNN_Over	RBFNN_Under	ANFIS_Over	ANFIS_Under
SPEI-3	86	104	85	105
SPEI-6	90	97	87	100
SPEI-9	89	95	88	96
SPEI-12	85	96	90	91

4.2 Weekly

Two-parameter analysis: The assessment of ANFIS and RBFNN based on weekly SPEI scales, as shown in Table 5, clearly indicated that for all seven performance measures, RBFNN exhibits much better results than ANFIS. The RBFNN provides a lower MAE, stronger correlation (r), and much higher NSE values over all timescales, but notably longer timescales. For example, in SPEI-12, RBFNN records an r of 0.85 and NSE of 0.72 reflecting strong predictive accuracy, while ANFIS lags with r = 0.56 and a negative NSE (−0.04), indicating poor reliability. ANFIS attains NSE with high negative values at short timescales (e.g., −1.45 at SPEI-3), indicating that owing to strong underfitting, the model performance is inferior to the baseline mean results.

Table 5. Weekly Evaluation

Performance Metric	RBFNN				ANFIS			
	SPEI-3	SPEI-6	SPEI-9	SPEI-12	SPEI-3	SPEI-6	SPEI-9	SPEI-12
MAE	0.58	0.54	0.41	**0.35**	1.13	0.98	0.69	0.62
r	0.65	0.67	0.82	**0.85**	0.34	0.31	0.50	0.56
NSE	0.39	0.44	0.63	**0.72**	-1.45	-1.79	-0.19	-0.04

Regarding the prediction trends, Table 6 lists the overprediction and underprediction values of the RBFNN and ANFIS models based on the weekly SPEI at four different timescales (SPEI-3, SPEI-6, SPEI-9, and SPEI-12). The data points for the weekly scale were more than 824, which can provide a stronger basis for analysing the prediction trends in contrast with the monthly data ($\geq$181). The prediction distribution was relatively uniform for RBFNN. Over-prediction values only slightly increased from 408 at the SPEI-3 scale to 430 at SPEI-12, and under-prediction shows a decline from 425 to 394. This suggests that RBFNN slightly overpredicts more for longer forecasting periods; however, the overall difference is not large. The discrepancy between the over- and under-predicted events remained relatively constant at all timescales, indicating model stability.

In contrast, ANFIS exhibited greater fluctuation and disharmony. What is remarkable is that the model underpredicts more at SPEI-3 (440) than it overpredicts (393), and such an underestimation trend persists for other timescales as well with somewhat smaller gaps (such as SPEI-12 404 over vs. 420 under). These findings imply that ANFIS has a markedly overprediction preference, especially for short periods, which may harm its efficiency in identifying drought extremes. On average, the RBFNN yields more robust pattern predictability across weekly scales compared with ANFIS, which shows greater oscillation and a bias to underestimate drought magnitude. This confirms the stability of the RBFNN, which is more suitable for the weekly drought forecast process.

Table 6. Monthly Over-and Under-Prediction

	RBFNN_Over	RBFNN_Under	ANFIS_Over	ANFIS_Under
SPEI-3	408	425	393	440
SPEI-6	413	417	411	419
SPEI-9	427	400	409	418
SPEI-12	430	394	404	420

4.3 Comparative Analysis on Temporal Granularity

Actual vs. predicted SPEI plots for the ANFIS and RBFNN models were also assessed visually on four timescales: SPEI-3, SPEI-6, SPEI-9, and SPEI-12, as shown in Figure 5. These visualizations offer insights into how closely the predictions of each model align with the observed drought situation at various levels of time aggregation. As shown in Figure 5, the drought trend lines were smoother, and the shapes of drought trends were more stable with higher SPEI timescales from SPEI-3 to SPEI-12 for both monthly and weekly temporal scales. Shorter scales (SPEI-3 and SPEI-6) are more sensitive to temporal fluctuations, while longer timescales (i.e., SPEI-9 and SPEI-12) show wider and smoother drought cycles.

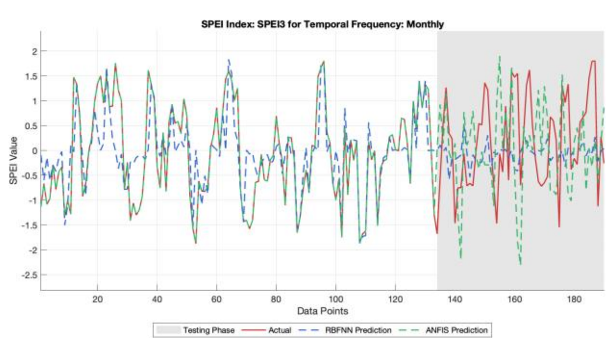
This process appears much smoother on a monthly timescale where the number of observations is smaller and less aggregated, which is not seen on weekly timescales as much as it has finer details to display along with higher level variability. Apparently, the RBFNN and ANFIS models generally show higher predictive performance for the weekly temporal scale analysed in all SPEI indices (SPEI3, SPEI6, SPEI9, and SPEI12). On the scale of weeks (Figure 5 (b), (d), (f), (h)), as can be seen, both models are able to produce very good approximation of the actual behaviour in the prediction period and hence they are not so different from each other in their predictive quality as far as sudden oscillations with high fidelity is concerned.

In contrast, when using the monthly temporal resolution (Figure 5 (a), (c), (e), (g)), both models predict with much lower skill; while they can capture some broader trends, they often fail to reproduce the amplitude and exact turning points of the observed data, leading to greater errors. The apparently equal performance between the two models on a weekly basis makes it difficult to point out one better than the other without quantitative measures, as both models seem to have problem strengths because a higher temporal resolution (weekly) gives much better prediction results for both RBFNN and ANFIS in this case.

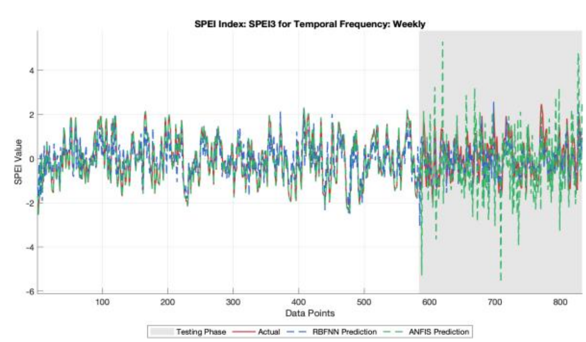
At both frequencies, ANFIS is never seen to be superior to RBFNN as it more closely follows actual values and smoother predictions in the confirmation phase Figure 5 (grey shaded region) testing stage. In the testing stage, ANFIS predictions are likely to drift, especially in shorter horizons, indicating instability and a lack of generalization properties.

Longer temporal scales (SPEI-9 and SPEI-12) and weekly temporal resolution can obtain more multifarious patterns for model learning under the assumption that the RBFNN has better flexibility and accuracy in all scenarios. This confirms that the RBFNN is a more accurate model for drought prediction under different time aggregations and drought intensity categories. These visual findings are consistent with the estimated statistical measures (MAE, r and NSE), which indicate that RBFNN performed better than ANFIS at various timescales. Better accuracy is obtained as the SPEI timescale increases, thus corroborating that longer aggregation time periods convey more reliable signals for ML models.

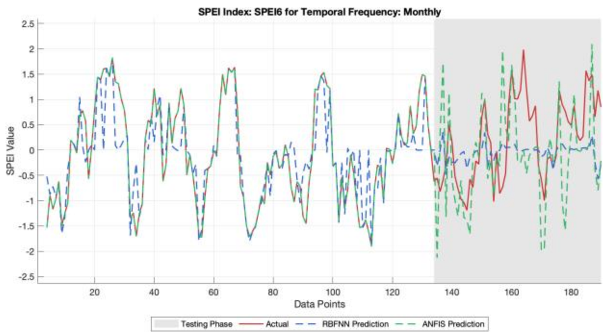
In addition, the weekly signal was found to be more predictive than the monthly signal, presumably because of the higher resolution, which gave a finer-grained input to use for building features with the models. The probability distribution of drought occurrences in the mild, moderate, severe, and extreme categories for both weekly and monthly timescales are presented in Table 7. In general, mild drought events were the most common findings, with percentages reaching 55.36% (SPEI-9 week) and 57.35% (SPEI-3 month). Moderate drought events were the second most abundant, account for 25.71%–34.22% of weekly and 25.81%–34.92% of monthly data, respectively. Extreme droughts experienced considerably lower percentages, ranging between 11.58% and 15.33% weekly, and increased to approximately 24.14% monthly (SPEI-9).



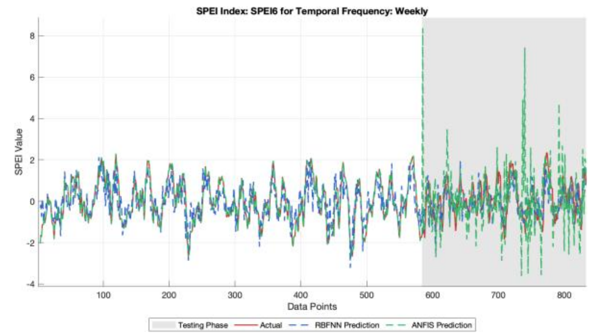
(a)



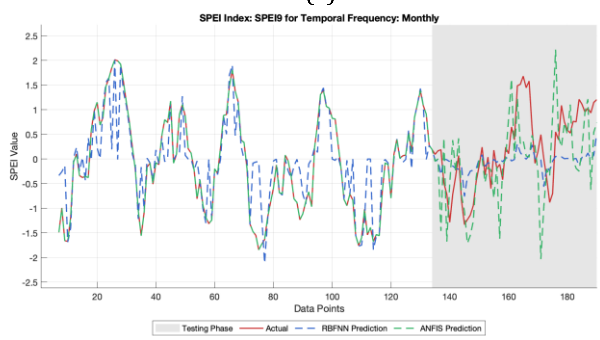
(b)



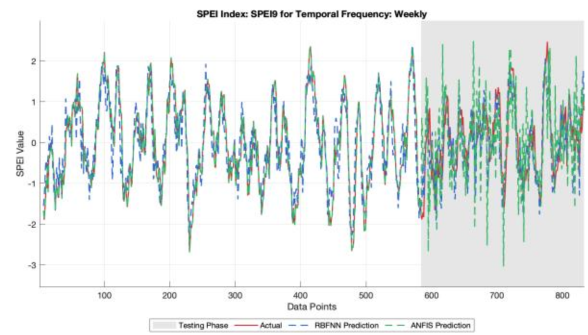
(c)



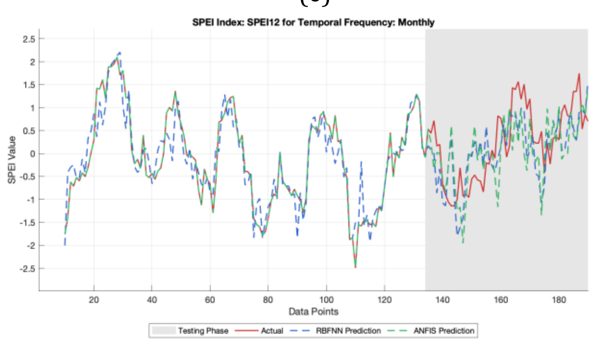
(d)



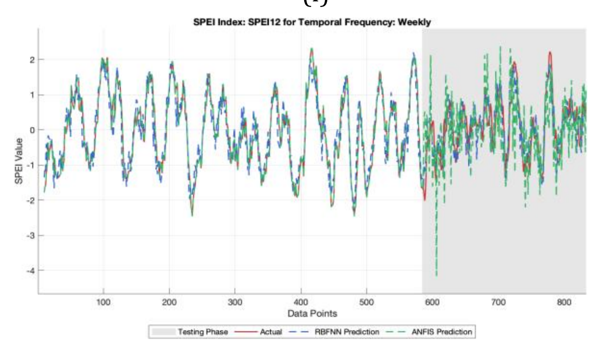
(e)



(f)



(g)



(h)

Figure 5. Actual vs RBFNN and ANFIS predictions plot (a,b) SPEI-3 monthly, weekly plot; (c,d) SPEI-6 monthly, weekly plot; (e,f) SPEI-9 monthly, weekly plot; (g,h) SPEI-12 monthly, weekly plot

Table 7. Evaluation of Actual Data

Performance Metric	Probability of Drought Occurrences (%)							
	RBFNN				ANFIS			
	SPEI-3	SPEI-6	SPEI-9	SPEI-12	SPEI-3	SPEI-6	SPEI-9	SPEI-12
Mild	48.54	55.09	55.36	48.34	57.35	49.21	44.83	53.23
Moderate	32.12	28.07	25.71	34.32	26.47	34.92	31.03	25.81
Severe	15.33	11.58	13.21	12.55	16.18	15.87	24.14	19.35
Extreme	4.01	5.26	5.71	4.80	0	0	0	1.61

The results of the best-performing model, RBFNN, in Table 8 exhibit a slight overestimation in mild drought events and underestimation in severe and extreme categories compared to the actual data. Weekly predictions show mild drought probabilities reaching 68.78% (SPEI-3), while severe droughts are predicted at much lower rates (e.g., 6.31% for SPEI-6). Severe and extreme droughts are less frequently predicted, with extreme droughts remaining under 5%, suggesting that the model is more sensitive to mild-to-moderate events at weekly resolution.

In monthly predictions, RBFNN also predicted milder events (up to 55.56%) and tended to under-predict moderate and extreme drought occurrences, such as 0% for SPEI-3 and SPEI-6 extreme events. The model appears more accurate for moderate conditions at weekly frequencies, especially for SPEI-9 and SPEI-12, where the probabilities closely match the actual trends. Interestingly, the severe category is more pronounced in monthly data, peaking at 29.63% at SPEI-3 and maintaining above 20% across other timescales. This suggests that the monthly RBFNN model may capture more severe drought impacts over time at the cost of underpredicting milder or shorter drought events. Overall, extreme drought remains minimally predicted, aligning with actual drought rarity.

Table 8. Evaluation of Best-Performed Model

Performance Metric	Probability of Drought Occurrences (%)							
	RBFNN				ANFIS			
	SPEI-3	SPEI-6	SPEI-9	SPEI-12	SPEI-3	SPEI-6	SPEI-9	SPEI-12
Mild	68.78	64.56	52.73	54.29	55.56	38.24	33.33	48.08
Moderate	20.36	24.76	33.82	32.86	14.81	35.29	37.04	28.85
Severe	9.05	6.31	10.55	11.79	29.63	26.47	25.93	21.15
Extreme	1.81	4.37	2.91	1.07	0	0	3.70	1.92

**Prediction data of the best RBFNNmodel*

RBFNN performs well in both temporal settings but exhibits stronger sensitivity to mild-to-moderate droughts in weekly data and a higher tendency to capture severe droughts in monthly settings. This dual strength makes the RBFNN a flexible and effective model for varying drought monitoring needs, with weekly settings better for early detection and short-term monitoring, and monthly settings more attuned to prolonged, severe drought conditions.

5. CONCLUSION

In conclusion, this study compared two types of ML: a RBFNN and an adaptive - fuzzy inference system (ANFIS). Both were applied to predict drought in terms of SPEI at different timescales (3, 6, 9, and 12 months), both weekly and monthly. Using five meteorological variables obtained from the Malaysian Meteorological Department, after training (70%) and testing (30%), the model performance indicated that RBFNN performed better than ANFIS in terms of MAE, NSE, and the correlation coefficient, particularly at longer drought timescales. RBFNN also displayed better correspondence with observed drought category distributions, especially mild and moderate ones, where ANFIS underestimated heavier conditions. Compared to monthly aggregation, the weekly temporal scale showed higher sensitivity and predictive accuracy of the RBFNN, indicating a high-resolution drought prediction by the RBFNN under the Malaysian climate. Thus, the results of this study confirmed that RBFNN performs better than ANFIS across both granularities, especially at longer aggregation intervals.

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Alisa Afendi: Conceptualization, Methodology, Analysis and Interpretation of Results;
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CONFLICT OF INTERESTS

No conflict of interest were disclosed.

ETHICS STATEMENTS

Our publication ethics follow The Committee of Publication Ethics (COPE) guideline. https://publicationethics.org/

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author upon reasonable request.

REFERENCES

[1] U. S. G. Survey, "The distribution of water on, in, and above the Earth," Oct. 2019. [Online]. Available: https://www.usgs.gov/media/images/distribution-water-and-above-earth

[2] S. Graham, C. Parkinson, and M. Chahine, "The Water Cycle," *NASA Earth Observatory*, Oct. 2010. [Online]. Available: https://earthobservatory.nasa.gov/features/Water

[3] O. National, and A. A. (NOAA), "What is drought?," 2018. [Online]. Available: https://www.weather.gov/media/owlie/2018_Drought.pdf

[4] H. H. Hasan, S. F. Mohd Razali, N. S. Muhammad, and A. Ahmad, "Hydrological drought across Peninsular Malaysia: implication of drought index," 2021, doi: 10.5194/nhess-2021-249.

[5] Z. bin Luhaim et al., "Drought variability and characteristics in the Muda River Basin of Malaysia from 1985 to 2019," *Atmosphere*, vol. 12, no. 9, p. 1210, 2021, doi: 10.3390/atmos12091210.

[6] B. G. World, "Malaysia Climate Risk Country Profile," 2021. [Online]. Available: https://climateknowledgeportal.worldbank.org/sites/default/files/2021-08/15868-WB_Malaysia%20Country%20Profile-WEB.pdf

[7] M. Van Ginkel, and C. Biradar, "Drought early warning in agri-food systems," *Climate*, vol. 9, no. 9, p. 134, 2021, doi: 10.3390/cli9090134.

[8] D. Cho, C. Yoo, J. Im, and D. Cha, “Comparative assessment of various machine learning-based bias correction methods for numerical weather prediction model forecasts of extreme air temperatures in urban areas,” *Earth and Space Science*, vol. 7, no. 4, 2020, doi: 10.1029/2019EA000740.

[9] A. Dikshit, B. Pradhan, and A. M. Alamri, “Temporal hydrological drought index forecasting for New South Wales, Australia using machine learning approaches,” *Atmosphere*, vol. 11, no. 6, p. 585, 2020, doi: 10.3390/atmos11060585.

[10] L. Fischer et al., “AI system engineering—key challenges and lessons learned,” *Machine Learning and Knowledge Extraction*, vol. 3, no. 1, pp. 56–83, 2020, doi: 10.3390/make3010004.

[11] D. A. Wilhite, M. V. K. Sivakumar, and R. Pulwarty, “Managing drought risk in a changing climate: the role of national drought policy,” *Weather and Climate Extremes*, vol. 3, pp. 4–13, 2014, doi: 10.1016/j.wace.2014.01.002.

[12] A. Subramanian, N. Palanichamy, K.-W. Ng, and S. Aneja, “Climate change analysis in Malaysia using machine learning,” *Journal of Informatics and Web Engineering*, vol. 4, no. 1, pp. 307–319, Feb. 2025, doi: 10.33093/jiwe.2025.4.1.22.

[13] Y. W. Soh, C. H. Koo, Y. F. Huang, and K. F. Fung, “Application of artificial intelligence models for the prediction of standardized precipitation evapotranspiration index (SPEI) at Langat River Basin, Malaysia,” *Computers and Electronics in Agriculture*, vol. 144, pp. 164–173, 2018, doi: 10.1016/j.compag.2017.12.002.

[14] M. Svoboda and B. A. Fuchs, “Towards a water secure world: Integrated Drought Management Programme—Handbook of Drought Indicators and Indices,” 2006. [Online]. Available: https://www.droughtmanagement.info/literature/GWP_Handbook_of_Drought_Indicators_and_Indices_2016.pdf

[15] S. M. Vicente-Serrano, S. Beguería, and J. I. López-Moreno, “A multiscalar drought index sensitive to global warming: the standardized precipitation evapotranspiration index,” *Journal of Climate*, vol. 23, no. 7, pp. 1696–1718, 2010, doi: 10.1175/2009JCLI2909.1.

[16] X. Wang, H. Liu, Z. Sun, and X. Han, “Soil moisture inversion based on multiple drought indices and RBFNN: a case study of northern Hebei Province,” *Heliyon*, vol. 10, no. 17, pp. e37426–e37426, 2024, doi: 10.1016/j.heliyon.2024.e37426.

[17] I. M. Sofian, A. K. Affandi, I. Iskandar, and Y. Apriani, “Monthly rainfall prediction based on artificial neural networks with backpropagation and radial basis function,” *International Journal of Advances in Intelligent Informatics*, vol. 4, no. 2, p. 154, 2018, doi: 10.26555/ijain.v4i2.208.

[18] S. M. Hosseini-Moghari, and S. Araghinejad, “Monthly and seasonal drought forecasting using statistical neural networks,” *Environmental Earth Sciences*, vol. 74, no. 1, pp. 397–412, 2015, doi: 10.1007/s12665-015-4047-x.

[19] K. S. Gyamfi, J. Brusey, and E. Gaura, “Differential radial basis function network for sequence modelling,” *arXiv*, 2020, doi: 10.48550/arXiv.2010.06178.

[20] J.-S. R. Jang, “ANFIS: adaptive-network-based fuzzy inference system,” *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 23, no. 3, pp. 665–685, 1993, doi: 10.1109/21.256541.

[21] M. Achite, E. Gul, N. Elshaboury, M. Jehanzaib, B. Mohammadi, and A. Danandeh Mehr, “An improved adaptive neuro-fuzzy inference system for hydrological drought prediction in Algeria,” *Physics and Chemistry of the Earth*, vol. 131, p. 103451, 2023, doi: 10.1016/j.pce.2023.103451.

[22] S. Poornima, and M. Pushpalatha, “Drought prediction based on SPI and SPEI with varying timescales using LSTM recurrent neural network,” *Soft Computing*, vol. 23, no. 18, pp. 8399–8412, 2019, doi: 10.1007/s00500-019-04120-1.

[23] H. Zhang, C. Di, X. Li, J. Li, and Y. Wang, “Spatio-temporal heterogeneity of the propagation from meteorological to hydrological drought: a case study of the Luanhe River Basin,” *Journal of Hydrology: Regional Studies*, vol. 62, p. 102890, 2025, doi: 10.1016/j.ejrh.2025.102890.

[24] H. Abbas et al., "Prevailing influence of local and global climatic factors on the propagation of meteorological to agricultural droughts and associated time lags in Pakistan," *Journal of Hydrology: Regional Studies*, vol. 62, p. 102875, 2025, doi: 10.1016/j.ejrh.2025.102875.

[25] A. I. Ahmed Osmanr et al., "A review on machine learning models for drought monitoring and forecasting," *Climate Risk Management*, p. 100758, 2025, doi: 10.1016/j.crm.2025.100758.

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