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A novel approach for predicting the standardised precipitation index considering climatic factors

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Abstract
Drought modelling is essential to managing water resources in arid regions to limit its impacts. Additionally, climate change has a significant effect on the frequency and intensity of drought. This research provides a novel approach to forecasting the standardised precipitation index (SPI 3), considering several climatic variables by employing hybrid methods including (i.e., data pre-processing represented by normalisation, cleaning (i.e., outliers and Singular Spectrum Analysis), and best model input (i.e., tolerance technique), in addition to, artificial neural network (ANN) combined with particle swarm optimisation (PSO)). The data on climatic factors were applied to build and evaluate the SPI 3 model from 1990 to 2020 for the Al-Kut region. The result revealed that data pre-processing techniques enhance the data quality by increasing the correlation coefficient between independent and dependent variables; and choosing the optimal input model scenario. Also, it was found that the PSO algorithm precisely predicts the parameters of the proposed model. Moreover, the finding confirmed that the supposed methodology precisely simulated the SPI 3 depending on several statistical criteria (i.e., R^2, RMSE, MAE).

Keywords: Drought, SPI, ANN, SSA, PSO, Iraq.

الخلاصة: تعد نمذجة الجفاف ضرورية لإدارة موارد المياه في المناطق القاحلة للحد من آثاره. بالإضافة إلى ذلك ، فإن تغير المناخ له تأثير كبير على تواتر وشدة الجفاف. توفر هذه الدراسة نهجًا جديدًا لمحاكاة مؤشر هطول الأمطار القياسي (SPI 3) استنادًا إلى العديد من المتغيرات المناخية من خلال استخدام تقنيات هجينة بما في ذلك (المعالجة المسبقة للبيانات التي تمثلها التطبيع والتنظيف (أي القيم المتطرفة وتحليل الطيف الفردي) ، وأفضل إدخال النموذج (أي تقنية التسامح) ، بالإضافة إلى الشبكة العصبية الاصطناعية (ANN) جنبًا إلى جنب مع تحسين سرب الجسيمات (PSO)). تم تطبيق البيانات الخاصة بالعوامل المناخية لبناء وتقييم نموذج SPI 3 من 1990 إلى 2020 لمدينة الكوت ، العراق. كشفت النتيجة أن تقنيات المعالجة المسبقة للبيانات تعزز جودة البيانات عن طريق زيادة معامل الارتباط بين المتغيرات التابعة والمستقلة ؛ واختيار سيناريو نموذج الإدخال الأمثل. كما لوحظ أن خوارزمية PSO تتنبأ بدقة بثوابت النموذج المقترح. علاوة على ذلك ، أكدت النتيجة أن المنهجية المفترضة تحاكي SPI 3 بدقة بناءً على عدة معايير إحصائية (على سبيل المثال ، R^2 ، RMSE، MAE).

1. INTRODUCTION

Drought is one of the most damaging natural disasters in the world, causing the largest economic losses; it occurs when precipitation falls below the long-period average rainfall [1]. At a global level, drought leads to twenty-two percent of the worldwide economic losses caused by natural catastrophes and thirty-three percent of the damages in terms of the number of persons impacted [2]. Droughts are classified into four categories: agricultural, socioeconomic, meteorological, and hydrological [3]. Drought is affected by climatic factors, same temperature and rainfall. There are also different drought indices, such as the standard precipitation index (SPI), reconnaissance drought index (RDI), standardised precipitation evapotranspiration index (SPEI), and effective drought index (EDI). McKee, Doesken [4] introduced SPI, the most commonly utilised drought indices that was approved by the World Meteorological Organization [5]. Furthermore, the SPI may be calculated for a different range of periods to give information on different kinds of drought [6].

Simulation drought is important for irrigated agriculture, water management, ecosystem health, and recreational tourism [7]. Also, early warnings of drought are essential for agricultural adaptation to changes in the climate [8]. Due to the machine learning (ML) capacity to deal with the complex nonlinear relationship between climatic variables and drought indices, different ML methods have succeeded in drought prediction [9, 10]. Traditional approaches suppose that the correlation between predictors and predictand is linear and may not be appropriate for answering real-world case problem [11]. Due to the complicated and nonlinear nature of the drought phenomenon, using artificially intelligent approaches (AI) in drought prediction has gained great interest [12]. AI models outperform conventional models as proven by Zhang, Li [13]. Drought prediction utilises a variety of AI models, such as artificial neural networks (ANNs) [14], random forests [15], support vector machines (SVMs) [16], and etc.

The ANN model's capacity to forecast nonlinear and nonstationary time series data in hydrological problems and water resources; therefore, considers an effective technique for drought prediction [17], as demonstrated by Das, Naganna [18] and Bari Abarghouei, Kousari [19]. Furthermore, the ANN technique was utilised in various hydrology areas and proved effective prediction precisely, including Apaydin, Taghi Sattari [20] for streamflow, Tiu, Huang [21] for water level, and Ömer Faruk [22] for water quality.

A hybrid approach integrates at least two techniques, the first being the primary approach and the other pre- or post -processing approach [23]. Various techniques have been employed to forecast drought indices. The hybrid approach outperforms the single approach; as a result, several research advise using the combined system to increase simulation precisely, like Khan, Muhammad [24] and Zhang, Li [13].

Recently, Alawsi, Zubaidi [25] reviewed drought prediction papers published in the last few years and advised:

1. Utilising singular spectrum analysis as a data pre-treatment approach,
2. Employing the hybridization of preprocessing with parameter optimization,
3. Using a multivariate strategy.

Accordingly, the aim of this research is to evaluate a novel approach (i.e., employing data pre-processing methods and the ANN method that combines with particle swarm optimisation) to simulate drought index.

The main objectives of this research are to:

1. Examine fourteen climate variables for 30 years to identify the extent to which climate variables influence the drought index.
2. Enhance the data quality and select the optimal independent factors,
3. Combine the ANN technique with the PSO algorithm to identify the best ANN parameters,
4. Assess the effectiveness of the PSO-ANN technique to simulate the drought index,
5. Help policymakers by offering a more scientific view on drought.

2. AREA OF STUDY AND DATA SET

Al-Kut is the capital of the Wasit province, and it is located on the Tigris Riverbank in the south of Baghdad. The area of the region is 17,153 square kilometres. On the other hand, Al-Kut has about 40 square kilometres of built-up area. The population was estimated to be over 400,000 in 2003, and it is expected to increase to over 750,000 by 2035 [26, 27]. Seasons in the Al-Kut region range from mild in the autumn and spring to cold in the winter and hot in the summer. The Iraqi meteorological authority states that the winter season starts in November and ends in March. The remaining periods are considered summer and often see their highest temperatures in the months of June, July, and August [27].

The information from the Iraqi metrological station was lost due to abnormal conditions (terrorism, wars, and embargoes). Therefore, climatic factors data were collected by the National Oceanic and Atmospheric Administration (NASA) [28]. The data on climatic factors were collected from 1990 to 2020. It includes rainfall (Rain) (mm/day), wet bulb temperature (Twet) (°C), top of atmosphere (TOA) (MJ /m²/day), minimum wind speed (Wmin) (m/s), maximum wind speed (Wmax) (m/s), minimum temperature (Tmin) (°C), range wind speed (Wrange) (m/s), maximum temperature (Tmax) (°C), mean temperature (Tmean) (°C), surface pressure (P) (kPa), dew forest (DF) (°C), wind speed (W) (m/s), specific humidity (SH) (g/kg), and relative humidity (RH) (percent). Figure 1 presents the boxplot and raw time series for SPI 3.

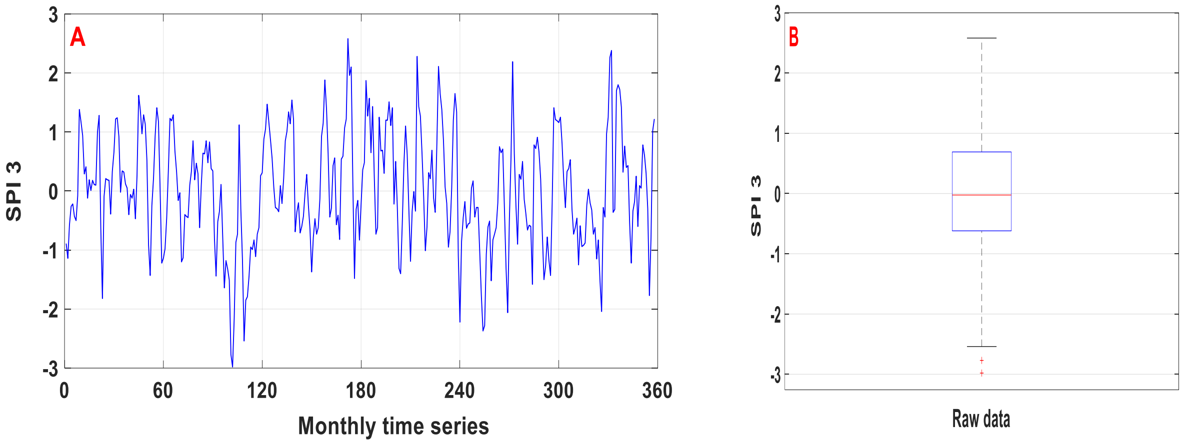

Figure 1 Box plot and monthly time series for Raw SPI 3.

3. METHODOLOGY

3.1.Standardised Precipitation Index (SPI)

SPI was initially presented by McKee, Doesken [4] to observe drought, and the World Meteorological Organisation identified it as a characteristic of meteorological drought [29]. This index requires monthly precipitation to compute [30]. The SPI is determined by mathematically modelling for the long-period rain data. This distribution is cumulative for a specific time scale. A gamma distribution is employed to fit the long-period rainfall data, which is then transformed into a normal distribution using the hypothesis of prospect resulting in the average SPI for the desired period and location being zero [18]. When the SPI value is greater than zero (i.e., more than the mean rainfall) represents wet periods. While SPI values less than zero (i.e., less than average rainfall) represent dry periods [24]. Table 1 shows a classification of drought according to SPI. Refer to McKee, Doesken [4] and Tigkas, Vangelis [31] for more details on this index.

Table 1 Classification of drought according to SPI [25].

Class	SPI values
Extremely wet	>2
Very wet	1.5 to 1.99
Moderately wet	1.0 to 1.49
Near normal	−0.99 to 0.99
Moderately dry	−1 to −1.49
Severely dry	−1.5 to −1.99
Extremely dry	<−2

3.2. Data Pre-processing

The data pre-processing consists of three approaches: normalisation, cleaning, and determination of the optimal model input.

3.2.1. Normalisation

The aim of this approach is to minimise the impact of outliers and make the time series have a normal distribution or close to normal [32]. In this research, the natural logarithm technique was utilised to normalise the time series and make it more static and reduce the predictors' collinearity [23]. This study employs the SPSS 24 statistics package.

3.2.2. Cleaning

Outliers and noise cause a negative effect on the efficiency of the suggested model [33]. As a result, data cleaning is essential to identify and modify the outliers and ignore the noise from the time series. Accordingly, the box and whisker approach was used to clean data from outliers. Also, singular spectrum analysis (SSA) was utilised for denoising time series [32].

The raw data have different noise signals such as shown in Figure 3. The pre-treatment signal effectively removes the noise from the raw data by decomposing it into several signals. Singular spectrum analysis (SSA) is an adaptive technique for the reduction of noise that is used in raw data decomposition [34].

SSA is a useful pre-processing method for predicting time series when integrated with neural networks (or similar techniques). It is employed in both linear and nonlinear data [35, 36]. This method was successfully employed in several areas, such as hydrology[37], industry [38], and stochastic process prediction [39].

3.2.3. Determination of the Optimal Model Input.

Selecting the independent factors that affect drought index as model input is essential in constructing any successful simulation model [40]. A tolerance technique and cross-correlation were employed to identify the optimal model input scenario. Pallant [41] recommended selecting the best predictors with a tolerance coefficient value of 0.2 or above is required to prevent multicollinearity between the independent variables.

3.3.Particle Swarm Optimisation (PSO)

PSO is an optimisation method which is being effectively implemented in a variety of areas to find the best solution; For example, single server optimisation Alharkan, Saleh [42], wireless sensor networks Dash, Panigrahi [43], and smart agriculture Jawad, Jawad [44]. PSO is a natural-system-based evolutionary computing method often used to resolve optimisation issues; it has fewer constants than most various algorithms [45]. This algorithm is used to get the optimal constants in a simulated model, resulting in the lowest error between the actual and forecast drought index. More information on PSO can be found in Poli [46].

3.4.Artificial Neural Network (ANN)

ANN is a technique for processing data that simulates human brain functions by utilising the same connections and behaviour as biological neurons [34]. Multilayer perceptron network (MLP) was applied a feed forward backpropagation (FFBB) that utilised the Levenberg–Marquardt (LM) technique for training the ANN model. The supposed ANN structure comprises four layers: the input layer with the best model inputs and two hidden layers with tansigmoidal activation functions for complex and nonlinear. The last layer contains SPI 3. The trial and error method may not necessarily offer the best answer, which is considered time-consuming. As a result, metaheuristic algorithms were integrated with ANN to choose the best learning rate value and the best number of neurons for hidden layers to gain the best input, output mapping and avoid underfitting and overfitting the model [32].

3.5.Performance Measurement Criteria

This study utilised three statistical criteria to assess the model's efficacy in simulating SPI 3. The determination coefficient (R^2), root mean squared error (RMSE), and mean absolute error (MAE) are the metrics used. To calculate them, use the following formula [47, 48]:

$$MAE = \frac{\sum_{i=1}^{N} |O_i - F_i|}{N} \quad (1)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (O_i - F_i)^2}{N}} \quad (2)$$

$$R^2 = \left[\frac{\sum_{i=1}^{N}(O_i - \bar{O}_i)(F_i - F_i)}{\sqrt{\sum(O_i - \bar{O}_i)^2 \sum(F_i - \bar{F}_i)^2}}\right]^2 \quad (3)$$

where:

O_i: measure SPI 3,

F_i: predicted SPI 3,

N: sample size,

$\bar{F}_i$: average of predicted SPI 3, and

$\bar{O}_i$: average of measure SPI 3.

In addition, during the validation stage, this work performed a graphical test to check the PSO-ANN model's capacity to simulate the SPI 3 data set. The residual analysis was also evaluated using the Shapiro-Wilk (S-W) and the Kolmogorov-Smirnov (K-S).

4. RESULTS AND DISCUSSION

4.1.Preparation of Input and Output Variables

According to Tabachnick and Fidell [33], all the time series (i.e., climatic factors) were normalised to minmise the effect of outliers (i.e., extreme data) to get a normal or near to normal distribution. After that, the remaining outliers were modified for dependent and independent variables. For instance, the time series and box plot for the cleaned SPI 3 time series is shown in Figure 2. This Figure shows that the time series has been cleared of extreme data compared to Figure 1.

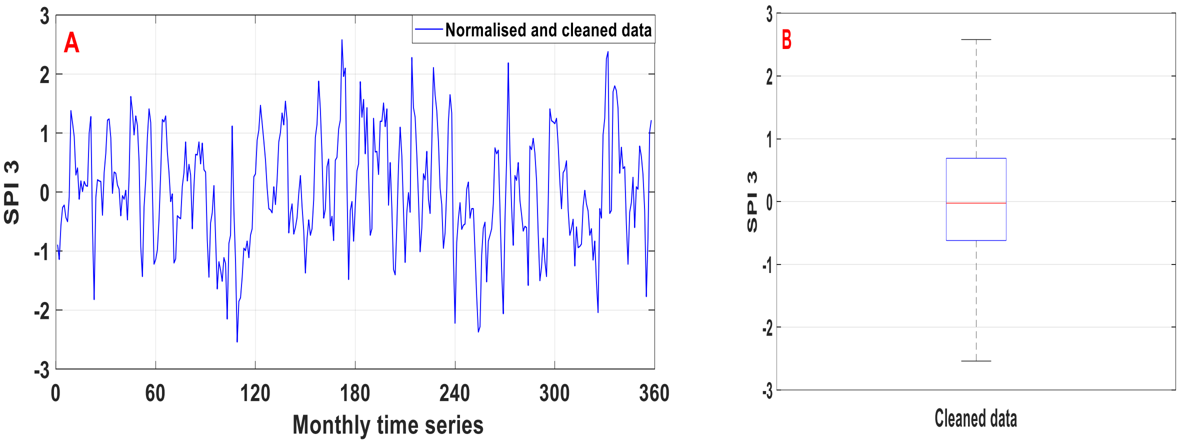

Figure 2 Boxplot and monthly time series for cleaned SPI 3 data.

The pretreatment signal approach, also known as SSA, was used to get denoise time series for SPI 3 and all meteorological data. In Figure 3, the first line displays the original data, the second line shows the new data, and the third and fourth lines indicate two noise components.

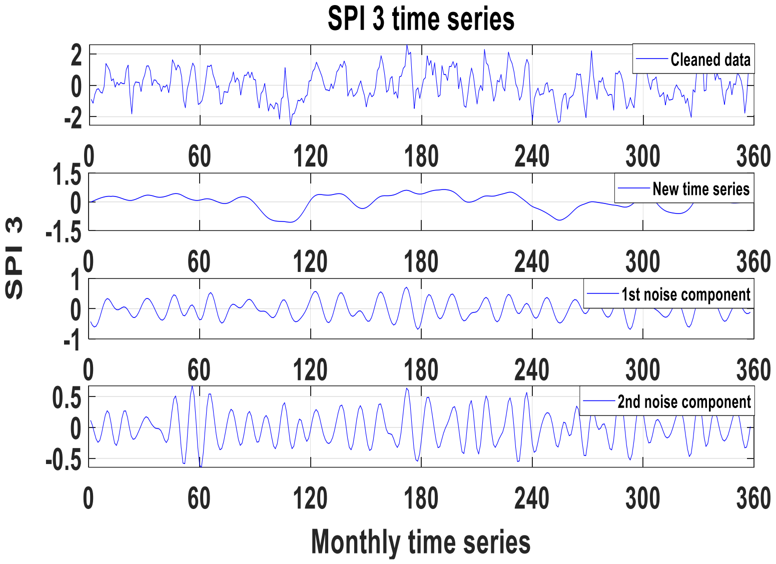

Figure 3 Original SPI 3 data and its components by using SSA.

A tolerance method was applied during the final stage of data pre-processing procedures to find the optimal model of input data (independent variables) that could precisely predicate the SPI 3 and prevent multicollinearity by deleting unimportant factors. The optimal model that considers tolerance values greater or equal to 0.2 for all independent factors was selected, as shown in Table 2.

Table 2 Collinearity statistics for the optimal model input for SPI3.

Output	Climatic factors	Tolerance value
SPI 3	Rain	0.292
	RH	0.241
	Twet	0.578
	Wmin	0.682

Data pre-processing was observed to increase the correlation coefficient (R) values between SPI 3 and independent factors, such as the R-value for relative humidity (from 0.218 to 0.86), rain (from 0.446 to 0.936), wet bulb temperature (from 0.106 to 0.448), and minimum wind speed (from -0.031 to -0.304). Pre-processing data enhances the quality of both independent and dependent data.

The data was then categorised into three sets: training (70%, 1990–2010); testing (15%, 2011–2015); and validation (15%, 2016–2020) according to Alawsi, Zubaidi [32] and Soh, Koo [10].

4.2.Analysis of the PSO Technique

The hybrid algorithm, PSO-ANN was implemented by applying the MATLAB toolbox (version 2019a) to determine the optimal hyperparameters of the ANN model. Five swarm sizes, 10, 20, 30, 40, and 50, were employed in the algorithm to identify the optimal number of hidden neurons (N1 and N2) and the optimal learning rate coefficient (Lr) of the ANN model. Each swarm size was applied five times with 200 iterations to gain the lowest error (i.e., the minimum fitness function). Figure 4 displays the PSO-ANN method performed in SPI 3, with the optimal fitness value for each swarm.

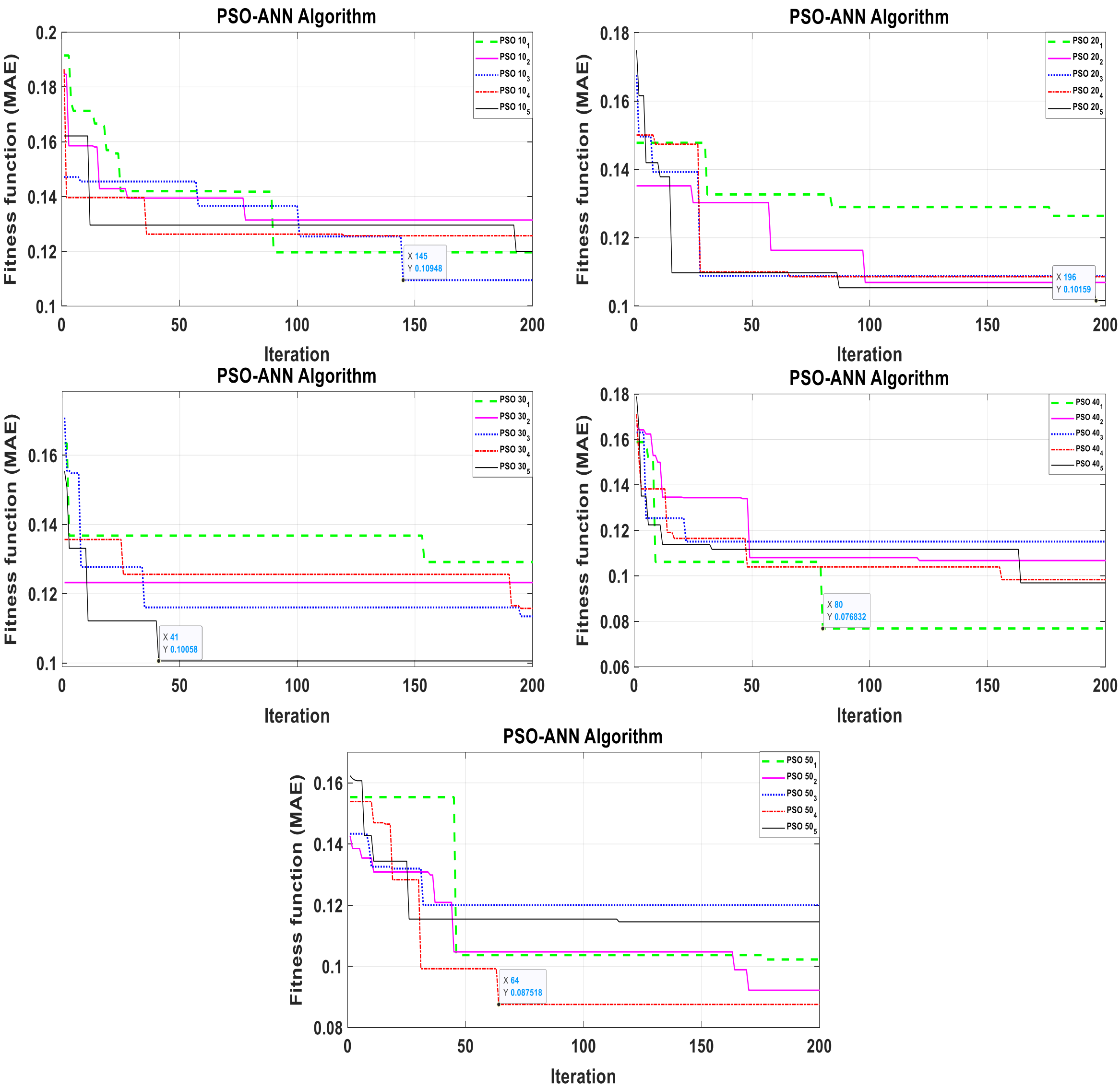

Figure 4 Performance of PSO algorithm.

Based on the fitness function (after 80 iterations, MAE = 0.076832), the optimal swarm size is (40_1), as shown in Figure 5. The simulation of SPI 3 has been improved by using the PSO algorithm's output to enhance ANN abilities. As a result, the optimal swarm size led to the following values for the ANN models' hyperparameters: Lr = 0.1528; N1 = 4; N2 = 8.

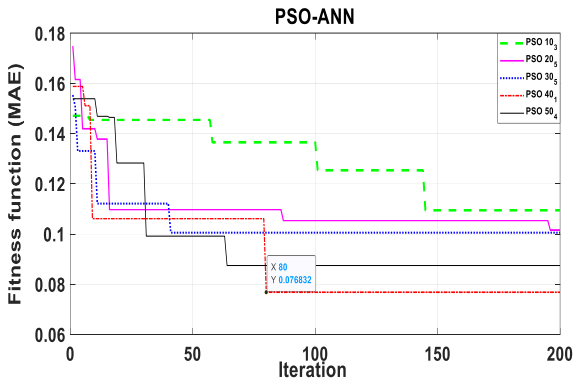

Figure 5 Fitness function versus iteration (PSO).

4.3.Performance Evaluation

After determining the optimal value of N1, N2, and Lr, the ANN model was constructed to simulate SPI 3. Numerous runs of the ANN model were performed to identify the optimal network to predict SPI 3 precisely. Various types of statistical tests were used to evaluate the model's efficacy (validation step). Table 3 presents the statistical indicators (R^2, MAE, and RMSE) for SPI 3. According to Dawson, Abrahart [49], the PSO-ANN, model showed good prediction accuracy for SPI 3.

Table 3 Performance assessment criteria for PSO in validation step for SPI 3.

Output	Algorithm-Model	MAE	R^2	RMSE
SPI 3	**PSO-ANN**	**0.216**	**0.86**	**0.247**

In addition, a graphical test was utilised during the validation stage to demonstrate the ability of the hybrid method to predicate the SPI 3 data. Figure 6 shows the observed and forecasted SPI 3 data using PSO-ANN. PSO-ANN forecasted data follows the pattern and frequency of the measured data. The fluctuating impact of climate variables can cause many minor deviations in the estimated data.

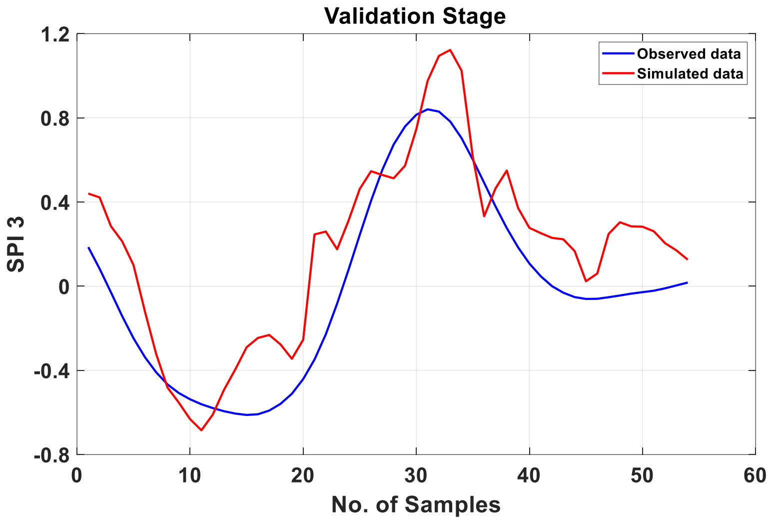

Figure 6 Comparison between simulate SPI 3 time series and observed time series for PSO-ANN for the validation stage.

Also, Table 4 displays the results of the Shapiro-Wilk (S-W) and Kolmogorov-Smirnov (K-S) tests that were utilised to evaluate the normality of the residual time series for the PSO-ANN model. According to Valentini, dos Santos [50], the results of the S–W and K–S tests indicated a p-value greater than 0.05, which demonstrates that the residuals have normality.

Table 4 Tests of normality for SPI 3

Output	S-W	K-S
SPI 3	**0.054**	**0.17**

Overall, the above findings of statistical testing show that:

1. The data pre-processing techniques enhance the raw data quality, especially the SSA method.
2. The tolerance method successfully chose the optimal predictor case without violating the multicollinearity supposition.
3. Wmin, Twet, Rain, and RH were identified as reliable predictors of SPI 3.
4. The PSO-ANN approach is a accurate technique for predicting drought index.

5. The proposed methodology precisely forecasted the drought index based on different measurement criteria.
6. The results show a significant correlation between climatic variables and drought.

This research highlights the suggested strategy for forecasting drought in areas with fluctuations in climatic and socioeconomic variables, such as Al-Kut. Therefore, policymakers and stakeholders may benefit from this strategy by using it to create accurate decisions and successful methods for irrigation system management.

5. CONCLUSIONS

The precision of futurity drought predictions is essential for agricultural irrigation, drought preparation, and risk management. Drought prediction is significantly affected by climate factors. Drought is effectively driven by wind speed, temperature, rainfall, and relative humidity. As a result, the influence of climatic factors is not being ignored in drought prediction. This research proposed a new hybrid technique for simulating drought index in Al-Kut City, Iraq, considering climatic variables for thirty years. The methodology encompasses data pre-processing methods and ANN combined with the PSO algorithm. The results show that data pre-processing methods, including singular spectrum analysis and tolerance technique, successfully minimise the noise from time series and delete unnecessary climatic factors, resulting in enhanced data quality and finding the best predictors model. This hybridisation demonstrates its powerful capacity to improve the created model's predictive accuracy; it can estimate the SPI 3 accurately based on several statistical criteria, such as $R^2 = 0.86$, RMSE = 0.247, and MAE = 0.2160. These results offer useful data to decision-makers, allowing the irrigation sector firm in Al-Kut to manage the irrigation system better. For future study, employing different data pre-treatment techniques, such as empirical mode decomposition (EMD). Also, utilising various drought indices such as standardised precipitation evapotranspiration index (SPEI) and reconnaissance drought index (RDI).

REFERENCES

1.Xu, D., et al., Application of a hybrid ARIMA-LSTM model based on the SPEI for drought forecasting. *Environ Sci Pollut Res Int*, 2022. **29**(3): p. 4128-4144.

2.Pham, Q.B., et al., Coupling Singular Spectrum Analysis with Least Square Support Vector Machine to Improve Accuracy of SPI Drought Forecasting. *Water Resources Management*, 2021. **35**(3): p. 847-868.

3.Banadkooki, F.B., V.P. Singh, and M. Ehteram, Multi-timescale drought prediction using new hybrid artificial neural network models. *Natural Hazards*, 2021. **106**(3): p. 2461-2478.

4.McKee, T.B., N.J. Doesken, and J. Kleist. The relationship of drought frequency and duration to time scales. in *8th Conference on Applied Climatology*. 1993.

5.Anshuka, A., F.F. van Ogtrop, and R. Willem Vervoort, Drought forecasting through statistical models using standardised precipitation index: a systematic review and meta-regression analysis. *Natural Hazards*, 2019. **97**(2): p. 955-977.

6.Gumus, V. and H.M. Algin, Meteorological and hydrological drought analysis of the Seyhan−Ceyhan River Basins, Turkey. *Meteorological Applications*, 2017. **24**(1): p. 62-73.

7.Adede, C., et al., A Mixed Model Approach to Vegetation Condition Prediction Using Artificial Neural Networks (ANN): Case of Kenya’s Operational Drought Monitoring. *Remote Sensing*, 2019. **11**(9): p. 1099.

8.Elbeltagi, A., et al., Estimating the Standardized Precipitation Evapotranspiration Index Using Data-Driven Techniques: A Regional Study of Bangladesh. *Water*, 2022. **14**(11): p. 1764.

9.Xu, L., et al., An evaluation of statistical, NMME and hybrid models for drought prediction in China. *Journal of Hydrology*, 2018. **566**: p. 235-249.

10.Soh, Y.W., et al., Application of artificial intelligence models for the prediction of standardized precipitation evapotranspiration index (SPEI) at Langat River Basin, Malaysia. *Computers and Electronics in Agriculture*, 2018. **144**: p. 164-173.

11.Agana, N.A. and A. Homaifar, EMD-Based Predictive Deep Belief Network for Time Series Prediction: An Application to Drought Forecasting. *Hydrology*, 2018. **5**(1): p. 18.

12.Nabipour, N., et al., Short-Term Hydrological Drought Forecasting Based on Different Nature-Inspired Optimization Algorithms Hybridized With Artificial Neural Networks. *IEEE Access*, 2020. **8**: p. 15210-15222.

13.Zhang, Y., et al., Multi-models for SPI drought forecasting in the north of Haihe River Basin, China. *Stochastic Environmental Research and Risk Assessment*, 2017. **31**(10): p. 2471-2481.

14.Belayneh, A. and J. Adamowski, Standard Precipitation Index Drought Forecasting Using Neural Networks, Wavelet Neural Networks, and Support Vector Regression. *Applied Computational Intelligence and Soft Computing*, 2012. **2012**: p. 1-13.

15.Dikshit, A., B. Pradhan, and A.M. Alamri, Short-Term Spatio-Temporal Drought Forecasting Using Random Forests Model at New South Wales, Australia. *Applied Sciences*, 2020. **10**(12): p. 4254.

16.Altunkaynak, A. and A. Jalilzadnezamabad, Extended lead time accurate forecasting of palmer drought severity index using hybrid wavelet-fuzzy and machine learning techniques. *Journal of Hydrology*, 2021. **601**: p. 126619.

17.Ali, Z., et al., Forecasting Drought Using Multilayer Perceptron Artificial Neural Network Model. *Advances in Meteorology*, 2017. **5681308**: p. 1-9.

18.Das, P., et al., Hybrid wavelet packet machine learning approaches for drought modeling. *Environmental Earth Sciences*, 2020. **79**(10): p. 221.

19.Bari Abarghouei, H., M.R. Kousari, and M.A. Asadi Zarch, Prediction of drought in dry lands through feedforward artificial neural network abilities. *Arabian Journal of Geosciences*, 2011. **6**(5): p. 1417-1433.

20.Apaydin, H., et al., Artificial intelligence modelling integrated with Singular Spectral analysis and Seasonal-Trend decomposition using Loess approaches for streamflow predictions. *Journal of Hydrology*, 2021. **600**: p. 126506.

21. Tiu, E.S.K., et al., An evaluation of various data pre-processing techniques with machine learning models for water level prediction. *Natural Hazards*, 2022. **110**: p. 121-153.

22.Ömer Faruk, D., A hybrid neural network and ARIMA model for water quality time series prediction. *Engineering Applications of Artificial Intelligence*, 2010. **23**(4): p. 586-594.

23.Zubaidi, S.L., et al., A Method for Predicting Long-Term Municipal Water Demands Under Climate Change. *Water Resources Management*, 2020. **34**(3): p. 1265-1279.

24.Khan, M.M.H., N.S. Muhammad, and A. El-Shafie, Wavelet based hybrid ANN-ARIMA models for meteorological drought forecasting. *Journal of Hydrology*, 2020. **590**: p. 125380.

25.Alawsi, M.A., et al., Drought Forecasting: A Review and Assessment of the Hybrid Techniques and Data Pre-Processing. *Hydrology*, 2022. **9**(7): p. 115.

26.Abed, Q.M.J.J.o.C.o.E.W., Geographical analysis of the low success rates of the sixth preparatory students in the city of Kut for the period (2015–2019)) *A study of population geography*. 2020. **2**(40).

27.Edan, M.H., R.M. Maarouf, and J. Hasson, Predicting the impacts of land use/land cover change on land surface temperature using remote sensing approach in Al Kut, Iraq. *Physics and Chemistry of the Earth, Parts A/B/C*, 2021. **123**: p. 103012.

28.NOAA. National Oceanic and Atmospheric Administration. Data tools: Find a station. 2021 [cited 2021 1 December 2021]; Available from: https://www.ncdc.noaa.gov/cdo-web/datatools/findstation.

29.Aghelpour, P., H. Bahrami-Pichaghchi, and O. Kisi, Comparison of three different bio-inspired algorithms to improve ability of neuro fuzzy approach in prediction of agricultural drought, based on three different indexes. *Computers and Electronics in Agriculture*, 2020. **170**: p. 105279.

30.Belayneh, A., J. Adamowski, and B. Khalil, Short-term SPI drought forecasting in the Awash River Basin in Ethiopia using wavelet transforms and machine learning methods. *Sustainable Water Resources Management*, 2015. **2**(1): p. 87-101.

31.Tigkas, D., H. Vangelis, and G. Tsakiris, DrinC: a software for drought analysis based on drought indices. *Earth Science Informatics*, 2014. **8**(3): p. 697-709.

32.Alawsi, M.A., et al., Tuning ANN Hyperparameters by CPSOCGSA, MPA, and SMA for Short-Term SPI Drought Forecasting. *Atmosphere*, 2022. **13**(9): p. 1436.

33.Tabachnick, B.G. and L.S. Fidell, Using Multivariate Statistics, ed. S. Edition. 2013: Pearson: Boston, MA, USA.

34.Zubaidi, S.L., et al., Urban Water Demand Prediction for a City That Suffers from Climate Change and Population Growth: Gauteng Province Case Study. *Water*, 2020. **12**(7): p. 1885.

35.Golyandina, N. and A. Zhigljavsky, Singular Spectrum Analysis for Time Series. 2020, Springer.

36.Zubaidi, S.L., et al., A Novel approach for predicting monthly water demand by combining singular spectrum analysis with neural networks. *Journal of Hydrology*, 2018. **561**: p. 136-145.

37.Ouyang, Q. and W. Lu, Monthly Rainfall Forecasting Using Echo State Networks Coupled with Data Preprocessing Methods. *Water Resources Management*, 2017. **32**(2): p. 659-674.

38.Al-Bugharbee, H. and I. Trendafilova, A fault diagnosis methodology for rolling element bearings based on advanced signal pretreatment and autoregressive modelling. *Journal of Sound and Vibration*, 2016. **369**: p. 246-265.

39.Khan, M.A.R. and D.S. Poskitt, Forecasting stochastic processes using singular spectrum analysis: Aspects of the theory and application. *International Journal of Forecasting*, 2017. **33**(1): p. 199-213.
40.Maier, H.R. and G.C. Dandy, Neural networks for the prediction and forecasting of water resources variables: a review of modelling issues and applications. *Environmental Modelling & Software,* 2000. **15**: p. 101–124.
41.Pallant, J., SPSS Survival Manual: A Step by Step Guide to Data Analysis Using IBM SPSS. 6th Edition ed. 2016: McGraw-Hill Education.
42.Alharkan, I., et al., Tabu search and particle swarm optimization algorithms for two identical parallel machines scheduling problem with a single server. *Journal of King Saud University - Engineering Sciences*, 2020. **32**(5): p. 330-338.
43.Dash, M., T. Panigrahi, and R. Sharma, Distributed parameter estimation of IIR system using diffusion particle swarm optimization algorithm. *Journal of King Saud University - Engineering Sciences*, 2019. **31**(4): p. 345-354.
44.Jawad, H.M., et al., Accurate Empirical Path-Loss Model Based on Particle Swarm Optimization for Wireless Sensor Networks in Smart Agriculture. *IEEE Sensors Journal*, 2020. **20**(1): p. 552-561.
45.Banerjee, S. and V.V. Dwivedi, Effect of signal to interference ratio on adaptive beamforming techniques. *Journal of King Saud University - Engineering Sciences*, 2018. **30**(4): p. 313-319.
46.Poli, R., Analysis of the Publications on the Applications of Particle Swarm Optimisation. *Journal of Artificial Evolution and Applications*, 2008. **2008**: p. 1-10.
47.Mohammadi, B. and S. Mehdizadeh, Modeling daily reference evapotranspiration via a novel approach based on support vector regression coupled with whale optimization algorithm. *Agricultural Water Management*, 2020. **237**: p. 106145.
48.Mohammadi, B., et al., Adaptive neuro-fuzzy inference system coupled with shuffled frog leaping algorithm for predicting river streamflow time series. *Hydrological Sciences Journal*, 2020. **65**(10): p. 1738-1751.
49. Dawson, C.W., R.J. Abrahart, and L.M. See, HydroTest: A web-based toolbox of evaluation metrics for the standardised assessment of hydrological forecasts. *Environmental Modelling & Software*, 2007. **22**(7): p. 1034-1052.
50. Valentini, M., G.B. dos Santos, and B. Muller Vieira, Multiple linear regression analysis (MLR) applied for modeling a new WQI equation for monitoring the water quality of Mirim Lagoon, in the state of Rio Grande do Sul—Brazil. SN *Applied Sciences*, 2021. **3**(1): p. 70.