Journal of Agrometeorology

ISSN : 0972-1665 (print), 2583-2980 (online)
Vol. No. 26 (4) : 466-472 (December - 2024)
https://doi.org/10.54386/jam.v26i4.2734
https://journal.agrimetassociation.org/index.php/jam

Research Paper

Meteorological and satellite-based data for drought prediction using data-driven model

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ABSTRACT

This work presents a data-driven model, the Artificial Neural Network-Multilayer Perceptron Neural Network (ANN-MLP), for use in meteorological drought deciles index (DDI) predictions over various climatic sub-zone. Two types of rainfall data from meteorological weather stations (WSs) and satellite-based estimates of PERSIANN (Precipitation Estimation from Remotely Sensed Information using Artificial Neural Network) were adopted. This work considered the calculated DDI (DDI original) from WSs to train and develop the proposed algorithm at three sub-zones (ANN-MLP-DDI models). The newly developed model was tested for DDI prediction using PERSIANN, and compared with the calculated DDI original from WSs. The results positively revealed that the ANN-MLP-DDI models showed high performance (Correlation coefficient r= 0.981) for DDI prediction against the DDI original from WSs. It can be concluded that data-driven models are feasible for drought prediction, and this work could help water managers in mitigating drought impacts and in providing information for policy makers

Keywords: Drought deciles index, Meteorological drought, Iraq, Multilayer perceptron, Data driven

Drought event predictions are a crucial issue across the globe for water resources managers and decision makers when working to mitigate droughts (Nandgude *et al.,* 2023). Drought is a hydro-meteorological phenomenon that has complex natural causes and imposes great costs on society, the economy, and the environment (Achite *et al.,* 2022). Iraq like many other arid and semi-arid countries has been affected climatologically by reduced rainfall average amount, from which droughts originate, and increasing temperatures due to climate changes (Suliman *et al.,* 2024). Drought prediction is necessary for crop water demand, water management, and electricity generation (Xu *et al.,* 2018; Khan *et al.,* 2024).

Drought is hydrologically based on surface water level, meteorologically based on the time rainfall remains under certain threshold, and agriculturally based on soil moisture reduction (Wilhite and Glantz, 1985). Rainfall data plays an essential role in the hydrological cycle for drought calculation and prediction (Beck *et al.,* 2017; Khajehei *et al.,* 2018). Accurate rainfall data are still challenging for hydrologists to obtain from Meteorological Weather stations (WSs) due to instrument uncertainties (Sun *et al.,* 2018). Rainfall data sets from satellite- and reanalysis-based products are another technique globally offered at spatial and temporal scales (Ji *et al.,* 2020). PERSIANN (Precipitation Estimation from Remotely Sensed Information using Artificial Neural Network), IMERG (Integrated Multi-Satellite Retrievals for Global Precipitation Measurement), CHIRPS (Climate Hazards Group InfraRed Precipitation with Station data), and TRMM (Tropical Measuring Mission Multi-Satellite Precipitation) are the common products adopted to obtain rainfall data-sets (Das *et al.,* 2024; Sridhara *et al.,* 2021). Having these rainfall products could support drought calculations and predictions, especially where WSs are sparse.

In this work, the Drought Deciles Index (DDI) has chosen among many other indices because of its ease of use as it needs low requirements for the calculation to be conducted; however, it is to be used then for DDI prediction by Data-driven models. Nevertheless, many other indices have employed for drought calculations such as Streamflow Drought Index (SDI), effective Reconnaissance Drought Index (eRDI), Standardized Precipitation Index (SPI), Reconnaissance Drought Index (RDI), and Standardized Soil Moisture Index (SSMI) (Tigkas *et al.,* 2022).

Data-driven model has been widely used to solve numerous

Article info - DOI: *https://doi.org/10.54386/jam.v26i4.2734*
Received: 10 September 2024; Accepted: 19 October 2024; Published online : 01 December 2024

issues of non-linear relationships. It is a robust tool applied in various applications in terms of hydrological prediction such as Artificial Neural Network-Multilayer Perceptron Neural Network (ANN-MLP), Random Forest (RF), Adaptive Neuro-Fuzzy Inference System (ANFIS), and Support Vector Machine (SVM) (Ditthakit *et al.,* 2023; Suliman *et al.,* 2020; Suliman and Darus 2019). For example, prediction of the soil moisture and Soil Water-Deficit Index (SWDI), which was presented by Zhu *et al.,* (2020) using SVM model and WSs data. Random Forest (RF) was considered for predicting Standardized Precipitation Evapotranspiration Index (SPEI) in Australia by Dikshit *et al.,* (2020). Deo *et al.,* (2017) applied Least Square Support Vector Machine (LSSVM) to predict Standardized Precipitation Index (SPI) in eastern Australia. Bouaziz *et al.,* (2021) have also predicted SPI in Tunisia by using The Extreme Learning Machines (ELM). Artificial Neural Networks (ANN) was employed to predict Nonlinear Aggregated Drought Indexes (NADI) by Barua *et al.,* (2012). Khan *et al.,* (2024) employed various Data-driven models for predicting the drought index SPEI over different climate-zones of the Kabul River basin. A comprehensible comparison for different data-driven models for drought prediction has been presented by Achite *et al.,* (2022); however, the studies presented Data-driven models as dependable tool for drought indices predictions.

This work aimed on assessing a data-driven model's ability, namely ANN-MLP, to predict the meteorological Drought Deciles Index (DDI) over different climatic zones of Iraq using Weather Stations (WSs) rainfall data and PERSIANN rainfall estimates. In order to systematically evaluate the accuracy of the new model and its effectiveness; however, this work objectives are: 1) Calculate DDI (original) based on 47-years of WSs; 2) Adopt the data sets used for DDI (original) to build ANN-MLP-DDI; 3) Predict DDI (simulated) using PERSIANN rainfall estimates; and 4) compare the simulated results with the original DDI. Drought predictions are relevant for climatologists, hydrologists, and decision-makers and are valuable in mitigating drought impacts, especially in regions with arid and semi-arid climates.

MATERIALS AND METHODS

Study area and data

Iraq is located in the Middle East with 438,320 km^2, and faces a decrease in rainfall due to global warming and increased summer temperatures. Its area has been dividied by Köppen's climate classification into three different zone: 1) a cold climate (BSk) as Zone-A; 2) a warmer climate (BSh) as Zone-B; and 3) a warm desert climate (BWh) as Zone-C. These zones contain different amounts of meteorological weather stations (WSs) as shown in Fig. 1. Monthly rainfall data are available for the period of 1970 to 1917 from only 22 WSs, which are scarce and inadequately distributed over Iraqi Köppen zones (Awchi and Suliman 2021). Consequently, this work assessed precipitation estimation from remotely sensed information using artificial neural networks-climate data records (PERSIANN) as an alternative rainfall data source for drought predictions. PERSIANN was developed by the University of California; however, it is produced from multi-satellite estimates associated with artificial neural network algorithms (Guo *et al.,* 2016; Ashouri *et al.,* 2014). PERSIANN provides continuous monthly rainfall estimates records starting from 1983-01-01, has been adopted for several climate change studies (Zhong *et al.,* 2019), and is avaliable on this website (www.ncei.noaa.gov).

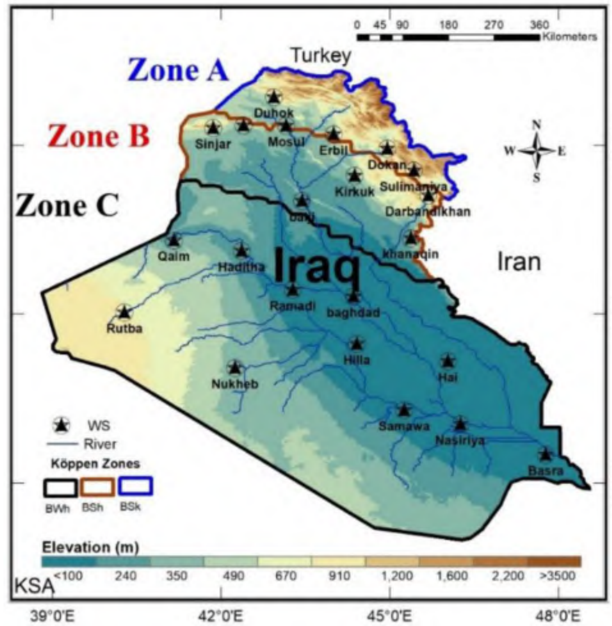

Fig 1: Study area

Drought deciles index (DDI)

The drought deciles index (DDI), which is suggested by Gibbs and Maher (1967) in Australia was considered for this work due to its simplicity; however, it requires only rainfall data for its calculations. DDI was calculated through determination of the cumulative frequency distribution; thus, the results were classified into 10 deciles, as shown in Table 1 (Mckee *et al.,* 1993; Dikici 2020; Suliman *et al.,* 2024). The average moving method was adopted for DDI measurements at each WS using monthly rainfall data. The average value of DDI was then carried out at each zone using Eq. (1) (Xia *et al.,* 2018) as:

$$\mathrm{DDI_{average}} = \sum_0^n \mathrm{DDI_{i,t}} \qquad (1)$$

where $\mathrm{DDI_{average}}$ is the average calculated DDI over each zone using a different number of WSs (n), and i is the WS. $\mathrm{DDI_{average}}$ for each zone was considered as output, and the rainfall data from each zone were adopted as inputs for training the data-driven model for possible PERSIANN assessment.

Table 1: Drought deciles (DDI) indices

Drought categories	Drought decile index (DDI)
Extremely drought (ED)	≤10%
Severely drought (SD)	10%-20%
Moderately drought (MD)	20%-30%
Nearly normal (NN)	30%-70%
Moderately wet (MW)	70%-80%
Very wet (VW)	80%-90%
Extremely wet (EW)	≥90%

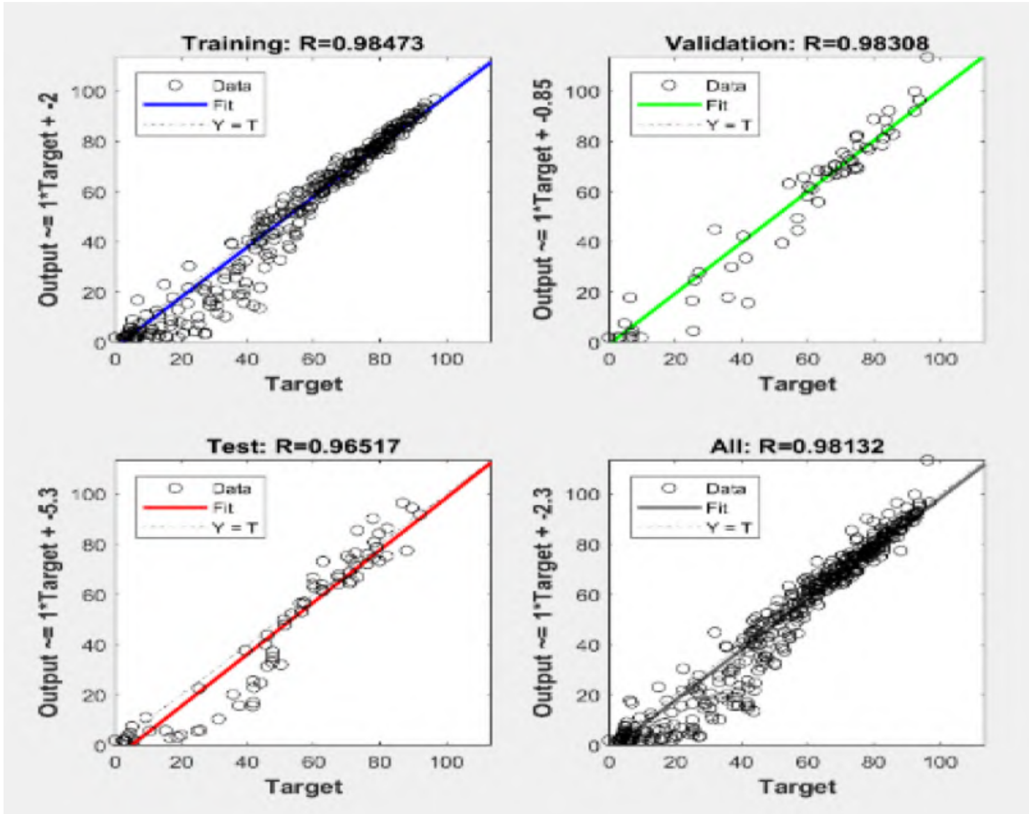

Fig 2: Results of optimal structures of training period at Zone-A

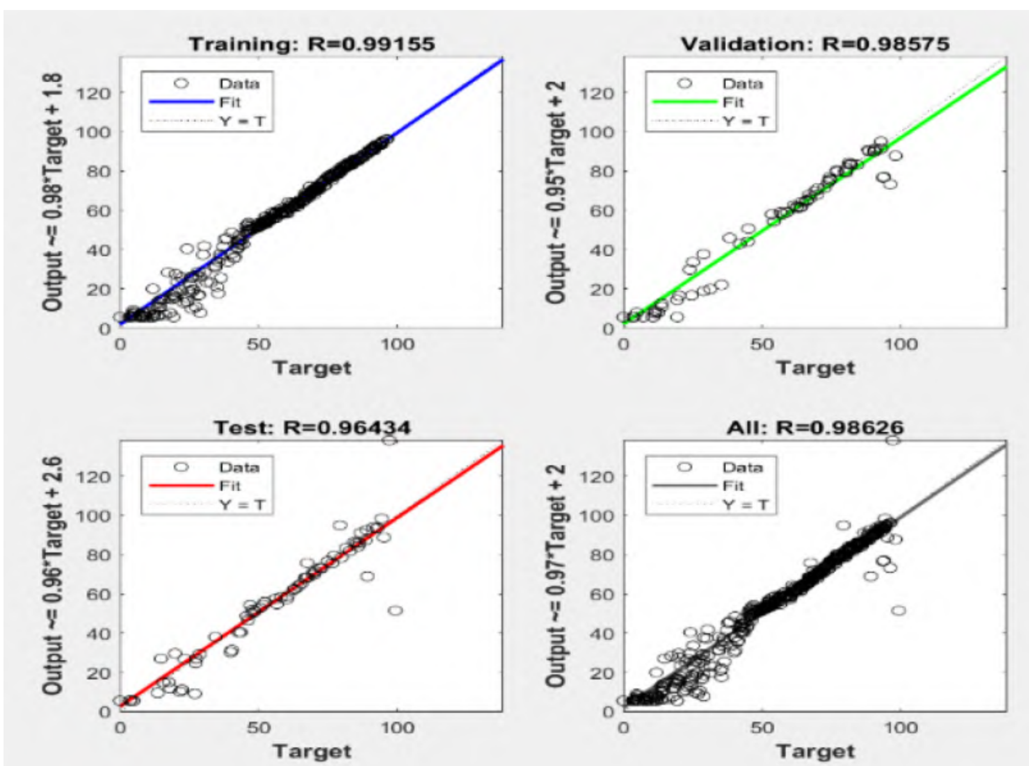

Fig 3: Results of optimal structures of training period at Zone-B

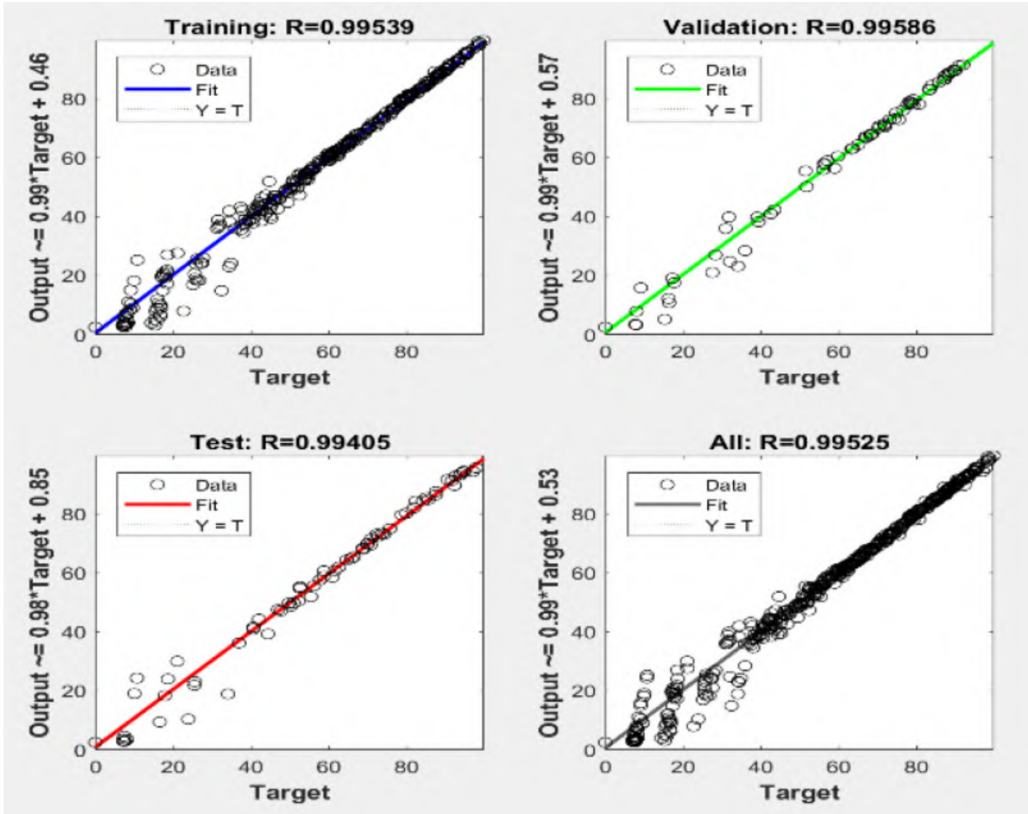

Fig 4: Results of optimal structures of training period at Zone-C

Data-driven model

Data-driven models like Artificial Neural Networks (ANN) are feasible, and popular applications, which are widely employed for drought prediction (Le *et al.,* 2016). Artificial neural networks-multilayer perceptron (ANN-MLP) feed forward neural network was chosen to evaluate its applicability for DDI predictions. This work proposed a new algorithm through obtaining the required input (from WSs), and outputs (the calculated DDI from WSs) for each zone. However, average monthly rainfall data for the available WSs (4 WSs at Zone-A, 7 WSs at Zone-B, and 11 WSs at Zone-C) for the period (1970-2017) were set as inputs. Furthermore, the average DDI from the WSs at each zone were considered as outputs. Therefore, the ANN-MLP models were trained using the proposed algorithm for each zone and their inputs and outputs were utilized as references.

Consequently, the best trained ANN-MLP-DD models at each zone were then tested for DDI prediction adopting PERSIANN as an input. The neural network-toolbox of the MATLAB software was considered in this work to create ANN-MLP-DDI. It is a flexible structure capable of identifying non-linear relationships (Suliman *et al.,* 2017). However, the obtained results from the trained models were compared using four indicators, which are the correlation coefficient (r), goodness of fit (R^2), Nash-Sutcliffe (NSE) (Nash and Sutcliffe, 1970), and Root Mean Square Error (RMSE) as given below.

$$r = \frac{\sum_{i=1}^{n} (DI_{org}-\overline{DI}_{org})(DI_{sim}-\overline{DI}_{sim})}{\sqrt{\sum_{i=1}^{n}(DI_{org}-\overline{DI}_{org})^2}\sqrt{\sum_{i=1}^{n}(DI_{sim}-\overline{DI}_{sim})^2}} \qquad -1 < r \leq +1 \tag{2}$$

$$R^2 = \frac{\left(\sum_{i=1}^{n} (DI_{org}-\overline{DI}_{org})(DI_{sim}-\overline{DI}_{sim})\right)^2}{\sum_{i=1}^{n} (DI_{org}-\overline{DI}_{org})^2 \sum_{i=1}^{n}(DI_{sim}-\overline{DI}_{sim})^2} \qquad 0 < R^2 \leq 1 \tag{3}$$

$$NSE = 1 - \frac{\sum_{i=1}^{n}(DI_{sim}-DI_{org})^2}{\sum_{i=1}^{n}(DI_{org}-\overline{DI}_{org})^2} \qquad -\infty < NSE \leq 1 \tag{4}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} \left(DI_{sim} - DI_{org}\right)^2} \qquad \infty < RMSE \leq 0 \tag{5}$$

where, n is the number of time series, $\overline{DDI}_{org}$ is the calculated DDI using WSs, $\overline{DDI}_{sim}$ is the simulated DDI by trained ANN-MLP-DDI, $\overline{DDI}_{org}$ and $\overline{DDI}_{sim}$ are their averages.

RESULTS AND DISCUSSION

Training drough decile index (DDI)

In this work, the performance of PERSIANN rainfall estimation over Iraqi zones was evaluated by the ANN-MLP-DDI model. The implemented algorithm used rainfall data from WS from different zones (Zone-A with 4 WSs, Zone-B with 7 WSs, and Zone-C with 11 WSs) as inputs and the measured DDI as output for training the ANN-MLP-DDI model. The best configuration was achieved through training processes using a different number of neurons and hidden layers. The best configuration from the trained ANN-MLP structures was chosen for DDI predictions using PERSIANN rainfall estimation at Zone-A, Zone-B, and Zone-C as

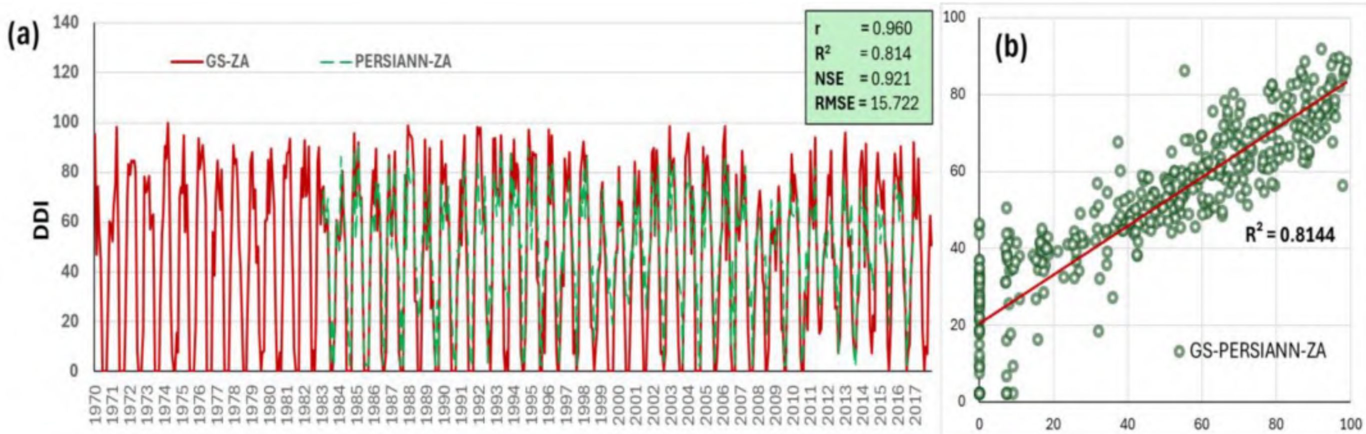

Fig 5: a) DDI calculations of Zone-A for WSs and PERSIANN data, b) Scatter plot of DDI values using WSs and PERSIANN

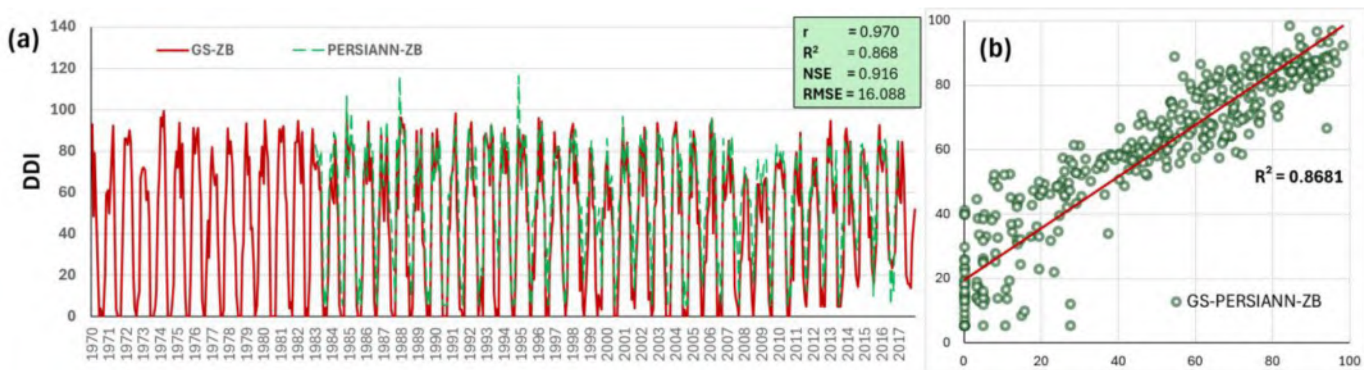

Fig 6: a) DDI calculations of Zone-B for WSs and PERSIANN data, b) Scatter plot of DDI values using WSs and PERSIANN

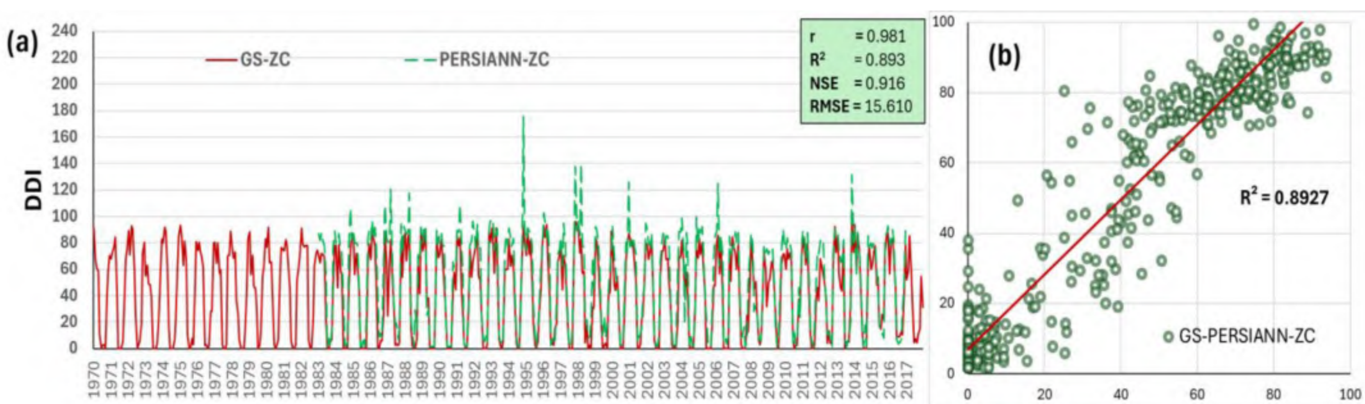

Fig 7: a) DDI calculations of Zone-C for WSs and PERSIANN data, b) Scatter plot of DDI values using WSs and PERSIANN

shown in Figs. 2, 3, and 4, respectively.

Validation of PERSIANN

The validation of the PERSIANN rainfall estimation was conducted using the optimal configuration of trained ANN-MLP-DDI. Figs. 5, 6, and 7 show the results of calculated DDI from WSs and the predicted DDI from PERSIANN based on ANN-MLP-DDI involving four different indicators (r, R^2, NS, and RMSE) for each zone as well. Generally, PERSIANN showed good performance over the three Iraqi zones. For Zone-A, the indicators' values found by PERSIANN were r=0.960, R^2=0.814, NS=0.921, and RMSE=15.722. For Zone-B, the indicators' values were r=0.970, R^2=0.868, NS=0.916, and RMSE=16.088, which are slightly better than Zone-A. For Zone-C, the indicators' values were r=0.981, R^2=0.893, NS=0.916, and RMSE=15.610, which were the highest values. The greatest relationship between WS and PERSIANN was found at Zone-A. Moreover, overestimations of the predicted DDI by ANN-MLP-DDI were found clearly at Zone-C in years 1995, 1987-1988, 2001, 2006, and 2013-2014. Zone-B also experienced overestimations of the predicted DDI in years 1995, 1988, 2001, 2006, and 2014; however, ANN-MLP-DDI underestimated in Zone-A. PERSIANN performed better at Zone-B and Zone-C with low annual precipitation, and showed a slight weakness at Zone-A, which is in line with the outcomes of by Suliman *et al.,* (2024). In general, trained MLP-NN-DDI models of the three zones performed satisfactorily in predicting DDI. This result realizes the capability of ANN-MLP for prediction and analyzing droughts over semi-arid Iraq.

CONCLUSION

In this work, the potential of data-driven models for drought deciles index (DDI) predictions using Meteorological and PERSIANN data sets is presented. Monthly precipitation data sets for a period of 47 years were obtained from 22-meteorological weather stations, and these data sets were used for DDI calculations in data-sparse areas of Iraq. Three different Köppen zones with different climatic characteristics were considered over the study area. The ANN-MLP-DDI model was built to predict DDI via the input and output variables from DDI calculations based on WSs data sets. Additionally, PERSIANN data was also assessed in terms of DDI prediction for the developed ANN-MLP-DDI model. The ability of DDI prediction was high with an R^2 value found by PERSIANN of 0.981. PERSIANN performed reasonable at Zone-C with its low annual precipitation rates and showed some weakness with the high annual precipitation rates of Zone-A with 0.81 R^2. Generally, the outcomes indicate that the ANN-MLP-DDI model was successfully established was capable of drought index DDI predictions.

ACKNOWLEDGEMENTS

Author would like to thank the Iraqi IMOS and NOAA for sharing the rainfall data used for this work. Author declares that no grant or financial assistance were received to complete this manuscript.

Fundings: No funding was involved

Data availability: Data are available on request basis only.

Conflicts of Interest: none

Author contributions**:** A.H.A. Suliman was responsible for developing, producing the methodology, and writing the article.

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