Integrated Artificial Intelligent with RS and GIS for Long-Term Drought Prediction

Bashar Muneer Yahya\textsuperscript{1*}, Dursun Zafer Seker\textsuperscript{2} and Basman Younus Hameed\textsuperscript{1}

\textsuperscript{1}Remote Sensing Center, Mosul University, Mosul, Iraq.
\textsuperscript{2}Istanbul technical university, Civil Engineering Faculty, Istanbul, Turkey.

\textsuperscript{*}E-mail: bashar1974@uomosul.edu.iq

Abstract. The accurate evaluation of drought plays an urgent role in the optimal solution for future development. The present research aimed to predict and assess drought in Nineveh governorate northwestern Iraq by integrated a fuzzy logic procedure with Geographical Information System (GIS) environment. Primary meteorological data for six stations were used in this study. Vegetation cover changes were detected using remote sensing analysis in which there was a decrease in the vegetation cover’s area by 17.7\% from 592.3 km\textsuperscript{2} in the year 1992 to 487.46 km\textsuperscript{2} in the year 2016. Standardized Precipitation Index (SPI) as a proxy for drought conditions was simulated by developing the model of Adaptive Neuro-Fuzzy Inference System (ANFIS) as an artificial intelligent approach where its performance reached to 82\% when evaluating the Nash-Sutcliffe coefficient and Root Mean Square Error (RMSE)as performance criteria. However, the long-term meteorological drought was an assessment where the results show that the drought level will intensify in a future by 10.1\% with more successive droughts levels. Those results were clarified through developing spatial distribution map for long-term drought simulation by employing the (GIS) as a database to develop future plans for the study area.

1. Introduction

All life components are negatively affected via a natural phenomenon referred to as drought. Yet, such phenomenon can be monitored easily, in which proactive solutions might be set for reducing its harms when identifying its predicted values for future. Many life sectors like environment, cultural, economy etc. are affected by drought factors that have a harsh impact on these sectors in several respects, especially if its effects last for a long period [1,2]. Drought can be characterized through its duration, severity, and spatial impact on a specific area, yet due to the various climate characteristics, there is a difficulty in determining when drought will start and where or when it will adversely affect a certain area [3]. In Iraq, the drought’s impact has lately become evident via many observations, such as the reduction in agricultural land and vegetation cover which in the past produced various economic crops [4]. Previous reports and researches indicating that all the parts of Iraq are suffering from drought, reaching advanced phases in certain parts. These studies are supported by the International Organization for Migration [5] which reported that drought was the main reason for the migration of 4263 families consisting of 25,578 individuals between 2007 and
2009 in many regions of Iraq like Salah Adin and the Nineveh governorates. The development of applications for solving problems associated with forecasting climate variables or drought indices is usually complicated as a result of many variables that controlled in one way or another for the issue under consideration. Artificial Intelligence (AI) might be specified as an application in computer science simulating the human’s capability to make logical decisions [6, 7]. AI help in solving difficult problems facing humans with cost-efficiency and reliability. Various tasks might be provided by AI such as speech recognition, decision-making, predict variables, images recognition, and so on. AI includes six main procedures, Evolutionary Computation (EC), Machine Learning (ML), Computational creativity, Fuzzy systems, Chaos theory and Probabilistic methods [8, 9, 10]. Based on fuzzy logic methods that developed by [11]. An ANFIS model was developed for simulating the long-term drought changes in the study area. It is well known that both fuzzy logic and artificial neural networks as two artificial intelligent approaches have advantages and disadvantages recognized by many applied studies according to many abilities [12, 13, 14, 15]. Artificial Neural Networks (ANNs) were developed as mathematical models simulating the nervous system in human mind for the purpose of resolving real world issues requiring complicated calculations [16, 17]. The output of the (ANNs) is a combination of input variables and fuzzy roles that already designed according to experience [18, 19]. There are various techniques of Remote Sensing (RS) used for detecting the vegetation changes (for instance, remote sensing indices, supervised classification, image differencing, correlation or rations [20] where these methods proved their efficiency and accuracy throughout the obtained results in many vegetation changes situations like desertification, fire and vegetation diseases. The Normalized Difference Vegetation Index (NDVI) can be defined as a quantified vegetation remote-sensing index used for measuring the levels of the difference between near-infrared and red spectrum observed or reflected from vegetation cover. Mostly, it is utilized for discriminating vegetated areas from non-vegetated ones, also it might be utilized for evaluating vegetation healthy status [21] this index was utilized originally via [22]. Standardized Precipitation Index (SPI) is the majorly utilized drought indices for estimating drought. In the literature reviews, there are many summaries of drought analysis using several drought indices and statistical methodologies as in the studies of [23] where drought was analyzed according to its magnitude and level in different areas using different procedures. When precipitation is lower than or fluctuates over the average value in any region, it has negative impacts on soil moisture, groundwater, and natural reservoir storage. This led Mckee, Doesken and Kleist to realize the need for a simple and flexible index that shows how low precipitation impacts the soil [24]. SPI is used in this study to assess drought in the study area because of its simplicity, its wide range of drought classification, its effective indication of soil moisture, its effectiveness in the predicting of short-term drought, and its spatial invariance in interpretation. For spatial management and data manipulation Graphic Information Systems (GIS) environments increasingly being regarded as a useful tool for many application like drought detection and monitoring as an example [25]. Today, GIS was used along with various up-to-date technologies such as AI and RS for various drought researches in which GIS has the ability for translating the results related to such up-to-date technologies into identified formulas enable classifying the drought as well as its extension over time in various forms which might be grasped easily [26, 27].

The present research has three main objectives:
1- Detect the effects of climate change and expansion drought area in the study area through vegetation cover analysis using remote sensing analysis and drought analysis using SPI index.
2- Develop ANFIS model based on four meteorological data as (temperature, wind speed, evaporation and rainfall) as input data that used to predict SPI values.
3- The average mean of the predicted SPI that’s gained from the ANFIS model was calculated and the final predicted SPI was used for assessing the meteorological drought. These results were integrated inside the GIS environment as separate layers to create spatial distribution maps for drought assessments.
2. Methods and Materials

2.1 Study area
Nineveh is one of the Iraqi provinces that located in northwestern of Iraq between longitude of (41° 30’ – 44° 30’) and latitude of (35° 00’ – 37° 00’) and has a dry and semi-arid climate. Figure 1, shows that the province has 37323 km² as total area, representing approximately 8.6% of Iraq’s total area. There are two considerations for monitoring, prediction, and assessment drought in the study area. Firstly, is the economic importance of this province for grain crops production such as wheat and barley, so protecting this area is an economic priority. Secondly are the recent environmental changes represented by sand and dust storms, the decline of vegetation cover, the fluctuation of rainfall, and the rise in temperature. These changes have negatively affected the population of the province environmentally and psychologically as stated in many local and international reports.

Figure 1. General view of the study area.

2.2 Materials
There are a total of six meteorological stations in the study area (Tel-Afar, Mosul, Hadher, Ba shiqah, Sinjar and Rabiaa) as illustrated in figure 2, showing a total of 4 weather variables records (temperature, rainfall, evaporation and wind speed) belonging to such meteorological stations between (1970 and 2017) have been utilized in this work as 540 samples regarding each one of the variables [28]. For obtaining realistic results when using Fuzzy logic as analysis procedure continues time series must be used to training and testing the designed artificial intelligence models [15, 29]. For remote sensing analysis including supervised classification as well as NDVI methods, multi-date satellite imagery was used, these imageries belong to
Landsat 7 satellite with path 170, row 35 captured on April 25th 1992 and May 16th 2016 captured via enhanced thematic mapper (ETM+) sensor onboard Landsat-7 satellite.

![Figure 2. Meteorological stations distribution in the study area.](image)

### 2.3 Methods

The Fuzzy Logic or multi-valued logic system was developed for simulating the thinking of the human nature regarding a problem under-study, in which the answer is not essentially no or yes (classic logic), the answer might go to another phase such as uncertain, vague and indecisive [30]. A fuzzy inference system includes several sections that are represent the structures of these system shown in Figure 3.

![Figure 3. Categories of the Fuzzy Logic Control system.](image)

Fuzzy sets Membership Functions (MF) can be used in a huge vary of domains in which facts are ambiguous, indistinct or uncertain such as in bioinformatics. The best approach for the MF to be defined is mathematically expressing it and clearly specifying its parameters. As indicated in the example submitted via [31,32]. Equation (1) is applied to carry the requirements of designed the Fuzzy logic system and via
utilizing max and min rules, the alternative expression with regard to equation (1) might be stated as shown in the equation (2).

\[ MF(x; a, b, c, d) = \begin{cases} 
0 & x \leq a \\
\frac{x-a}{m-a} & a < x \leq m \\
\frac{x-n}{b-n} & n \leq x \leq b \\
\frac{d-x}{d-c} & c \leq x \leq d 
\end{cases} \] (1)

\[ MF(x; a, b, c) = \max \left( \min \left( \frac{x-a}{b-a}, \frac{c-x}{c-b}, 0.3, \frac{x-n}{b-n}, 0.8, \frac{d-x}{d-c} \right), 0 \right) \] (2)

Where, a is the lowest possible value, m, n, b and c are the middle possible value and d is the max possible value in the judgement interval. If the lowest possible value= middle possible value= max possible value then the fuzzy numbers functions get a crisp number.

The model of NFIS is specified via ANN and Fuzzy Logic model consists of Non-linear Auto-regressive Network with Exogenous inputs (NARX) created for predicting SPI based on the predicting weather the variable records with regard to 6 meteorological stations. Also, NARX is one of the significant procedures to predict and model the time series tacking into consideration, the non-linearity and complexity of time series patterns as indicated in the equation 4.

\[ y(k+1) = f_{\text{ANN}}(y(k), y(k-1), \ldots y(k-n+1), u(k), u(k-1), \ldots u(k-m+1) + \varepsilon(k)) \] (3)

In which, \( y(k+1) \) represents the projected output of the model, \( f_{\text{ANN}} \) represents the nonlinear function indicating the behaviour of the system, \( y(k), u(k) \) and \( \varepsilon(k) \) were output, input as well as the vectors of the approximation error at \( k, n \) and \( m \) time instances the order of \( u(k) \) & \( y(k) \). ANFIS can be defined as a combination of NN and Fuzzy Logic created via [8]. Majorly, it was specified as a representation of the graphical network regarding the Sugeno-type fuzzy systems which are connected with capabilities of the neural learning. In addition, the network consists of nodes with certain functions collected in layers.

Furthermore, the ANFIS has the ability of constructing a network realization of IF / THEN rules which might be indicated by [12] as can be seen in ‘Figure 4’ showing the develop ANFIS’s flow chart.

NDVI is used for finding vegetation cover changes in the area of the study. It might be mathematically represented via equation (4) in the following way:

\[ \text{NDVI} = \frac{(\text{NIR} - \text{RED})}{(\text{NIR} + \text{RED})} \] (4)

In which, \( \text{NIR} \) represents the reflection in near infrared spectrum and \( \text{RED} \) represents the reflection in red range of spectrum. In this formula, the results are generating a value that is in the range from -1 to +1, in which values between -1 and 0 are representing the non-vegetated regions like the urban land or abandoned land and, while the values more than 0 to +1 are representing the current vegetation in area under-study. Put differently, high yield of the NDVI value in the case where the high reflectance in NIR channel and the low reflectance in red channel and vice versa have been identified.
The use of the NDVI is significant, particularly in three sectors, first in evaluating, differentiating and demonstrating the global or local vegetation cover specified via green bio-mass of farming, forests along with the rangeland vegetation cover. Second, the NDVI might be utilized to indicate the drought offering an early warning process. Thirdly, the NDVI might be utilized to indicate the earth surface moisture. The image’s continuous grey tone is converted via the density slicing into density interval series or each corresponding to certain digital ranges. The method of density slicing might be utilized for showing the areas bounded via polygons. The approach is excellent in separating the gray levels which might be little to viewer.

SPI is acting as one of the drought monitoring indicators with regard to early warning, which allow assessing the severity and extent of the drought. In SPI, the major statistical analysis is based on how the data of the time series have been converted to normal distributions by means of Gamma Distribution Probability Function where the arithmetic average value equals 0 [33]. In such index, the positive values are indicating that there has been an elevation in the precipitations from yearly average values, which has been specified as wet period. The differences between positive values as well as yearly average related to precipitation is representing a precipitation surplus, whereas the negative values indicating the fact that there were deficits from precipitation’s yearly average, which has been specified as period of the drought. Also, deficiency is representing differences between negative values as well as yearly average regarding the precipitations in investigated year. A study conducted by [24] developed rules used to classify the levels of the dryness, in

Figure 4. Developed flow-chart structure of ANFIS.
which the values ≤-1 are indicating the conditions of the drought, while the values ≥1 are indicating the conditions of the wetness.

3. Results
For the purpose of achieving the aim of the present research, as well as matching the goals as it has been stated in the section of the introduction, results that have been produced from the variety of the utilized approaches in the present research have been given below:

3.1. Remote Sensing Analysis
In this section, the levels of the NDVI have been calculated, where it has been discovered that the levels of the vegetation have been in the range between -0.548 and 0.280 and between -0.10 and 0.642 for the images (16-5-2016) and (25-4-1992), respectively as has been illustrated in Figure 5.

![Figure 5](image)

**Figure 5.** The analysis of the NDVI for part of the area of the study.

Images that have been resulted from the application of this approach were at the grey levels, which makes it infeasible for human eyes to be capable of identifying those levels and easily separating them for the purpose of making the result of the NDVI clearer and for the estimation of the vegetation changes ‘impact, the approach of the density slicing has been utilized for the classification of the level of the NDVI range, that has been split to three classes based upon the available vegetation in the area of the study. Those levels are a non-vegetation area in the case where the value of the NDVI is less than zero, area of low vegetation in the case where the value of the NDVI has been in the range from (0 to 0.20), and area of high vegetation in the case where the value of the NDVI is higher than 0.20. The results of the classification have shown that the class of the low-density vegetation cover has reduced by a rate of 20 % and the class of the high-density vegetation cover has been decreased by a rate of 80 %, which is why, the land percentage that has been categorized under non-vegetation class has been increased as shown in Figure 6. The NDVI digital analysis for between 1992 and 2016 has shown four classes (which are: non-vegetation cover, water, high-density vegetation cover and low-density vegetation cover) where vegetation cover class’s area has been reduced by 17.70 % from 592.3 km² in 1992 to 487.46 km² in 2016. The rate of the area that has been transferred to the non-vegetation cover (i.e., the area of the drought) category which has increased from 251.10 km² in 1992 to 355.94 km² in 2016. This percentage of decrease is expected to accelerate as a result of the effects of the phenomenon of the desertification in the area, besides other reasons, which include the
approaches of the uncontrolled overgrazing, which is utilized by the breeders of the livestock as well as many inhabitants that have turned away from the agricultural life and migrated to cities.

![Image of NDVI density slicing maps](image)

**Figure 6.** The maps of the NDVI density slicing.

### 3.2. Develop the ANFIS Model

The initial step in the development of a fuzzy model has been identified by the definition of linguistic variables with a function of the membership (i.e., the phase of fuzzification). The benefits of linguistic variables are quantitatively and qualitatively describing the fuzzy sets for the purpose of making them beneficial and giving the understandable meaning to the experts and for the computer processors to obtain correct values for outputs. The data-set of the inputs based on the fuzzy sets for the speed of the wind, evaporation and temperature variables have been categorized as high, moderate and low, whereas the rainfalls have been classified into very high, high, moderate, semi-moderate, low, and very low. The Membership Functions (MF) have been characterized for every one of the input and output variables. Those functions have to be designed for the purpose of verifying the main condition in which the designed Membership Functions have to be overlapping with the nearest Membership Function as can be seen from Figure 7.

In order to test the capability of the generalization of ANFIS at every one of the epochs, the command genfis-1 function has been utilized. A procedure of validation has been performed for the overfitting of data that has been utilized for the training of the ANFIS model, for every training epoch. Following 52 batch learning epochs, the developed model of the ANFIS has shown sufficient validity and stability. In order to test ANFIS’s capability of generalization at every one of the epochs, the function of validation data has been utilized. A process of validation has been performed for the purpose of the overfitting of data that has been utilized for the training of the ANFIS model, for every training epoch. Following 52 batch learning epochs, the developed model of the ANFIS has shown sufficient validity and stability. For the purpose of ascertaining ANFIS’s efficiency performance, the Determination Coefficient $R^2=0.905$, Nash-Sutcliffe coefficient $CE=0.830$, Root Mean Square Error $RMSE=0.935$, and Mean Absolute Percentage $MAPE=17.390\%$ where the accuracy of the performance has been $82.61\%$, and that made this system
sufficient and reliable for the study area’s SPI prediction. MAPE value has been compared statistically against the actual and the predicted values of the SPI-12.

The result has shown a sufficient indication of reliability of advanced ANFIS. Such results may be of a higher effectiveness in the case where the MAPE has been decreased through the engagement of other meteorological factors, having a strong association with the data of the actual SPI or through the addition of more training data to a model (prediction of the values of the SPI-12 for a while prior to 1970). Following the testing and the running of the model, a considerable convergence has been exhibited between the values of the SPI-12 that have been predicted by the model and the actual values of the SPI. The average error of the prediction has been found 27.78 % as can be seen from Figure 8.

3.3. Drought Analysis and assessment
The drought was measured in 3 periods between 1970 and 1992, 1992 to 2017 and for a predicted period between 2017 and 2026. The average yearly rainfalls for the area of the study have been 512.60 mm. The
results of the drought evaluation between 1970 and 1992, and between 1992 and 2017 has shown that the area of the study has been influenced by different drought where the rainfall deficit amount has been in the ranged between 27% and 34%. The calculated drought duration (DD), drought magnitude (DM), average drought intensity (ADI), and years of the drought values in two periods have been computed as can be seen from table 1, where the years of the drought have been increased by 1.8% which has caused an increase in the DM by 106.5 mm throughout the two studied time periods. Such analyses had confirmed the analysis results of remote sensing about the vegetation declines and the increase in the land of the desertification in the area of the study. After the records of the predicted rainfalls between 1970 and 2026, which have been obtained from the model of the ANFIS have been involved in this comparison, and based on table 2 the maximum drought magnitude value (i.e., 4655 mm) had occurred in the station of Hadher with a 148.62 mm/year ADI and a 1.90 per year DD.

| Stations | Actual rainfall records | Predicted rainfall records | Increased drought magnitude (mm) |
|----------|-------------------------|---------------------------|----------------------------------|
| Mosul    | 46.5 3433 2.3 95.74 48.3 3539.5 2.4 99.67 106.5 | Total DM 19021 mm | Total DM 20279.5 mm |
| Sinjar   | 52.7 3134 3.8 128.36 53.9 3368.3 3.9 137.94 234.3 | | |
| Tel-Afar | 54.0 3038 3.2 131.21 56.3 3271.7 3.6 139.24 188.7 | | |
| Rabiaa   | 51.4 2709 2.9 101.63 52.8 2911.8 2.4 109.24 202.8 | | |
| Bashiqah | 48.7 2007 2.7 85.23 49.4 2136.7 2.9 90.47 129.7 | | |
| Hadher   | 58.8 4655 1.9 148.62 61.5 5051.5 2.0 161.28 396.5 | | |

4. Discussion
The drought years’ percentage has been increased by 10.10% with the increase in the magnitude of the drought by 1258.5 mm throughout the predicted nine years up to 2026 in the entire area of the study. In the case where that percentage keeps increasing each nine years, the area of the study will be suffering from an exceptional drought that will definitely result in affecting the environment in general and the vegetation cover and agricultural structure in particular. In addition to that, the predicted results’ analysis has shown that the levels of the drought in the western and the southern regions of the area of the study (i.e. Tel-Afar, Hadher and Sinjar) have been increased throughout the predicted period (between 2017 and 2026) by 6.20% as the year of the drought with an increase in the magnitude of the drought by 819.5 mm, in comparison with the eastern and the northern parts (i.e. Rabiaa, Bashiqah and Mosul) where the year of the drought is 3.90% with expected increase in the magnitude of the drought that has been 439 mm. All of the conditions...
of the drought have been observed that the whole area of the study has been influenced by a variety of the levels of drought, where average wet years and average drought years have been estimated as 45.60 % and 54.40 % respectively. In addition to that, the analysis of the drought has shown that the conditions of the severe drought ranged between -1.521 and -1.862, moderate drought range between -1.053 and -1.495, and the extreme drought ranged between -2.107 and -2.865. For the long-term assessment of the drought, the SPI-12 values have been directly associated with the state of stream flows, ground-water levels and reservoirs levels. Those values may be considered as an explanation of environmental changes that result from the drought and the desertification which may take place in a region throughout a long time. After the analysis of SPI12 for the area of the study, utilizing the predicted and the actual SPIs, it has been discovered that, in general, the area will experience conditions of extreme drought except for the region of Sinjar, where it is predicted that the condition of the drought will be severely dry as has been listed in table 3.

| Station | Moderate drought | Severe drought | Extreme drought |
|---------|------------------|----------------|-----------------|
| Mosul   | -1.158           | -1.862         | -2.267          |
| Sinjar  | -1.48            | -1.685         | 2015-2016       |
| Tel-Afar| -1.319           | -1.540         | 2014-2015       |
| Hadher  | -1.192           | -2.267         | 2020-2026       |
| Rabiaa  | -2.107           | -2.865         | 2017-2018       |
| Bashiqah| -1.373           | -1.521         | 2014-2015       |

GIS was used to prepare a long-term spatial distribution map based upon the actual and the predicted SPI-12 as shown in Figure 9. This distribution map was addressed based on the levels of the drought (severe, moderate and extreme which have possibly taken place in the area of the study in predicted period between 2017 and 2026). As a result of drought years’ increase and the decrease in mean annual rain-fall (512.6 mm to 396.7 mm), a condition of the moderate drought has been noticed, which had an impact on the whole area of the study, which ranged between (-1.053 and -1.495) as can be seen from Figure 9a. The severe drought will have an impact on the area of the study as well, where it ranges between (-1.521 and -1.862) as can be seen from Figure 9b. The eastern part will be adversely influenced by the condition of the extreme drought that ranges between (-2.107 and -2.865). The area of the study is part of Tigris Riverfeeding area in Iraq over several tributaries, which indicates lower levels of the river water in future; which is why, the system of the ground-water recharging id going to be damaged and impacted adversely on ground-water wells’ supply that have been scattered in the area of the study as can be seen from Figure 9c.

5. Conclusions
There are numerous advantages to the assessment of a region’s drought conditions with the use of SPI, due to the fact that it only requires one input type in a form of the rain-fall records and simple mathematical formulas. The index of the SPI has been identified with its capability in the classification of the droughts into extreme, severe, or moderate for the purpose of giving a more explicit indication of conditions of any of the areas in the terms of drought effects. In addition to that, there is a possibility in calculating the characteristics of the drought through the calculation of its intensity, duration, average and magnitude. The
drought conditions were studied in the study area during three periods. In the first and second period, 1970 to 1992, 1992 through 2017, the rainfall records of six meteorological stations in the study area were used for assessment the drought conditions while the third period included the extension of the rainfall records up to the year 2026 by a designed artificial intelligence model by ANFIS for drought assessment.

The use of this model in predicting future values of short-term SPI-3 and long-term SPI-12 can be useful for the monitoring and analysis of all future cases of drought scenarios and can assist in the management and evaluation of agricultural and environmental projects in the study area. The effects of such drought are starting to appear through the decline of natural vegetation cover and encroaching dunes, particularly in the western and the southern regions of the area of study. To prevent the dangers of drought in the study area, effective solutions and rapid plans must be implemented to reduce the growth of this phenomenon. Such plans may include exploitation of precipitation in the rainy years and harvesting it with one of the rainwater harvesting techniques according to the geological and geomorphological nature of the region. Irrigation systems should be developed in the region and decrease the irrigation losses to the lowest possible extent. The remaining natural vegetation should be preserved, and natural drought-tolerant plants should be cultivated to stabilize the soil and prevent its erosion and thus turning into sand storms. All of these actions together can contribute to reducing the drought phenomenon and its impact on the study area.

6. References
[1] Alam A, Rahman M and Saadat A 2013 Monitoring meteorological and agricultural drought dynamics in Barind region Bangladesh using standard precipitation index and Markov chain model. International Journal of Geomatics and Geosciences, 3(3), pp.511-524.
[2] Al-Bakri J, Al-Khreisat A, Shawash S, Qaryouti E and Saba M 2018 Assessment of Remote Sensing Indices for Drought Monitoring in Jordan. Asian Journal of Geoinformatics, 17(3).
[3] Morid S, Smakhtin V and Bagherzadeh K 2007 Drought forecasting using artificial neural networks and time series of drought indices. International Journal of Climatology, 27(15), pp.2103-2111.
[4] UNEP, How Environmental Damage Causes Food Insecurity in IRAQ. World Environmental Day, Technical Assessment Report, Accessed June 2013. http://www.uniraq.org/index.php?option=com_k2&view=item&task.
[5] Al-Faraj F, Scholz M and Tigkas D 2014 Sensitivity of surface runoff to drought and climate change: Application for shared river basins. Water, 6(10), pp.3033-3048.
[6] Walczak, S. (2019). Artificial neural networks. In Advanced Methodologies and Technologies in Artificial Intelligence, Computer Simulation, and Human-Computer Interaction (pp. 40-53). IGI Global.

[7] HungQ, Babel S, Weesakul S and Tripathi K2009. An artificial neural network model for rainfall forecasting in Bangkok, Thailand. Hydrology and Earth System Sciences, 13(8), pp.1413-1425.

[8] Traore S, Luo Yand Fipps G2016 Deployment of artificial neural network for short-term forecasting of evapotranspiration using public weather forecast restricted messages. Agricultural Water Management, 163, 363-379.

[9] Hsu K, Gupta V, and Sorooshian S 1995 Artificial neural network modeling of the rainfall-runoff process. Water resources research, 31(10), 2517-2530.

[10] Ghimire S, Deo R, Downs N and Raj N2019 Global solar radiation prediction by ANN integrated with European Centre for medium range weather forecast fields in solar rich cities of Queensland Australia. Journal of cleaner production, 216, 288-310.

[11] Zadeh, L. A. (1965). Fuzzy sets. Information and Control 8:3, doi:10.1016/S0019-9958(65)90241-X.

[12] Jang S, 1993 ANFIS: adaptive-network-based fuzzy inference system. IEEE transactions on systems, man, and cybernetics, 23(3), pp.665-685.

[13] Nayak C, Sudheer P, Rangan M and Ramasastri K 2004 A neuro-fuzzy computing technique for modeling hydrological time series. Journal of Hydrology, 291(1-2), pp.52-66.

[14] Yousif, J. H., Al-Balushi, H. A., Kazem, H. A., &Chaichan, M. T. (2019). Analysis and forecasting of weather conditions in Oman for renewable energy applications. Case Studies in Thermal Engineering, 13, 100355.

[15] Yahya B and Seker D 2019 Designing weather forecasting model using computational intelligence tools. Applied Artificial Intelligence, 33(2), 137-151.

[16] Jain A, Mao J and Mohiuddin K 1996 Artificial neural networks: A tutorial. Computer, 29(3), pp.31-44.

[17] Basheer I and Hajmeer M 2000 Artificial neural networks: fundamentals, computing, design, and application. Journal of microbiological methods, 43(1), pp.3-31.

[18] Lara L, Rasche L and Schneider U 2017 Modeling land suitability for Coffeaarabica L. in Central America Environ Model. Software, 95, 196 – 209.

[19] Jamshidi R, Karimi A and Haghshenas M 2018 Risk assessment of particulate matters in a dentistry school using fuzzy inference systems. Measurement116, 257 – 263.

[20] Lambin F and Ehrlich D 1997 Land-cover changes in sub-Saharan Africa (1982–1991): Application of a change index based on remotely sensed surface temperature and vegetation indices at a continental scale. Remote sensing of environment, 61(2), pp.181-200.

[21] Ahmad A, Upadhyay R, Lal B and Singh D 2018 Change Detection of Sodic Land in Raebareli District Using Remote Sensing and GIS Techniques In Environmental Pollution Singapore pp. 487-498.

[22] Rouse Jr, Haas H, Schell Aand Deering W 1973 Monitoring the vernal advancement and retrogradation (green wave effect) of natural vegetation. Prog. Rep. RSC 1978-1, Remote Sensing Center, Texas A&M Univ., College Station, E73-106393, 93 (NTIS No. E73-106393).

[23] Salahedin M, Temeliye Kand Montaseri M 2014 Analysis of hydrological drought classes’ transition using SPI (a case study: Urmia Lake watershed). International Journal of Biosciences (IJB), 4(1), pp.452-462.

[24] McKee B, DoeskenJ and Kleist J 1993 The relationship of drought frequency and duration to time scales. In Proceedings of the 8th Conference on Applied Climatology American Meteorological Society, Vol. 17, No. 22, pp. 179-183.
[25] Yu, J., Lim, J. and Lee, K.S., 2018. Investigation of drought-vulnerable regions in North Korea using remote sensing and cloud computing climate data. *Environmental monitoring and assessment*, 190 (3), p.126.

[26] Hellwig N, Graefe U, Tatti D, Sartori G, Anschlag K, Beylich A, Gobat J and Broll G 2017 Upscaling the spatial distribution of enchytraeids and humus forms in a high mountain environment on the basis of GIS and fuzzy logic. *European Journal of Soil Biology*, 79, pp.1-13.

[27] Belal A, El-Ramady H, Mohamed E and Saleh A 2014. Drought risk assessment using remote sensing and GIS techniques. *Arabian Journal of Geosciences*, 7(1), pp.35-53.

[28] Iraqi Meteorological Network Data. 2017, Documentation. https://www.http://www.agromet.gov.iq.

[29] Zhang, G., Patuwo, B.E. and Hu, M.Y., 1998. Forecasting with artificial neural networks: The state of the art. *International journal of forecasting*, 14 (1), pp.35-62.

[30] Aghelpour, P., Bahrami-Pichaghchi, H., & Kisi, O. (2020). 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*, 170, 105279.

[31] Ross J 2005 Fuzzy logic with engineering applications. John Wiley & Sons.

[32] Sivanandam N, Sumathi Sand Deepa N 2007. Introduction to fuzzy logic using MATLAB (Vol. 1). Berlin: Springer.

[33] Türkeş MandTatlı H 2009 Use of the standardized precipitation index (SPI) and a modified SPI for shaping the drought probabilities over Turkey. *International Journal of Climatology: A Journal of the Royal Meteorological Society*, 29 (15), 2270-2282.

**Acknowledgments**

The authors are grateful to the Iraqi Ministry of Higher Education and Scientific Research and Mosul University for providing financial support. The authors are also grateful to the Iraqi Ministry of Transport for providing the rainfall data.