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Short-term and Long-term Drought Forecasts in Iraq Using Neural Networks and GIS

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Abstract. Drought is a dangerous phenomenon that affects the general life of the environment. Iraq is one of the countries that is facing drought periodically, especially in the last decades due to the great weather changes in the world including global warming, which resulted in less rainfall below normal levels. Therefore, it must be thought of drought forecasting because it is an important role in the planning and management of the water resources in Iraq. In this Study, Recurrent neural networks (RNN) were used as representing of Artificial Neural Networks (ANNs), which is a non-linear kind of ANNs where the output from it will feedback again as input for the next step. This type of neural network can simulate weather conditions with high precision such as rain, wind, earthquake, drought, and temperature. The model used to forecast droughts is the standardized precipitation index (SPI) series as a drought index in Iraq. The two-time scale which is used in this study, which is SPI 6 which represents short term drought and SPI 24 which represent long term drought. RNN was used to make forecasts for the SPI for the period 2020-2030. The assessment of the work and efficiency of RNN was regressing by (R), mean square error (MSE), and root mean square error (RMSE). Twenty-Four stations were selected to represent all study area (Iraq). Geographic information system (GIS) was used with the aid of Inverse distance weighted (IDW) to represent the forecasted drought for April month from years (2025 and 2030). The results showed that the study region (Iraq) suffered from varied drought levels in different periods ranging from mild to extreme drought, also the study showed improvement by decreasing the drought situation for period 2020-3030, which must be invested well.

Keywords: ANN, drought, RNN, Standardized precipitation index, SPI.

1. Introduction.
Drought is a natural phenomenon that occurs when precipitation is significantly lower than normal [1]. Drought in particular is one of the biggest threats to human survival, imposing serious adverse impacts to social, economic and environmental sustainability [2]. The drought of meteorological maybe follows by hydrology drought that will affect flows of river, lakes level, and aquifer storage [3].

The long period of drought cause declined in agricultural production and growth, livestock development diminished and desertification of lands, etc. [4]. Drought and its impact appeared to increase in many countries of the world due to changes in the atmosphere, including the phenomenon of global warming and other problems. The phenomenon of global warming and expansion especially in recent decades has affected the climate dramatically, leading to an increase in the risk of drought and floods alike. Little predicts of drought characteristics like frequency, termination, and initiation can make it both hazard and catastrophic [5].

Drought can be considered a hazard cause its natural phenomenon it's occurrence unpredictable, but by following it, studying its characteristics and using modern methods, it's occurrence can be predicted. Drought is considered as catastrophic because of the failure in precipitation system, affecting the water that supplies all of the natural and agricultural systems as well as effect on the various human activities [6].

Iraq is one of the countries in Asia, specifically in the Middle East that suffered from the recent periodic drought due to the great weather fluctuations [7]. high temperature and lack of rain, which negatively affected on the water resources, vegetation in Iraq and expansion of the desert area in the whole country, which will cause in the future on lands desertification and migration for people who live in areas that exposed to the impact of drought [8].

The aims of this study are to make an idea of the drought periods by forecasting the SPI using ANN, in order to take the necessary preparation to face it.

2. MATERIALS AND METHODS

2.1 STUDY AREA

The study considered the entire area of Iraq within its borders. Iraq lies in a semi-arid region between longitudes 38° 45' and 48° 45' and latitudes 29° 5' and 37° 22' with an area of 437,049 km2 [9]. Iraq location map with adjacent countries shown in figure (1).

Figure 1. Iraq location map with adjacent countries [9].

It has different terrain types including mountainous territory in the north and northeast, desert territories in the west and south-west, and marshlands in the south, resulting in different climate characteristics from a region to another [10]. Iraq can be divided into three main regions: the north, middle, and south. Climate conditions are different with respect to the place. Iraq in terms of weather

can be described as hot and dry at summers, and cold wet at winters. Iraq climatic conditions are influenced by Mediterranean and low-pressure region that focuses on the Arabian Gulf in the summer. The daily temperature records in summer were mostly high; they sometimes exceed 45°C in different locations of Iraq, especially in the south region. Seventy percent of precipitation falls from October to April, while from June to August it is predominately rainless. Precipitation season also changes from a year to another, sometimes rainfall is within the normal limit and does not represent a serious threat, whereas in some seasons it's severe and causes erosion for some soft-land in addition to many damages in the social and agricultural reality [11].

2.2 DATA USED
Rainfall data were collected from 24 stations during the period 1950-2016 from Iraq metrological stations. The rainfall collected data included monthly recordings as well as the annual average rainfall for all stations. The locations of the stations (longitude and latitude) are shown in table (1).

Table 1. The locations of the meteorological stations.

No.	Name of Station	Longitude	Latitude
1	BAGHDAD	44.24	33.2
2	NASIRIYA	46.14	31.01
3	BASRA	47.78	30.5
4	AL_HAI	46.03	32.1
5	KIRKUK	44.24	34.28
6	RUTBA	40.17	33.02
7	DIWANIYA	44.59	31.59
8	MOSUL	43.09	36.19
9	NAJAF	44.32	32.03
10	NUKHAIB	42.27	32.03
11	SAMAWA	44.16	31.18
12	HILLA	44.26	32.29
13	KUT	45.45	32.3
14	KERBALA	44.01	32.37
15	AMARA	47.1	31.51
16	AL_KHALIS	44.53	33.84
17	SAMARRA	43.9	34.11
18	RAMADI	43.2	33.45
19	HEET	42.83	33.64
20	ANAH	41.98	34.37
21	TUZ	44.64	34.89
22	TIKRIT	43.63	34.65
23	BAIJI	43.49	34.94
24	SINJAR	41.87	36.33

2.3 STANDARDIZED PRECIPITATION INDEX (SPI)
McKee et al. (1993) developed the Standard Precipitation Index (SPI) for the purpose of defining and monitoring [12], using SPI will provide some important advantages for researchers. First, it relies on rainfall data as an input to describe drought. Secondly, drought can be described by SPI for different time scales. Third, SPI can be used effectively to compare different conditions of drought between

regions and different time periods. When extracting SPI values for different time scales, negative values indicate dry periods and positive values indicate wet periods [13]. Table (2) shows the classification of drought based on the range of SPI values.

Table 2. Classification of drought based on values of SPI [12].

Value of SPI	Classification
≥2	Extremely wet
1.5 to 1.99	Severely wet
1 to 1.49	Moderately wet
0 to 0.99	Mild wet
−0.99 to 0	Mild drought
−1.49 to −1	Moderately drought
−1.99 to −1.5	Severely drought
−2≥	Extremely drought

The computation of the SPI requires fitting a probability distribution to aggregated monthly precipitation series (3, 6, 12, 24, and 48) months. The probability function density transformed into a standardized index, which its values are represented classification for the drought. The SPI computed only when there are long and continuous records of data (30 years at least). Gamma distribution is the best observational model for precipitation data to represent probability distribution. The equation shown below represents the Gamma distribution [14, 15].

$$g(x) = \frac{1}{\beta \alpha \Gamma(\alpha)} \, x^{\alpha-1} e^{\frac{-x}{\beta}} \quad , \; for \; x > 0 \qquad\qquad \dots \dots (1)$$

Where;

α > 0 (parameter of shape), β > 0 (parameter of scale), x > 0 (precipitation amount) and Γ(α) is a value that taken by standard function mathematical which known as Gamma function, it is described as integral as shown in the equation (2)[14, 15].

$$\Gamma(\alpha) = \int_0^\infty x\alpha\text{-}1 \; e\text{-}y \; dx \qquad\qquad \dots\dots(2)$$

For modeling observed data with density function gamma distributed, it's important to estimate β and α parameters. Different ways to estimation these parameters. The approximation for Thom (1958) was used for probability in McKee (1997) [12].

$$\alpha = \frac{1}{4A}\left(1 + \sqrt{1 + \frac{4A}{3}}\right) \qquad\qquad \dots\dots (3)$$

$$\boldsymbol{\beta} = \frac{\bar{x}}{\alpha} \qquad\qquad \dots\dots (4)$$

Where for observations n;

$$A = \sum_{i=1}^{n} ln(xi) \qquad ..... (5)$$

After coefficients β and α are estimating, the probability function density g(x) is integrated due to x then it can be finding the probability cumulative G(x) that a certain quantity of rain observed for a specific month and a specific scale time [14, 15].

$$G(x) = \int_0^x g(x)dx = \frac{1}{\beta\Gamma(\alpha)} = \int_0^x x\alpha\text{-}1 \; e^{\frac{-x}{\beta}} \, dx \qquad ..... (6)$$

The function of Gamma, not a definition at x=0 (There is no precipitation), so the probability cumulative becomes [14]:

$$H(x) = q + (1 - q)G(x) \quad ..... (7)$$

Where, q meaning no precipitation, H(x) refers to the probability cumulative of observed precipitation. The probability cumulative convert into standardized normal distribution (Z) with variance unit and null average then get SPI index [14, 15].

$$Z = SPI = -\left(t - \frac{c_0+c_1t+c_2t^2}{1+d_1t+d_2t^2+d_3t^3}\right) \quad for \; 0 < H(x) \le 0.5 \qquad\qquad ... (8)$$

$$Z = SPI = +\left(t - \frac{c_0+c_1t+c_2t^2}{1+d_1t+d_2t^2+d_3t^3}\right) \quad for \; 0.5 < H(x) < 1 \qquad\qquad ... (9)$$

Where;

$$t = \sqrt{ln\left[\frac{1}{(H(x))^2}\right]} \qquad for \; 0 < H(x) \le 0.5 \qquad\qquad ..... (10)$$

And,

$$t = \sqrt{ln\left[\frac{1}{1-(H(x))^2}\right]} \qquad for \; 0.5 < H(x) < 1 \qquad\qquad .... (11)$$

Where,

H(x): the probability cumulative of observed precipitation.

x: precipitation.

c0, d0, c1, d1, c2, d2: constants values, the magnitude of these constants

c0 =2.515517   c1 =0.802853   c2 =0.010328

d0 =1.432788   d1 =0.189269   d2 =0.001308

2.4 ARTIFICIAL NEURAL NETWORKS (ANNS)
Artificial Neural Networks (ANNs) are a type of nonlinear flexible models or frameworks that had the ability to discover adaptive patterns from analysis data. From many papers and research, it is shown that

the adequate nonlinear number of processing units, ANNs had ability to learn from the experience and make estimation for any functional complicated relationship with high level of accuracy [16].

ANNS consists of neurons or elements arranges in interconnected three layers. The first layer is input, second is hidden layer includes one or more layer and third is output layer as shown in Figure (2). The input layer consists of neurons transmitted information to second layer (hidden layer) and the last information is transformed to output layer [17].

All neurons have inputs weighted (W) (synapses) which are convertible parameters that transform ANNs to a parameterized framework layer as shown in Figure (3). ANNs models have an activation function which determines output from a given input. In general, activation function types that used are step, linear, sigmoid, tanh, etc. [18].

In this research Recurrent neural networks (RNN) used as representing of ANNs, RNN is a non-linear kind of ANNs where the results or output from this model are fed back again as input for next step. In conventional ANNs, suppose that inputs and outputs discrete from each other, in many cases of problems that is not a good idea. It is termed as recurrent since the task will done for all elements in time series depending on the computation's previous output. RNN has a memory caught data about what has been determined yet. This type of neural network can simulate weather conditions with high precision such as rain, wind, earthquake, drought, and temperature, etc. RNN has input-delay feature where not all data is tested in once time but by a certain number of data step by step [19].
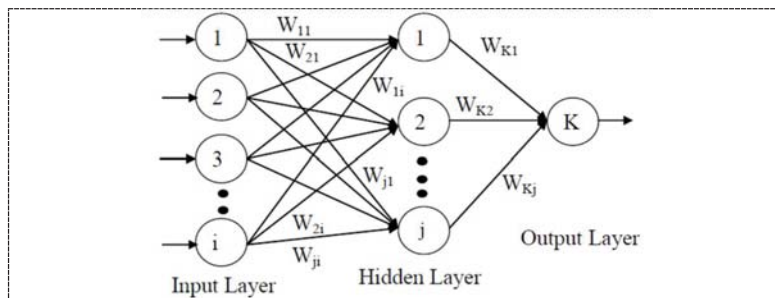

Figure 2. Schematic diagram of Artificial Neural Networks (ANNs) [17].
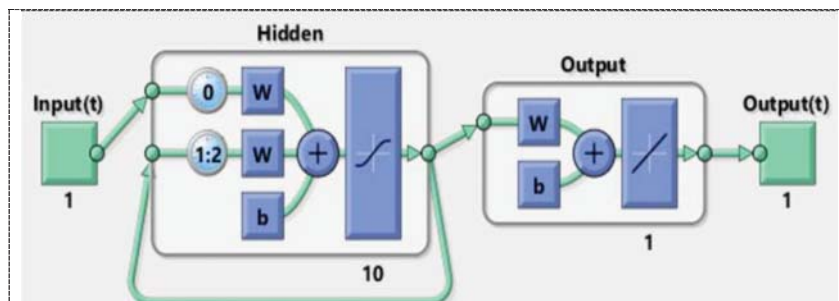

Figure 3. scheme of RNN [18].

The stepest descent used as a technique in RNN which make minimizes for the function in weight space, weights will modify in opposite way of error due to the weights. Input data corresponds to output data called training group [20]. The computed error gave in an equation below:

$$e = \frac{1}{2}\sum_k (d_k - o_k)^2 \qquad\qquad ….. (12)$$

Where, ok and dk refers to real output and required output (k= node output), the term e (error) must be minimized by modifying weights (layer output) relative to $-\frac{\partial e}{\partial_{w_{kj}}}$ as shown in equation below[24]:

$$\Delta w_{kj} = -\frac{\eta \partial e}{\partial_{w_{kj}}} \qquad\qquad ….. (13)$$

Where, j is a hidden node, k is output, w_{kj} is weight between k and j.

It's possible to write:

$$\Delta w_{kj} = \eta \delta_k o_j \qquad\qquad ….. (14)$$

Where η is rate learning, output for j is a hidden node. Also δ_k given in the equation below:

$$\delta_k = o_k(1 - o_k)(dk - ok) \qquad\qquad ….. (15)$$

The weight modification for the lower layer node j (layer input or hidden layer) shown in the equation below:

$$\Delta w_{ij} = \eta \delta_j o_i \qquad\qquad ….. (16)$$

Where, o_i is the node j output layer and δ_j is:

$$\delta_j = o_j(1 - o_j)\sum_k \delta_k w_{kj} \qquad\qquad ….. (17)$$

The k in equation (15) refers to a node k of a higher layer (layer output or hidden layer).

Fast training can be done if momentum α term added to weight modification in equations (14 and 15). Therefore, the new equation will be [20]:

$$\Delta w_{ji}(t + 1) = \eta \delta_j o_j + \alpha \Delta w_{ji}(t) \qquad\qquad ….. (18)$$

3. RESULT AND DISCUSSION
After extraction SPI time series of drought for both short-term (spi6) and long-term (spi24), drought periods were statistically analyze for short and long terms for all 24 meteorological stations during duration 1950-2016 at months (October-April). Percent of occurrence for the SPI classes was calculated for both terms are shown in the figures (4 and 5).
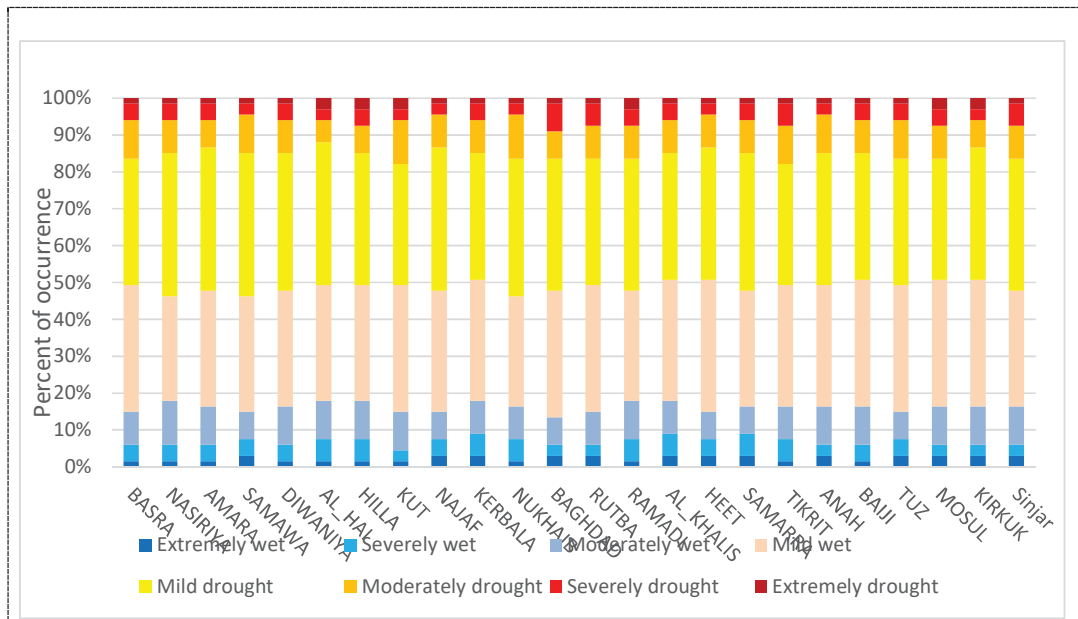
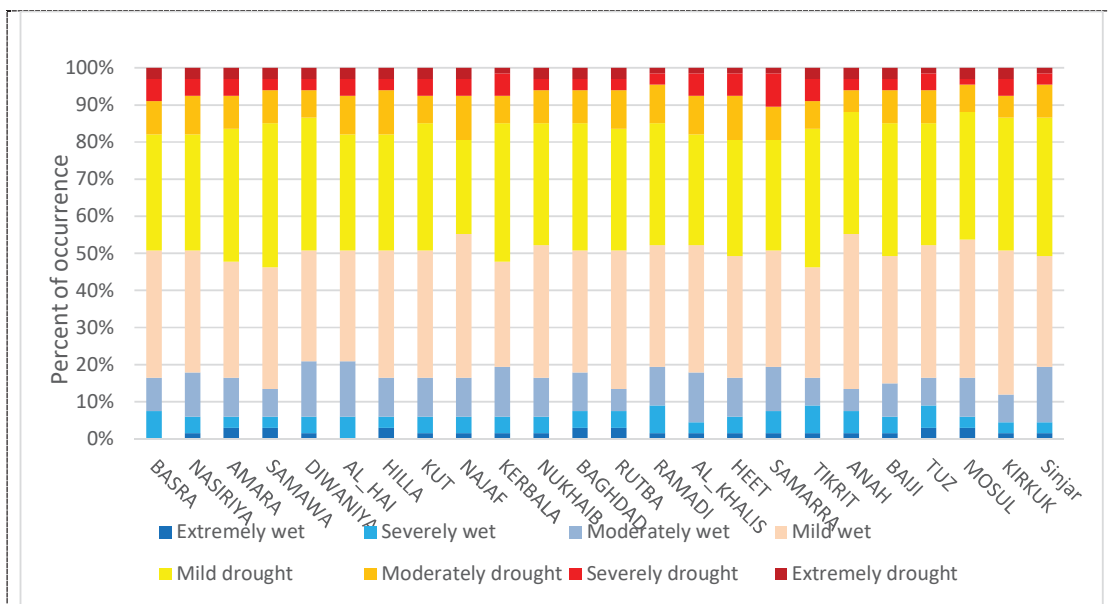**Figure 4**. Percent of occurrence for the SPI 6 during 1950-2016 at months (October-April).

Figure 5. Percent of occurrence for the SPI 24 during 1950-2016 at months (October-April).

Figure (4) clarify SPI 6 time scale for all 24 stations during the period 1950-2016 for months (October-April). The southern region of Iraq was almost equal intensity with respect to drought classification, whereas in the middle region it can be seen that Baghdad capital exposed to a clear

severely class of drought. In additional, the west region of Iraq was almost same levels of classes except severely class is high. Also, the north region of Iraq (Kirkuk and Mosul) suffered from obvious extreme drought.

Figure (5) shows percent of occurrence for SPI 24 time scale for all stations in Iraq during the period 1950-2016 for months (October-April). The southern region of Iraq, it can be noticed that the extreme, severe and moderate was almost equal. Whereas for middle region, it is obvious there were some differences especially in Najaf, also the west region almost was equal in drought classes. The northern region of Iraq was almost equal in drought classification except for Kirkuk, it can be noticed that the severe drought level higher than other cities and provinces in this region.

Modeling and forecasting done for both short-term (spi6) and long-term (spi24) where the assessment for the performance results is mean square error (MSE), Root mean square error (RMSE) and regression (R).

Results for SPI 6 and Spi 24 for duration 1950-2016 were gotten from SPI program, and insert them into ANN to model and forecast spi for period 2020-2030. Values of Spi for both terms were divided into two parts for ANN, the first part was used for training and the other for testing. One hidden layer used with 40 neurons inside, training function that used is 'trainscg' with 10 input delay for spi 6 and 15 delay for spi 24.

A sample of regions and governorates were choose to clarify results for the rest of the regions. Table (3 and 4) and figures (6 to 11) station's name, R, MSE, RMSE and series time between output from training and target (test) data, which refers to efficient results for Spi 6 and SPI 24.

The results shown have high accuracy where MSE close to zero and RMSE very small values with 100% regression(R).

Table 3. Name of station, R, MSE, RMSE and time of training for SPI 6.

No.	Name of station	R	MSE	RMSE	Time of training
1	Nasirya	1	9.24e-15	9.61e-08	5:15 min.
2	Anna	1	1.72e-14	1.31e-07	5:43 min.
3	Mosil	1	1.26e-14	1.53-07	4:46 min.

Table 4. Name of station, R, MSE, RMSE and time of training for SPI 24.

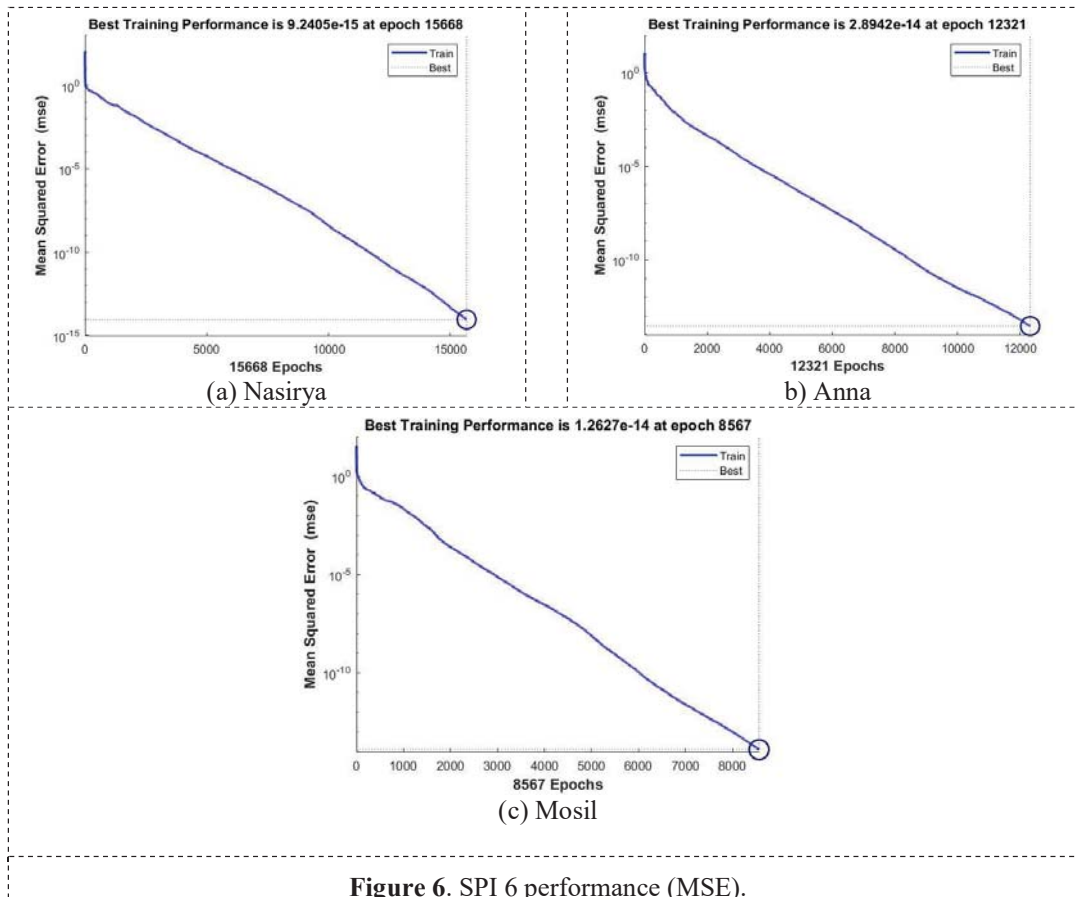| No.	Name of station	R	MSE	RMSE	Time of training
1	Nasirya	1	2.67e-14	1.63e-07	6:09 min.
2	Anna	1	2.89e-14	1.70e-07	5:37 min.
3	Mosil	1	4.93 e-14	2.22e-07	6:31 min.

(a) Nasirya
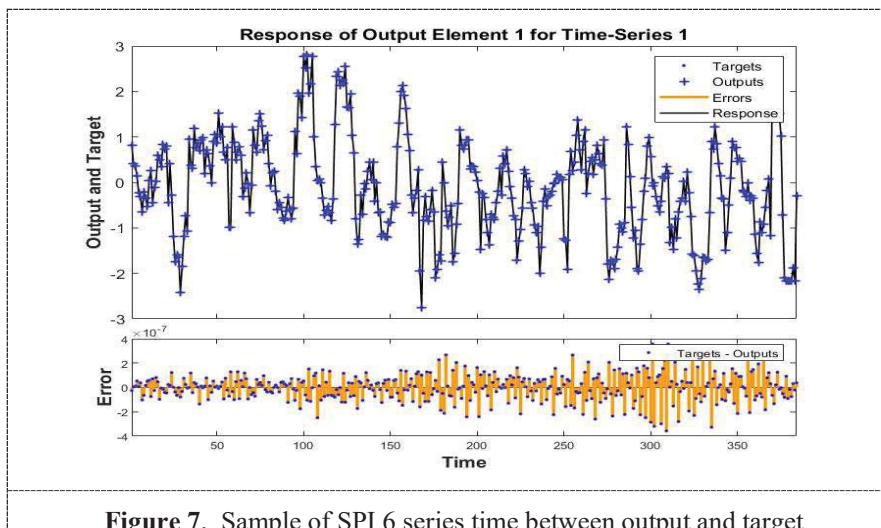
b) Anna

(c) Mosil

Figure 6. SPI 6 performance (MSE).

Figure 7. Sample of SPI 6 series time between output and target

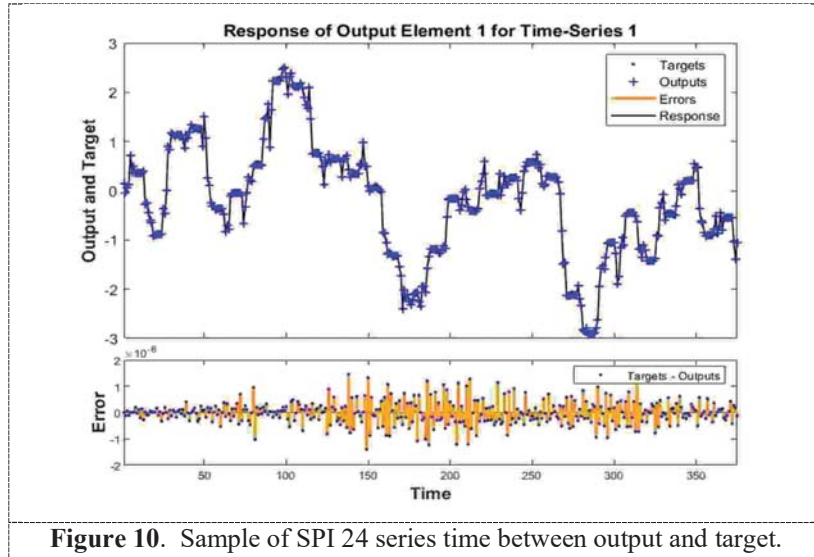**Figure 8**. SPI 6 month regression (R).

(a) Nasirya

b) Anna

(c) Mosil

Figure 9. SPI 24 performance (MSE).
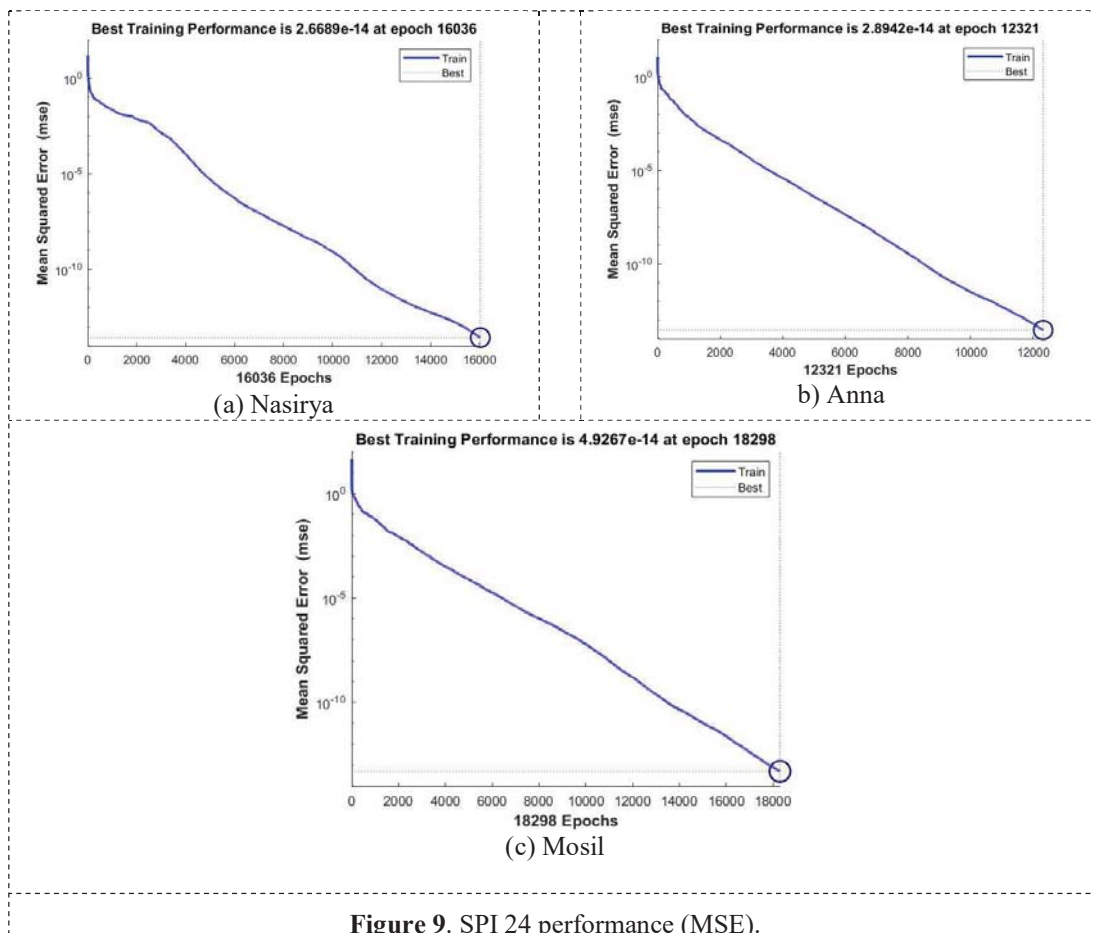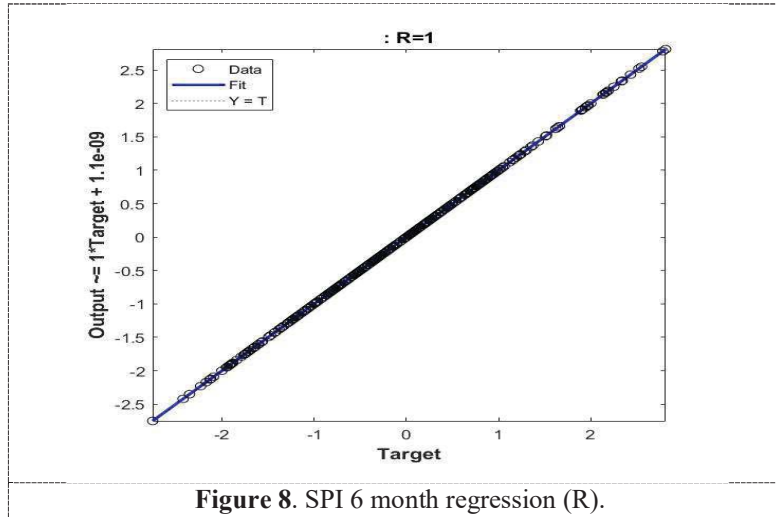
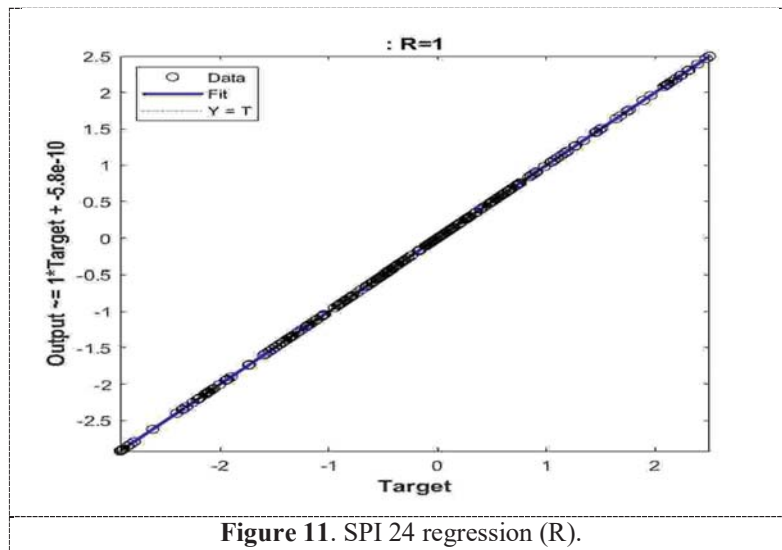**Figure 10**. Sample of SPI 24 series time between output and target.

Figure 11. SPI 24 regression (R).

After getting high accuracy for modeling Spi 24 for three stations, Spi 6 and SPI 24 forecasting done for 10 years forward during the period 2020-2030. Figure (12 and 13) show percent of occurrence for the SPI 6 and SPI 24 forecasting during 2017-2030 at months (October-April).
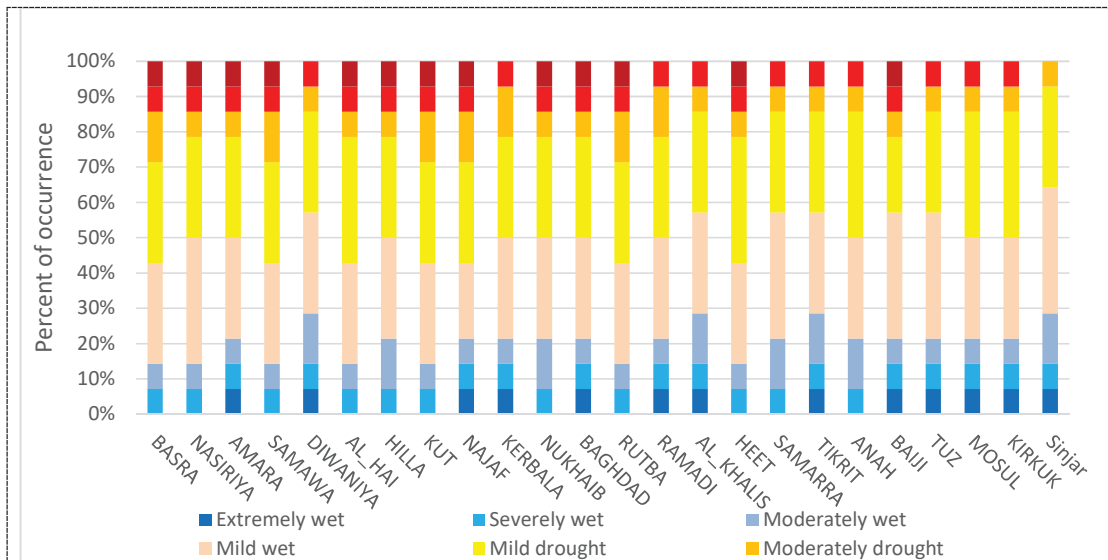
Figure 12. Percent of occurrence for the SPI 6 forecasting during 2020-2030 at months (October-April).

Figures (12) shows Percent of occurrence of the SPI 6 forecasting during 2020-2030 at months (October-April). the drought levels of most southern and middle cities and provinces are somewhat high classes of drought, while in the west region of Iraq at Rutba city it can be seen that the classes of drought is high. The northern region are almost moderate and convergent.

Figures (13) shows Percent of occurrence for the Spi 24 forecasting during 2020-2030 at months (October-April). The figure shows that the Amara province in southern region suffers from high levels of drought, while the middle region of Iraq almost same level scale of drought. Nukhaib city at west region of Iraq will suffers from extreme level of drought. In addition, the figure (13) shows that the northern region of Iraq will be dry and moderate classes of drought.

Spatial drought distribution used to represent Spi 6 and Spi 24 for April month for years (2025 and 2030) in figures (14 to 17).
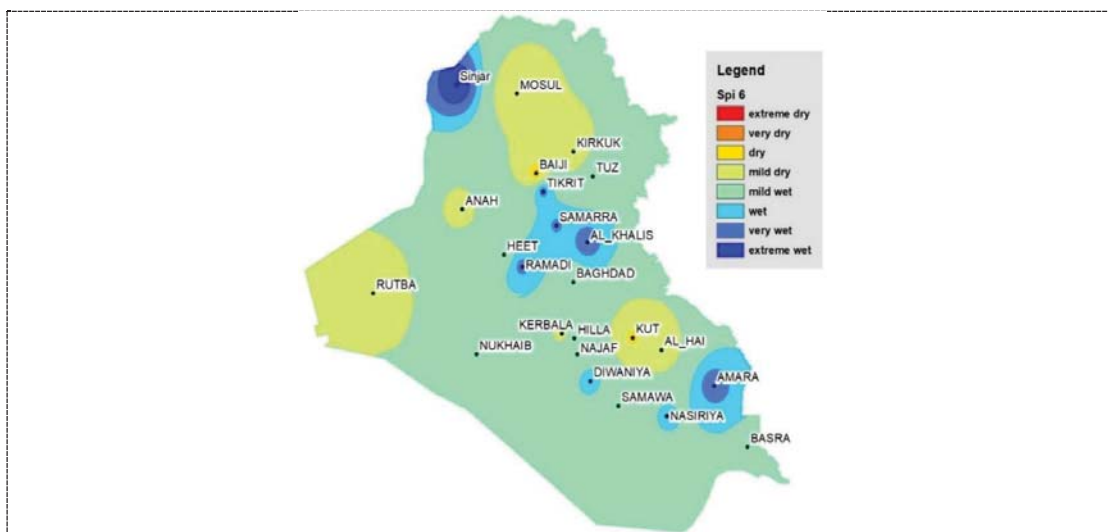

Figure 13. Spatial drought distribution map for Spi 6 at Apri month from 2025.

Figure (14) shows Spi 6 drought spatial distribution map for April from the year 2025. It can be seen that the southern region ranging between mild wet and very wet at Amara province, while most of the middle region of Iraq will be mild wet with some parts will have mild dry and very wet level. The west region of Iraq will ranging between wet at Nukhaib city and dry at Rutba city. The northern region of Iraq will expose to mild wet and mild dry with extreme wet at Sinjar city.
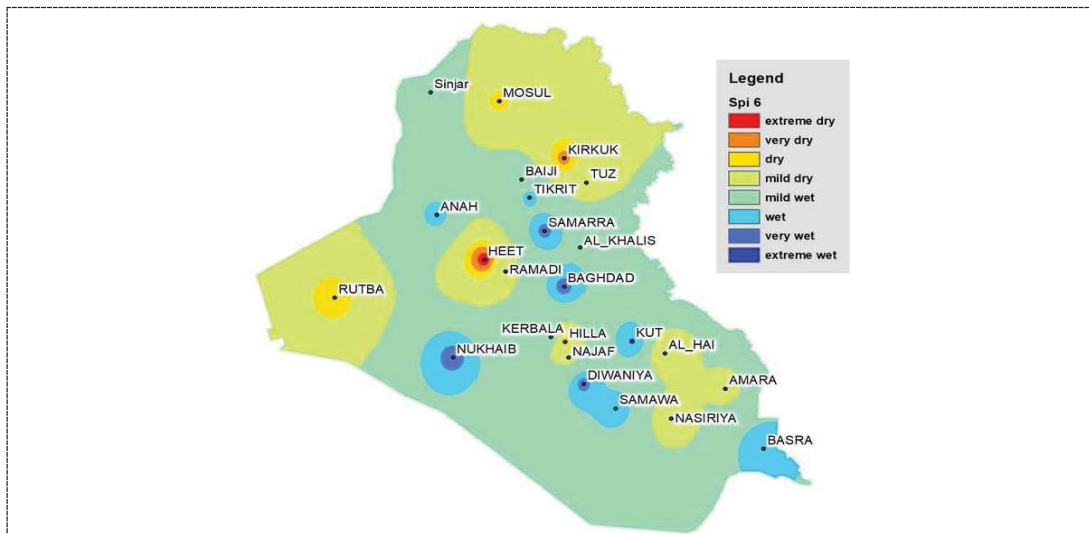

Figure 14. Spatial drought distribution map for Spi 6 at April month from 2030.
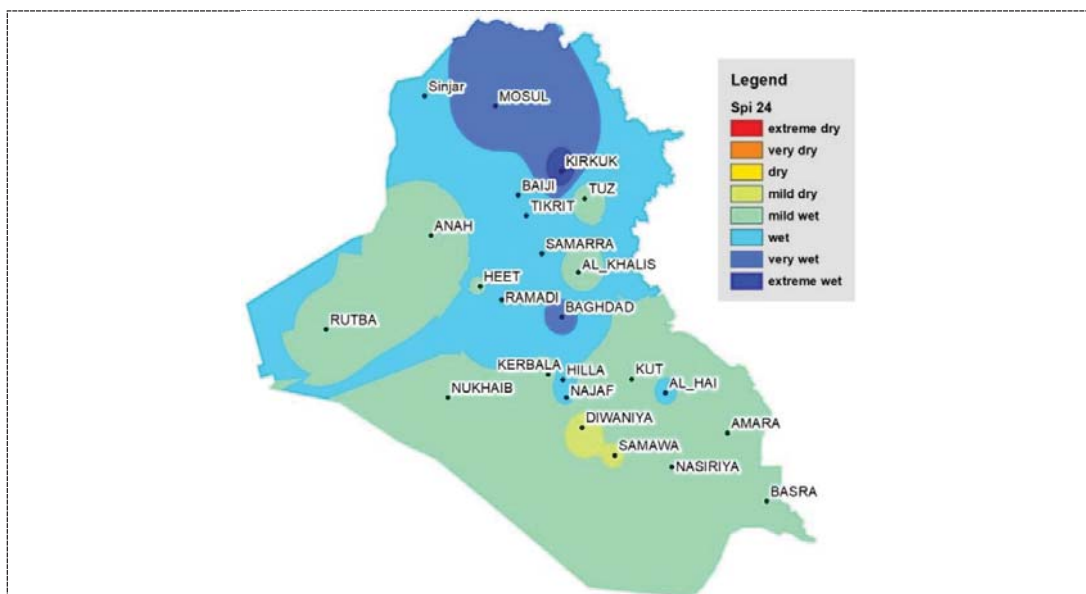

Figure 15. Spatial drought distribution map for Spi 24 at April month from 2025
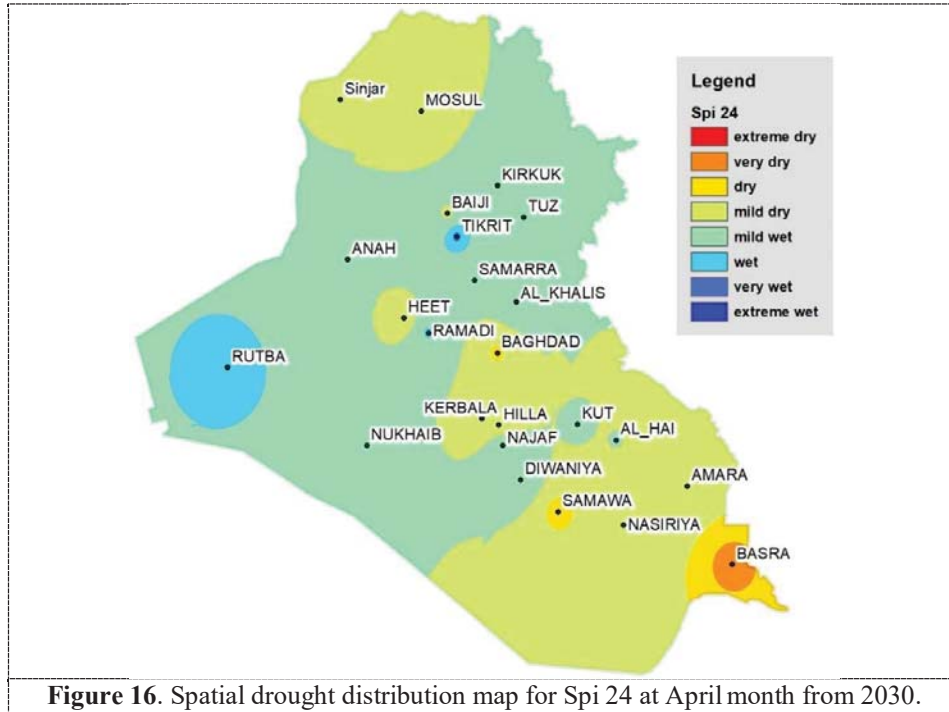
Figure 16. Spatial drought distribution map for Spi 24 at April month from 2030.

Figure (15) shows Spi 6 month spatial distribution map for April month for the year 2030. The southern and middle region of Iraq will be wobbling as shown in figure, while most of west and northern regions of Iraq will be mild dry, dry at Rutba city, very dry at Kirkuk city and mild wet at Sinjar city and its adjacent area.

Figure (16) shows Spi 24 spatial distribution map of drought levels for April month for the year 2025. All southern region will be mild wet, while the middle and west regions of Iraq will expose to mild wet and wet class of drought towards the north. The northern region of Iraq varies from wet to extreme wet at Kirkuk province.

Figure (17) shows Spi 24 spatial distribution map of drought levels for April for the year 2030. The southern region of Iraq will be mild dry with very dry class at Basrah province. Whereas the middle of Iraq , the part that adjacent to southern region will be mild dry and other part towards north region will be mild wet while the west region of Iraq will ranging from mild wet to wet at Rutba city. In addition, the northern region will varies between mild wet and mild dry class of drought.

4. CONCLUSION

. 1- Percent of occurrence for drought in short term (SPI 6) during the period 1950-2016 at months (October-April) was about 52%, whereas for the long term (SPI 24) during the period 1950-2016 at months (October-April) was about 51%.

2- Recurrent neural networks (RNN) was used to make forecasting which proved its effective analysis through training the time series of drought for short and long terms analysis and reaching very high accuracy, where the results from RNN show that regression (R) was 100 %, performance (MSE) and Root Mean Square Error (RMSE) were close to zero for all stations.

3- Percent of occurrence for drought short term (SPI 6) during forecasting period 2020-2030 at months

(October-April) will be about 49%, while for the long term (SPI 24) during forecasting period 2020-2030 at months (October-April) will be about 48%. Wet periods will be higher than dry periods, which must be invested in the future.

4- Drought distribution on the map of Iraq for the month (April) from years (2025 and 2030), generally for both terms the year 2025, most regions in Iraq will be wet which must be invested and preserve these water resources as well as protecting areas that will expose to extreme wet from risk of flooding that may result. Whereas, the year 2030 will expose to varying drought which must take into consideration.

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