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Drought Monitoring Based on Predicted SPI Using Fuzzy Controller System

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ABSTRACT

Drought monitoring is one of the most difficult steps required for optimal planning it must be diligently calculated to ensure success in future plans. In this study, a fuzzy logic control system was developed to monitor drought in the long term based on the values of the Standardized Precipitation Index (SPI-12) and several climate variables. The system applied meteorological data obtained from the meteorological station of the city of Mosul northwest of Iraq and showed that the predicted data confirms the observed data. To verify this conformity further, the accuracy of the prediction and the errors were calculated to test the validity of this system in drought monitoring and the performance efficiency of the system was found to be equal to 82.3%. The system showed high flexibility and capability to represent several different scenarios because of its wide range in designing and selecting Membership Functions and the number of data variables that can be used as its input. Based on the output data and the accuracy of the operation of the system, this system can be recommended to serve as an effective tool for long-term drought monitoring to develop optimal future plans in environmental and agricultural fields in the study area.

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مراقبة الجفاف بناءأ على مؤشر SPI باستخدام نظام المنطق الضبابي

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الملخص

تعتبر مراقبة الجفاف من أصعب الخطوات المطلوبة للتخطيط الأمثل، لذا يجب حسابها بعناية من أجل ضمان النجاح في الخطط المستقبلية. في هذه الدراسة، تم تطوير نظام المنطق الضبابي لرصد الجفاف على المدى الطويل بناءً على قيم مؤشر هطول الأمطار القياسي (SPI-12) وعدد من المتغيرات المناخية. تم استخدام بيانات الأرصاد الجوية التي تم الحصول عليها من محطة الأرصاد الجوية لمدينة الموصل شمال غرب العراق كمدخلات في النظام المصمم. أظهرت النتائج المستحصلة من هذا النظام أن هناك توفق في نمط البيانات المدخلة والبيانات المتنبا بها. للتحقق من هذا التوافق بشكل أكبر تم حساب دقة التنبؤ والأخطاء الاحصائية المحتملة لاختبار صلاحية هذا النظام في مراقبة الجفاف ووجدت كفاءة أداء النظام تساوي 82.3٪. أظهر النظام مرونة عالية وقدرة على تمثيل عدة سيناريوهات مختلفة بسبب النطاق الواسع في تصميم واختيار دوال العضوية وعدد من المتغيرات التي يمكن استخدامها كمدخلات. بناءً على بيانات المخرجات ودقة تشغيل النظام، يمكن التوصية بهذا النظام ليكون بمثابة أداة فعالة لرصد الجفاف على المدى الطويل لوضع خطط مستقبلية مثالية في المجالات البيئية والزراعية في منطقة الدراسة.

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Introduction

Drought is a major factor that negatively affects the environment, especially when integrated with other factors, including human or natural causes. Drought in its different types and stages has received great attention in various scientific fields including subjects like the risk of droughts, drought prediction, forecasting or monitoring, etc. Various methods have been used to demonstrate the high impact of drought on environmental deterioration (Yahya and Seker, 2019; Kang, et al. 2021).

The impact of drought on Iraq has become apparent, especially in the deterioration and decline of agricultural land (UNEP, 2013). Several factors have contributed to the acceleration of drought in Iraq, especially in the last previous years, including climate change and irregular migration as a result of successive wars and other causes. A report by the International Organization of Migration showed that drought was the main factor in the displacement of 4,263 families (25,578 individuals) in the years between 2007 and 2009 and that 80% of these displaced families previously lived in the governorates of Salah al-Din and Nineveh.

Yaseen, et al. (2012) conducted a comprehensive investigation of the drought levels in Iraq using remote sensing and geographic information systems. The results of his study showed that 14.4% of the land was subjected to a slight drought, 61.6% to moderate drought, and 0.8% to extreme drought and he found that the Northern region of Iraq is susceptible to the impact of drought factors. Several methods can be used in long-term drought monitoring, such as (fuzzy logic), which can be defined as a simplified system that interprets input data and identifies their relationship to one scenario or another, and delivers an output that confirms the relationship.

In 1964 the fuzzy logic term was presented by Lotfi A. Zadeh when he highlights his theory about the fuzzy set. During ten years till 1975, he continued to strengthen the foundation of fuzzy set theory to include many important axes like (decision-making, similarity relations, linguistic hedges, etc.) (Zadeh, 1964; Zadeh, 1975; Zimmermann, 1991). The theory of fuzzy sets has been used in various fields of drought analysis. Where fuzzy logic (Pesti, et al., 1996) assesses the drought according to it is general circulation patterns. A fuzzy rule was developed (Pongracz, et al., 1996) to predict regional drought depending on palmer index characterization. (Ozgur, et al., 2011) developed a combination model based on the principles of wavelet and fuzzy logic for long-term drought forecasting. (Ashok, et al., 2011) made an expanded article review on drought modeling.

The questions of the study can be stated as follows: What are the factors that contribute to the occurrence of drought in the study area? Can the results be compared with the observed data and is there a true relationship between the observed input and output data?

With this in view, this study has been carried out with the following objectives:

1. To understand the drought event throughout scenarios that may be happened in the study area.

2. To driver's pattern of drought as influenced by local climate using meteorological variable data from the weather station.

3. To adopt a new strategy by developing an FCS system that can be used to predict the drought in Nineveh Governorate and compare its results with previously prepared SPI data and validate this system by examining the efficiency of the system performance.

The study area

The governorate of Nineveh is located in northwestern Iraq, between longitudes (41º 30' – 44 º 30' and latitudes 35º 00' – 37 º 00'). It shares borders with Syria and several Iraqi governorates. Nineveh is the third-largest governorate in terms of size. Its total area is 37,323 km2 (8.6% of the total size of Iraq). The provincial capital of this governorate is Mosul city. The population is currently more than two million people. It contains nine major administrative units (Tel-Afar, Sinjar, Sheikhan, Sharqat, Hamdania, Tilkaif, Baaji, Bashiqah, and Rabiaa) as given in (Fig. 1).

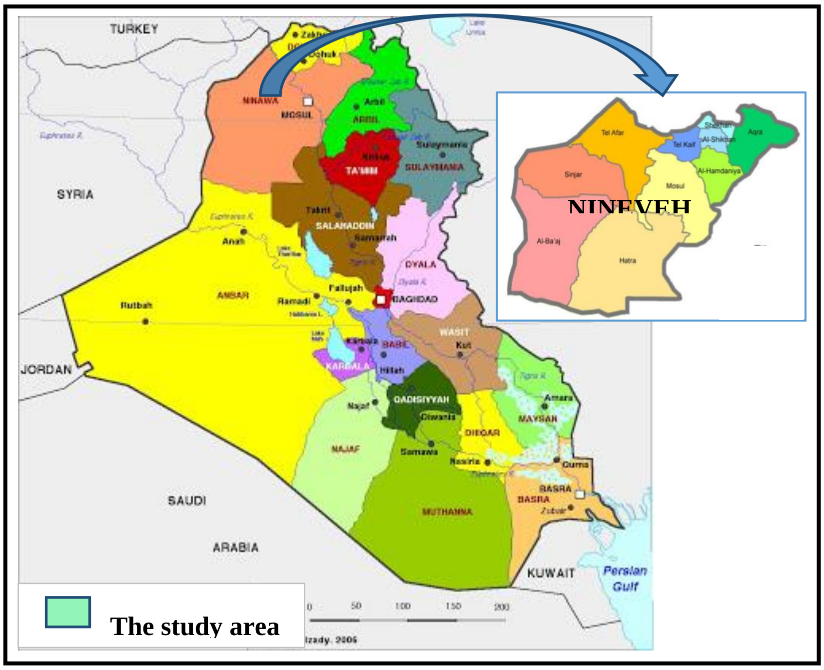

Fig.1. Map shows the study area location

The climate of Nineveh is dry and hot in summer and cold in winter. The average temperature is 22.8 ° C and the average rainfall is 357 mm per year. The peak solar radiation rate is 636.44 mm/w/cm2 in the summer with an annual average sunshine of 9.5 hours a day. The annual average wind speed is 1.3 m/sec. with annual average evaporation of 178.94 mm and average mean relative humidity is 51.33 % (Hamdani, 2007).

Data used

All meteorological data in this research is presented as the monthly total average for Mosul station for the period (1970-2014) with the standardized precipitation index (SPI-12) that was prepared in previous work (Ministry of Defense, 1945; Ministry of Transportation, 1960; The Iraqi Ministry of Transportation 2015).

Fuzzy logic control system framework

The general framework of the system is divided into three main parts that work together to give the final image of the designed system as in (Fig.2). The first part is (The Fuzzification Process) which defines the input data and the type of member functions that control the data. The second part of the system includes the (Fuzzy Conditional Statement) which is considered the main part of the system that translates the predicted scenarios through fuzzy rules derived from experience. The third part (Defuzzification Process) is the part that consolidates the input data with the scenarios to produce certain results that embody the idea of the study.

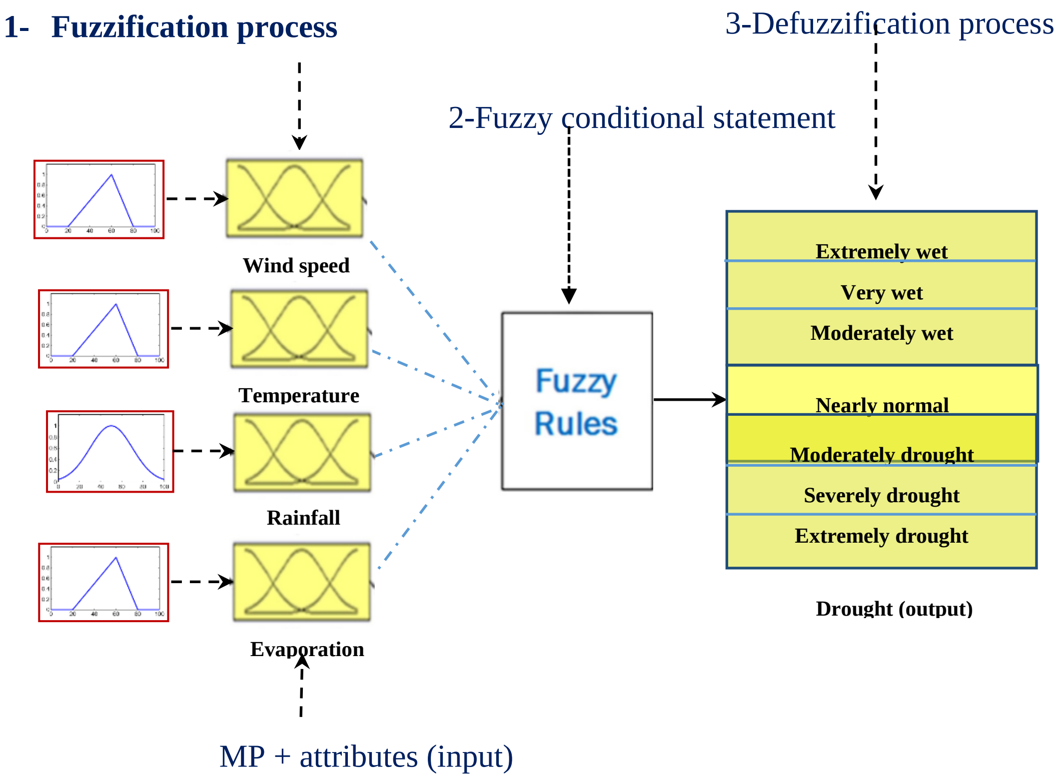

Fig. 2. The generic framework of (FCS)

Designing the fuzzy control system

The fuzzy control system was designed based on the general framework parts of as follows:

1. Define FCS concepts and fuzzification

Two requirements must be present as a first step in the design of the FCS. The first requirement is the fuzzy sets variables which are variables chosen based on the strength of the correlation relation with the standardized precipitation index data. The first selection consisted of six variables but the correlation coefficient among these variables showed that two of these variables (sunshine and humidity) had a weak correlation coefficient, so they were excluded from the list of data inputs leaving the other four variables (wind speed, temperature, rainfall and evaporation) that were relied upon in designing the first part of the system framework as in Fig. 3 and Table 1.

The four linguistic variables (wind speed, temperature, rainfall, and evaporation) are entered as input data to control the output variable (drought) and each of them was classified according to linguistic values as (low, moderate, and high for wind speed, temperature, and evaporation) and (very low, low, semi- moderate, moderate, high, very high for rainfall) listed in Table 2.

Table 1. The Correlation Coefficient (R) values

Linguistic Variables	Correlation Coefficient (R)
wind speed	0.53
Temperature	0.52
Sun shine	0.14
Rainfall	0.82
Humidity	0.12
Evaporation	0.63

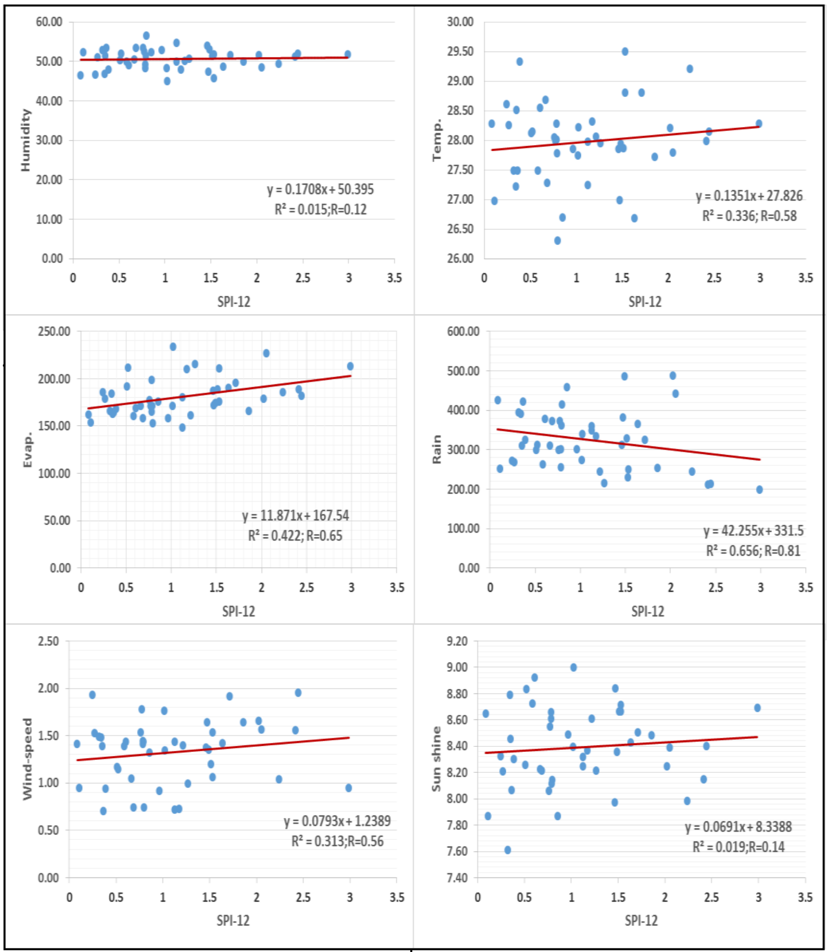

Fig. 3. Correlation behavior of selected variable and SPI-12

The output (drought) is also divided into seven linguistic variables similar to the classification of standard precipitation index SPI-12 categories similar to the description made by (Mckee, et al., 1993) as extremely wet, very wet, moderately wet, near normal, moderately dry, severely dry, and extremely dry as displaced in (Fig. 4).

Table 2. Fuzzy logic control system concepts

The fuzzification process			
fuzzy set	linguistic values	MP	MP range
wind speed	Low	Triangular	0-0.4
	moderate		0.4-1.5
	High		1.5-3.0
temperature	Low	Triangular	0-5
	moderate		5-30
	High		30-45
rainfall	very low	Gaussian	0-50
	Low		50-100
	semi- moderate		100-150
	moderate		150-300
	High		300-400
	very high		400-600
evaporation	Low	Triangular	0-100
	moderate		100-300
	High		300-400

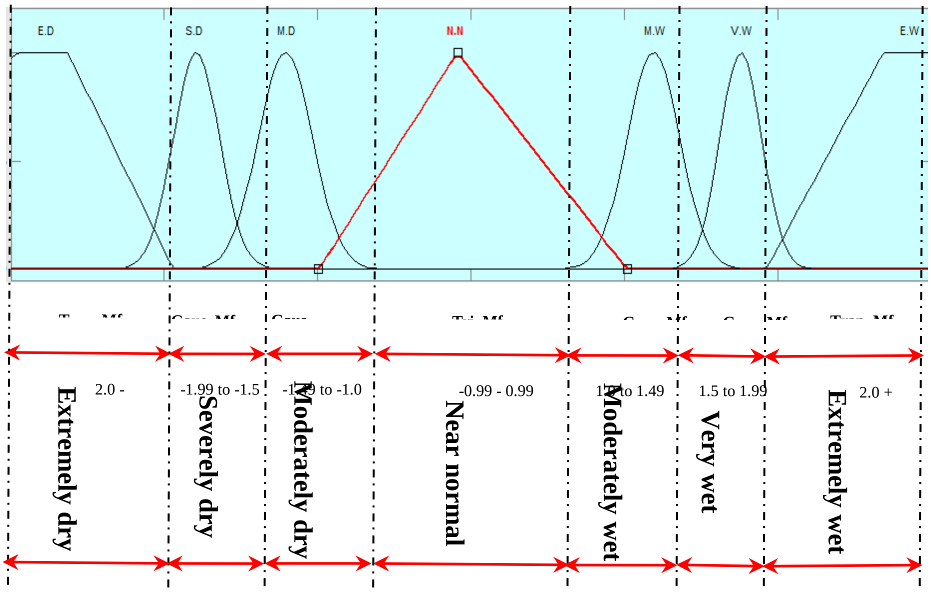

Fig. 4. Output characteristics according to fuzzy logic concepts

These sets cover the necessary range of variation for each variable and are controlled by the membership function which determines the degree of membership (from 0 to 1) between the real value inputs (linguistic variable) and the linguistic values Table 2. The second requirement is the membership functions (MF) that characterized the fuzzy sets. There are many types of membership functions. By trying and error to get the best results, membership functions are chosen for each fuzzy set as given in Table 2. For the output (drought) two membership functions (MF) are chosen. The trapezoidal function is used for extremely dry and extremely wet categories and Triangular function is used for the near normal category and the Gaussian function is for severely dry, moderately dry moderately wet, and very wet as presented in (Fig. 4). Now we can define fuzzification as a process that involves the linguistic variable with their classified linguistic values and assigning membership functions for each linguistic variable as given in Table 1.

2. Fuzzy conditional statement (fuzzy rule)

This step discusses the fuzzy conditional statement (fuzzy rule) which is the key idea in fuzzy logic. These rules translate all expected scenarios that could occur to the phenomenon under study based on the (If-Then) statement assumed as:

IF x is A THEN y is B ……………… (1)

Where A and B are linguistic values and can be called the antecedent and consequence respectively. Many antecedents can be entered into the system to get one or multi consequences.

Fifty fuzzy rules were described and applied to cover the scenario of the drought event changes in the study area where the rules from 1 to 5 describe extreme drought event when they are no rainfall and humidity or they are at very low level and other variables are wavering between moderate to high, the rules from 6 to 13 inventory all the extremely wet events when rainfall and humidity are very high and other variables are low.

Rules from 14 to 21 describe all cases of nearly normal drought when all variables wavering between very low to moderate. The rules from 22 to 29 describe severe drought events when rainfall and humidity waver between very low to low and other variables between moderate to high and the rules from 30 to 37 describe moderate drought events when rainfall and humidity waver between very low to semi-moderate and all variables wavering between moderate and high.

A rule from 38 to 45 describes all cases of very wet drought when rainfall and humidity are wavering between semi-moderate to very high and all variables waver between low and moderate. Rules from 46 to 50 describe all cases of moderately wet when rainfall and humidity are wavering between semi-moderate to high and all variables waver between low and moderate.

Mamdani method was used in this work as one of the fuzzy control system methodologies that translates the fuzzy set theory based on human experiences. It was proposed in 1975 by Ebrahim Mamdani depending on his experience in controlling the steam engine and boiler combination and built up his theory on the efforts of Zadeh's 1973 study on fuzzy logic. (Mamdani, 1975; Jimoh, et al., 2013; Hoque, et al., 2021).

There are four steps for solving Mamdani inference mechanism as:

a-Calculate the firing strength for each rule in the rule-base

b-Determine which rules are on using the firing strengths

c-Determine implied fuzzy sets — perform fuzzy implication

d-Determine overall implied fuzzy set — perform fuzzy aggregation

For solving the Mamdani Inference Mechanism steps we must define the firing strength as the degree of certainty that the entered linguistic variables (antecedent) give rational output (consequence). Calculation of firing strength depends on linguistic operators used in the fuzzy inference system like (AND, OR, NOT). The fuzzy rules must be (on) that’s mean the linguistic variables must be greater than zero when firing strength is calculated (Calvo, et al 2002; Jehanzaib et al. 2021). For example, on the fuzzy rules used in this study where the characters of six variables give one output variable (extremely dry) based on the (IF-THEN) rule and (AND) operator an example:

IF (high wind speed) and (high sunshine) and (high temp.) and (very low humidity) and (very low rainfall) and (high evaporation) THEN (drought is extremely dry).

The Mamdani (min) function was applied to determine the firing level (α) for a rule above considering the weight factor equal one to give the value which represents the firing strength of the rule as given in (Fig. 5) as follows:

α= min {μ (wind speed=2.46), μ (sunshine= 8.18), μ (temp. =37.8). μ (humidity=22.5), μ (rain=31.9), μ (evaporation= 362)}

α= min {2.46, 8.18, 37.8, 8.18, 31.9, 362} =-2.61

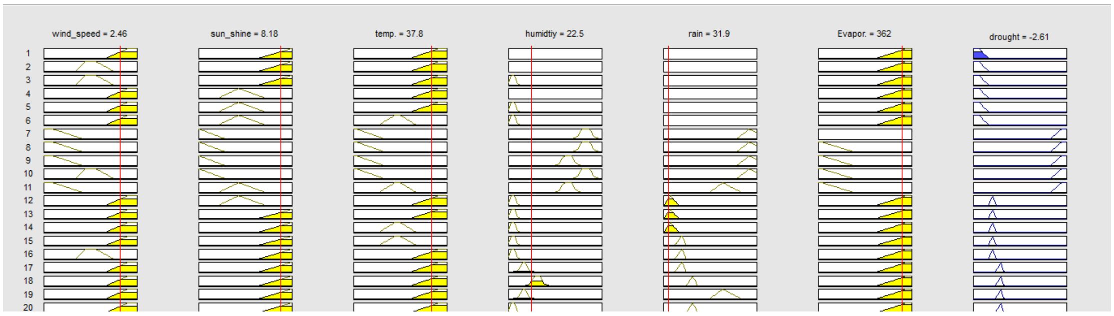

Fig. 5. Fuzzy logic rules showing the min firing level (α)

Now we need to unify the outputs of all the rules by applying the aggregation process that combines output fuzzy sets into a single set taking into account the maximum truth value (Pham and Castellani, 2002) as given in (Fig. 6) as follows:

max= {μ (wind speed=0.862), μ (sunshine= 2.82), μ (temp. =7.18). μ (humidity=75.3), μ (rain=555), μ (evaporation= 72.3)}

max= {0.86, 2.82, 7.18, 75.3, 555, 72.3} =2.58

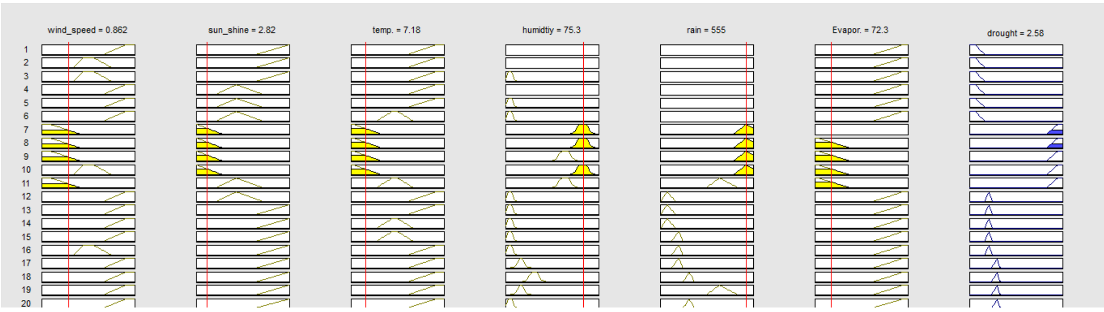

Fig 6. Fuzzy logic rules showing the max firing level (α)

3. Defuzzification process

The last step of (FCS) generic framework is how to convert the input values (linguistic variables) to numerical values (crisp values). This operation is solved by the defuzzification process. There are several defuzzification methods but the most commonly used is the centroid technique or center of gravity (COG) adopted in this work (Timothy, 2010; Agboola, 2013) and can be expressed as:

$$Z = \sum_{i=1}^{n} \alpha i . yi / \sum_{i=1}^{n} \alpha i \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \textbf{(2)}$$

Where:

z =the output values (crisp value)

α_i = the fuzzy implication (firing strength) of the i^{th} rule

y_i =the consequent of each rule.

Therefore, using the result estimated from equation 2 the amount of drought can be predicted as given in Table 3.

Performance Evaluation

To predict SPI-12 values, four variables (meteorological data) for the period (1970-2014) were used in the fuzzy controller system as truth data and previous SPI-12 results for the study area were used as observed data to make a comparison with the predicted results were the average prediction error is 36 % as given in Table 3, Fig. 7.

Table 3. Predicted SPI-12 values using fuzzy logic control system

Year	Actual SPI-12	Predicted SPI-12	Prediction error %	year	Actual SPI-12	Predicted SPI-12	Prediction error %
1970	-1.016	-0.521	19.5	1993	0.854	0.623	38.7
1971	1.470	1.356	24	1994	-1.462	-0.987	25.9
1972	2.053	1.552	24.4	1995	1.511	0.956	20.9
1973	1.635	1.854	5.0	1996	2.022	1.859	16.4
1974	0.084	0.16	61.0	1997	1.125	0.856	23.9
1975	-0.606	-0.212	66.0	1998	0.786	0.354	54.9
1976	0.342	0.658	34.0	1999	-1.53	-0.954	24.2
1977	1.022	0.753	19.2	2000	0.244	-0.123	39.9
1978	-0.585	-0.321	45.1	2001	1.713	1.125	21.7
1979	-1.172	-0.845	27.9	2002	-2.443	-1.647	28.7
1980	-1.124	-0.625	26.1	2003	-0.760	-1.358	49.6
1981	-0.687	-0.329	24.3	2004	0.268	0.644	58.3
1982	0.796	0.421	47.1	2005	0.350	0.194	57.4
1983	-0.108	-0.021	66.0	2006	1.4868	1.241	23.2
1984	-0.362	-0.854	48.1	2007	0.6640	0.325	51.0
1985	-0.963	-0.628	21.7	2008	-0.388	-0.125	67.7
1986	0.774	0.354	42.1	2009	-2.238	-1.726	18.5
1987	-1.857	-1.425	17.9	2010	-0.509	-0.916	45.4
1988	-2.414	-1.865	29.0	2011	-2.986	-2.158	20.4
1989	-1.216	-0.621	34.2	2012	-1.529	-1.098	21.6
1990	-0.783	-0.485	50.0	2013	0.521	0.254	52.1
1991	0.792	0.624	38.9	2014	-1.264	-0.754	33.4
1992	0.319	0.724	55.9	Average Prediction Error =36 %			

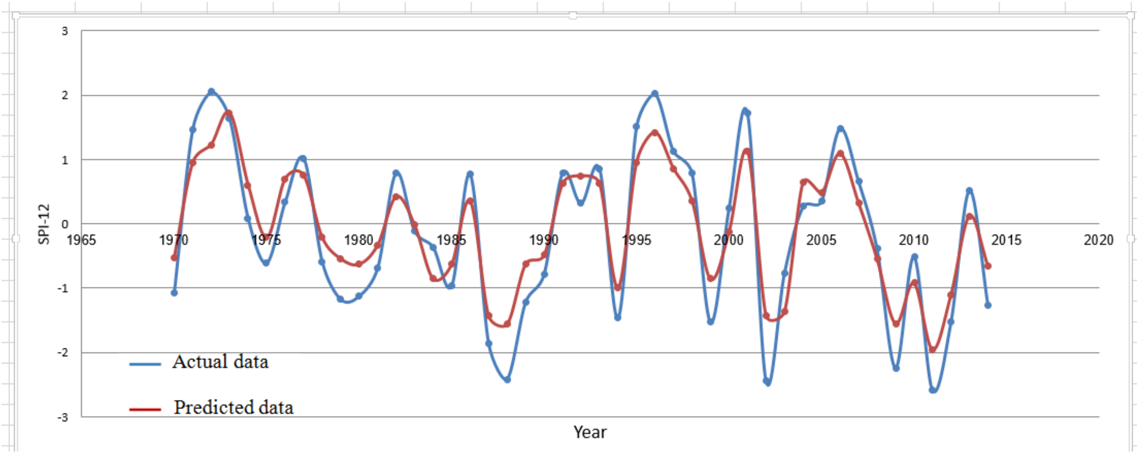

Fig. 7. Comparison between the actual and predicted SPI-12

As found in many kinds of literature they are several numbers of model efficiency criteria that are used to evaluate the performance of various development models (Crochemore, et al., 2015) the best performance of a model is when the correlation is high and the errors are as small as possible. To ascertain the efficient performance of the fuzzy controller system in this study, the coefficient of determination (R^2), root mean square error (RMSE), and mean absolute percentage error (MAPE) were used to test the performance accuracy of the model as follows:

1. Coefficient of determination (R^2)

The degree of correlation between observed data and predicted model results is estimated by the coefficient of determination (R^2) where the best results of this relationship accrue when the correlation is high and the errors are as small as possible and this coefficient value ranges from 0 to 1. For this study, the estimated correlation coefficient was (R^2=0.905) indicating that there is a perfect positive relationship between the observed values of (SPI-12) and predicted results Fig. 8.

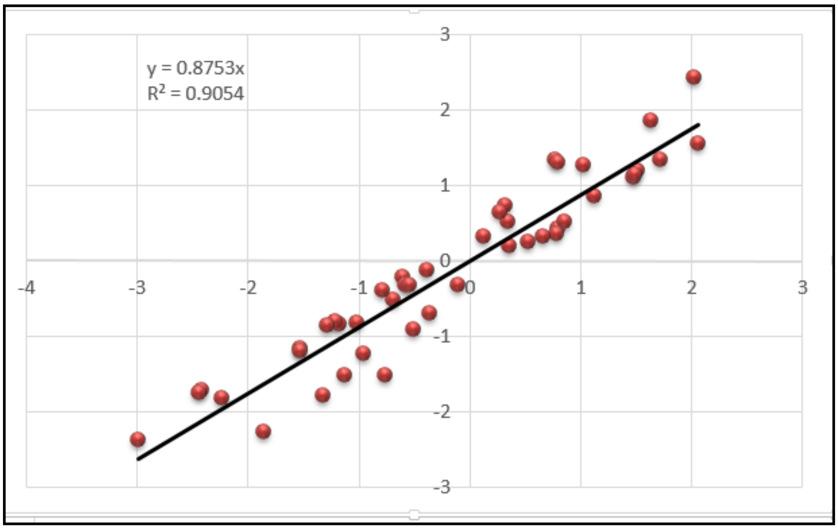

Fig. 8. Correlations relationship between the actual and predicted values

2. Root mean square error (RMSE)

To measure the prediction accuracy of the models the RMSE was widely used as one of the model efficiency criteria for evaluating the performance of a model (Bowden et al. 2012). By using the Eqs. (3) the RMSE was 0.721.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(R_{pi} - R_{oi})^2} \qquad (3)$$

CE was used to compare the goodness of fit between the observed data and the predicted values. The value of CE was ranged by (Ramanarayanan et al. 1997; Donigan and Love 2003; Moriasi et al. 2007) according to the results of their research in this filed Table 4. By using the Eqs. (4) the CE was 0.83 and this indicates that the system has a good performance level.

$$\mathrm{CE} = \left[1 - \frac{\sum_{i=1}^{n}(R_{pi} - R_{oi})^2}{\sum_{i=1}^{n}(R_{oi} - R_a)^2}\right] \qquad (4)$$

Table 4. Model performance level according to CE values

CE value	model performance level
greater than 0.5	acceptable or satisfactory
0.65–0.75	taken as fair
0.75–0.85	taken as good
above 0.85	taken to represent very good

3. Mean absolute percentage error (MAPE)

Performance accuracy can be measured by estimating the mean absolute percentage error (MAPE) of the observed and predicted data by using equation 3.

$$\mathrm{MAPE} = 1/n \sqrt{\sum_{i=1}^{n}\left(\mathrm{observed(i)} - \mathrm{predicted(i)}\right) \ / \mathrm{observed(i)}} \quad \textbf{……………………. (3)}$$

Where n= the number of observations = 44

Therefore MAPE = 17.39%

Accuracy= 100- MAPE =82.61%

The performance of the system was evaluated by estimating the sum of model efficiency criteria (R2=0.905, RMSE =1.351, CE=0.83 and MAPE = 17.39%) where the performance accuracy was 82.61% that make the system reliable and efficient for SPI-12 prediction for the study area.

Results and Discussion

The aim of this study is to attempt long-term drought monitoring using fuzzy logic by developing a control system based on meteorological variables as a linguistic input and comparing the outputs with the standardized precipitation index SPI-12 values prepared for the study area.

Four variables were selected according to their correlation relation with the values of the standardized precipitation index (SPI-12) as shown in Fig. 3. The results when operating the system show that these variables have the capability to predict SPI-12 values with an average prediction error of (36%) as illustrated in Table 2 and Fig. 7. A positive correlation was obtained between observed and predicted (SPI-12) values. The correlation coefficient between these values (R^2 = 0.905), (RMSE =0.712), and (CE = 0.83) show that the quality of the performance of the system is acceptable by (82.61%). The value of MAPE (17.39%) was statistically compared to observed and predicted (SPI-12) values and show a good indication of the reliability and quality of the developed system which could become more effective in drought control if MAPE is reduced by identifying other meteorological variables that have a strong correlation coefficient with the observed SPI-12 values or adding more training data to the system (determining SPI-12 values for the period before 1970).

Conclusion

The fuzzy control system may be a good solution for drought monitoring that manifested many advantages easy to design and develop according to the accumulated experience of the operator in various fields which gives the decision makers a quick look at the reality of a problem or environmental impact to take precautions. In this study, a fuzzy control system was developed to use as a tool for one of the environmental impact detectors (long-term drought monitoring) this system was tested in terms of performance accuracy equal to 82.61% with high efficiency throughout the value of MAPE that equal 17.39%.In future studies, different approaches might be developed to find more options for monitoring the drought like Artificial Neural Networks using the NARX approach comparing the results with a developed fuzzy control system to find which model has effective and efficient performance.

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