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Annual Rainfall Forecasting by Using Mamdani Fuzzy Inference System

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Abstract: This research aims to study the relationship between climatic large-scale synoptic patterns and rainfall in Khorasan region. Fuzzy Inference System (FIS) was used in this study to predict rainfall in the period between December to May in the region. Soft computing is an innovative approach to construct computationally intelligent systems that are supposed to possess humanlike expertise within a specific domain, adapt themselves and learn to do better in changing environments and explain how they make decisions. Unlike conventional artificial intelligence techniques the guiding principle of soft computing is to exploit tolerance for imprecision, uncertainty, robustness, partial truth to achieve tractability and better rapport with reality. In this study, 33 years of rainfall data analyzed in khorasan region, situated at the northeastern part of Iran. This research attempted to train Fuzzy Inference System (FIS) based prediction models with 33 years of rainfall data. For performance evaluation, the model predicted outputs were compared with the actual rainfall data. Simulation results reveal that soft computing techniques are promising and efficient. The Root Mean Square Error by using Fuzzy Inference System model was obtained 52 millimeter.

Key words: Soft computing, climate, rainfall forecasting, fuzzy system, artificial intelligence

INTRODUCTION

Seasonal rainfall forecasts can have significant value for resources planning and management e.g., reservoir operations, agricultural practices and flood emergency responses. To mitigate this, effective planning and management of water resources is necessary. In the short term, this requires a good idea of the upcoming season. In the long term, it needs realistic projections of scenarios of future variability and change (Abraham *et al*., 2001).

Karamouz *et al*. (2005) used a model based on fuzzy rules and neural networks using large-scale climatic signals to predict rainfall in the western Iran (the basins of Karoon, Karkheh and the western border). Their results showed that except for the southwest region, where both models had similar errors of above 35%, in the northwest and the western regions, the error of the fuzzy model was 8.4%; that is, 13% lower than that of neural network. Halide and Ridd (2000) used fuzzy logic to rainfall prediction. The fuzzy logic technique is used to model and predict local rainfall data. The RMSE

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between data and model output is found to be 319.0 mm which is smaller than that by using either the local rain or the Niño 3.4 alone of 349.2 and 1557.3 mm, respectively.

Wong *et al*. (1999) constructed fuzzy rule bases with the aid of SOM and back propagation neural networks and then with the help of the rule base developed predictive model for rainfall over Switzerland using spatial interpolation.

Bardossy *et al*. (1995) implemented fuzzy logic in classifying atmospheric circulation patterns. Özelkan *et al*. (1996) compared the performance of regression analysis and fuzzy logic in studying the relationship between monthly atmospheric circulation patterns and precipitation. Pesti *et al*. (1996) implemented fuzzy logic in drought assessment. Baum *et al*. (1997) developed cloud classification model using fuzzy logic. Fujibe (1989) classified the pattern of precipitation at Honshu with fuzzy C-means method. Galambosi *et al*. (1999) investigated the effect of ENSO and macro circulation patterns on precipitation at Arizona using Fuzzy Logic. Vivekanandan *et al*. (1999) developed and implemented a fuzzy logic algorithm for hydrometeor particle identification that is simple and efficient enough to run in real time for operational use. Hansen (2003) applied fuzzy k-nn weather prediction system to improve the technique of persistence climatology by past and present weather cases.

Shao (2000) established fuzzy membership functions, based on cloud amount, cloud type, wind speed and relative humidity, to compose a fuzzy function of weather categorization for thermal mapping. Liu and Chandrasekar (2000) developed a fuzzy logic and neuro-fuzzy system for classification of hydrometeor type based on polar metric radar measurements, where fuzzy logic was used to infer hydrometeor type and the neural network-learning algorithm was used for automatic adjustment of the parameters of the fuzzy sets in the fuzzy logic system according to prior knowledge. Suwardi *et al*. (2006) have used of a neuro-fuzzy system for modeling wet season tropical rainfall. The models resulted low values of the RMSE indicated that the prediction models are reliable in representing the recent inter-annual variation of the wet season tropical rainfall.

In this study, Fuzzy Inference System (FIS) has used for predicting the rainfall time series. The soft computing model described above were trained on the rainfall data corresponding to a certain period in the past e the prediction model made by using FIS over some other period.

MATERIALS AND METHODS

Area Under Study

The area of this study is Khorasan province in North east of Iran in Fig. 1. Total precipitation from December to May over a period of 33 yeas (1970-2002) was selected as data of our interest in this research.

Data of 37 stations including four Synoptic, five climatology and 28 rain gauges (all belong to Iranian Meteorology organization) were selected for each year.

Calculating of Local Average Rainfall

Digitizes Elevation Model (DEM) is used to get the amount of local average rainfall.

Data

Except for rainfall data which were obtained from the Weather Bureau, all other required data were adopted from the site NOAA (www.cdc.noaa.goy) in the networks of 2.5×2.5 degrees in the period between 1970 and 2002.

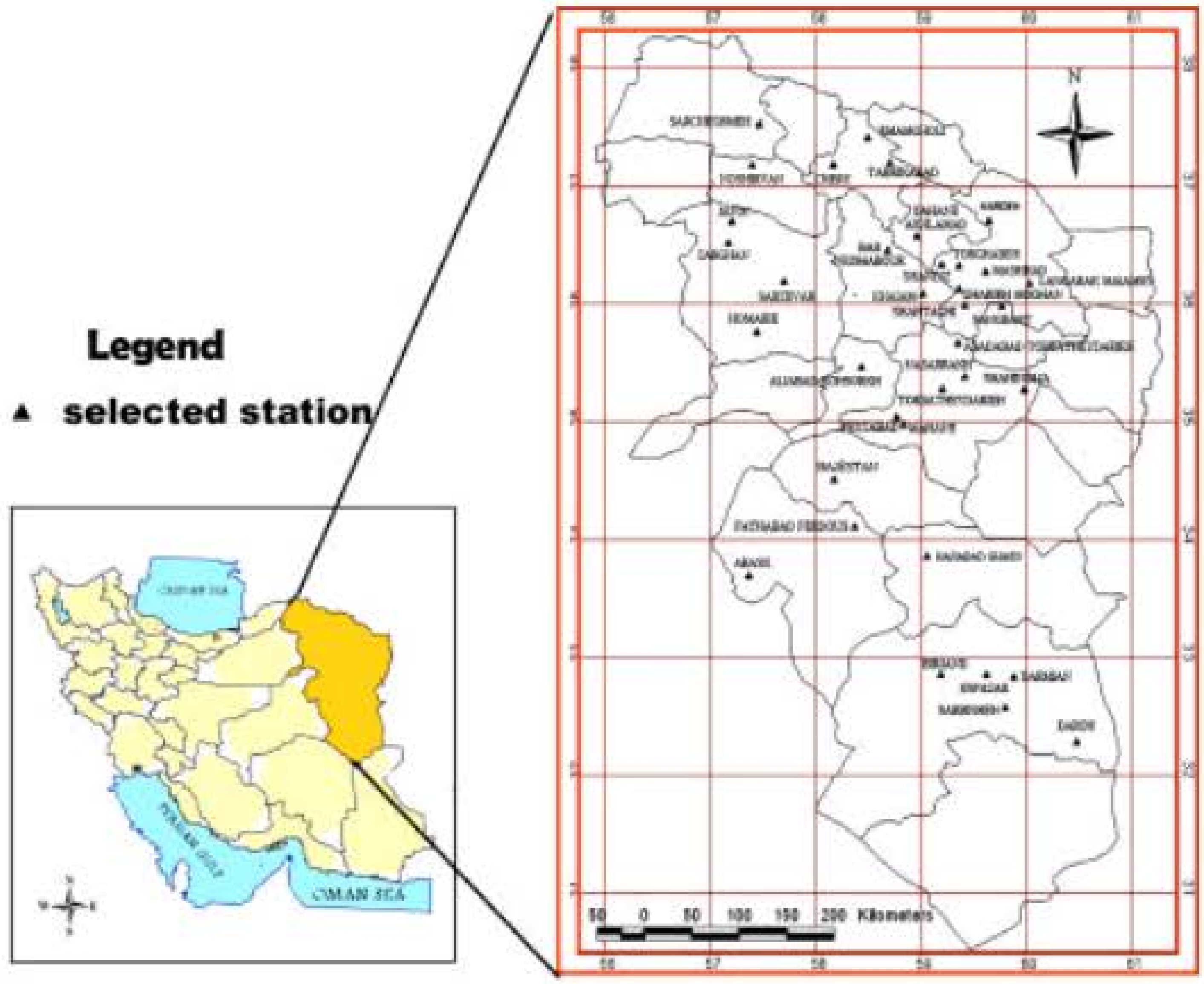

Fig. 1: Map of area of study with selected stations

Identification of Predictors

Here the aim is to identify predictors for Iranian seasonal rainfall, which can then be used in forecast models. The two main requirements for any useful predictors are (i) good relationship with the seasonal rainfall and (ii) reasonable lead-time (i.e., months to season). Our earlier work indicated that seasonal rainfall in the region is strongly correlated with predictors. So, the first step is to look for relationship with standardized predictors during the pre-monsoon seasons (Jun-Nov) and follow up with correlations between the rainfall and large-scale ocean-atmospheric variables (SSTs, SLPs and so on). This approach of correlation with large-scale ocean-atmospheric circulation variables used to identify predictors for seasonal rainfall forecasting in the Northern East of Iran.

Correlation with Large-Scale Variables

The study tries to check of predictors large-scale aspects and also the seasonal rainfall correlation with Predictors such as SSTs and SLPs and so on during pre- season rainfall (June-Nov). In this research, the correlations that are significant at 95% confidence level have been selected. Name and coordinates that are used for relation between rainfall and remote linkage Controlling have shown in Fig. 2.

The selected predictors are: Standardized pressure of Aden gulf., Standardized pressure of South of Persian gulf, Standardized pressure of north of Red sea, Standardized pressure of south of Red sea, The difference of pressure standardized between Adriatic Sea and south of Persian Gulf, The difference of pressure standardized between Aral Lake and north of Khazar Lake, The difference of pressure standardized between south of Persian gulf and Arab Sea, The difference of pressure standardized between Oman Sea and south of Persian Gulf, The difference of pressure standardized between south

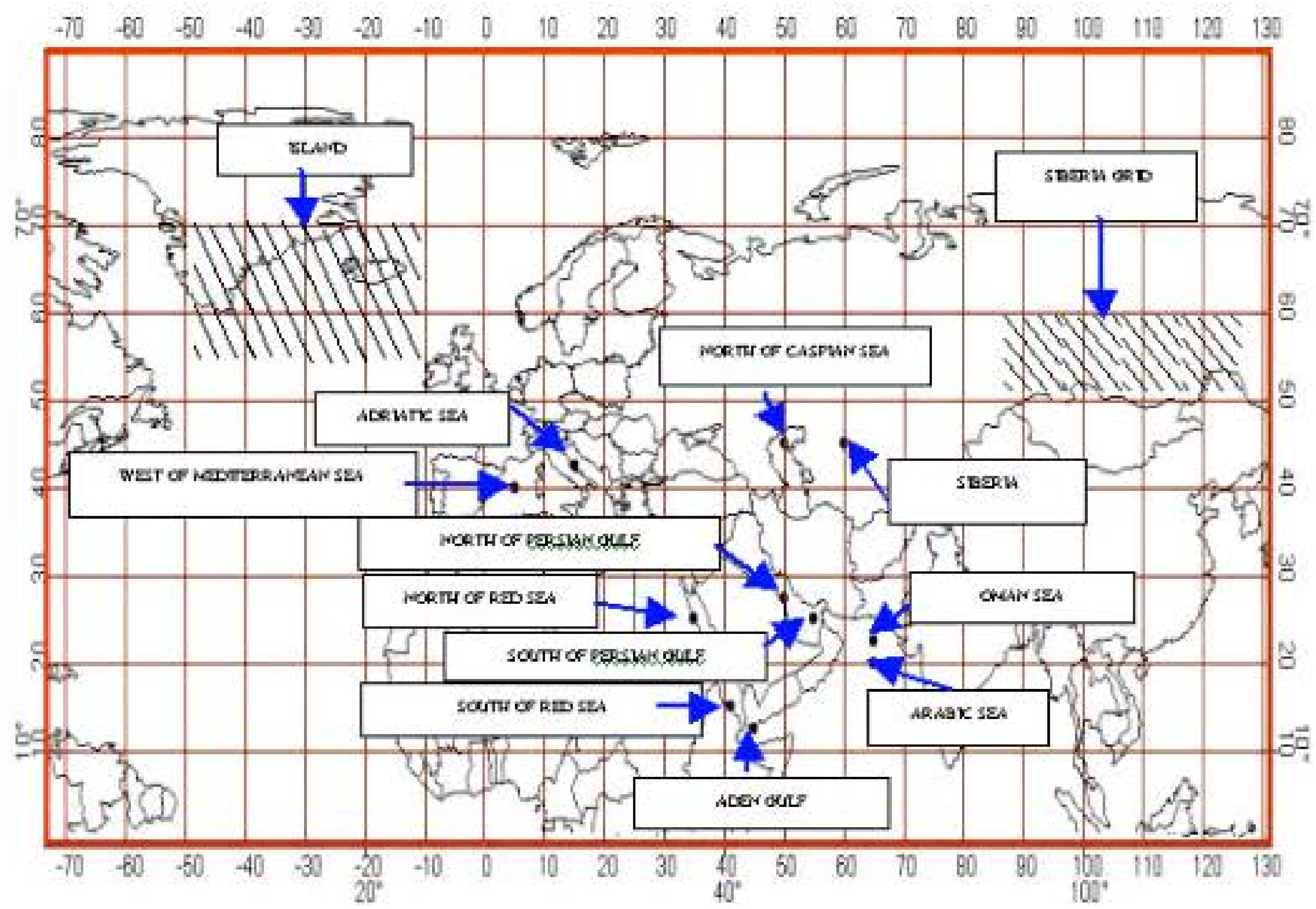

Fig. 2: Name and coordinates that have used for relation between rainfall and Remote Linkage Controlling

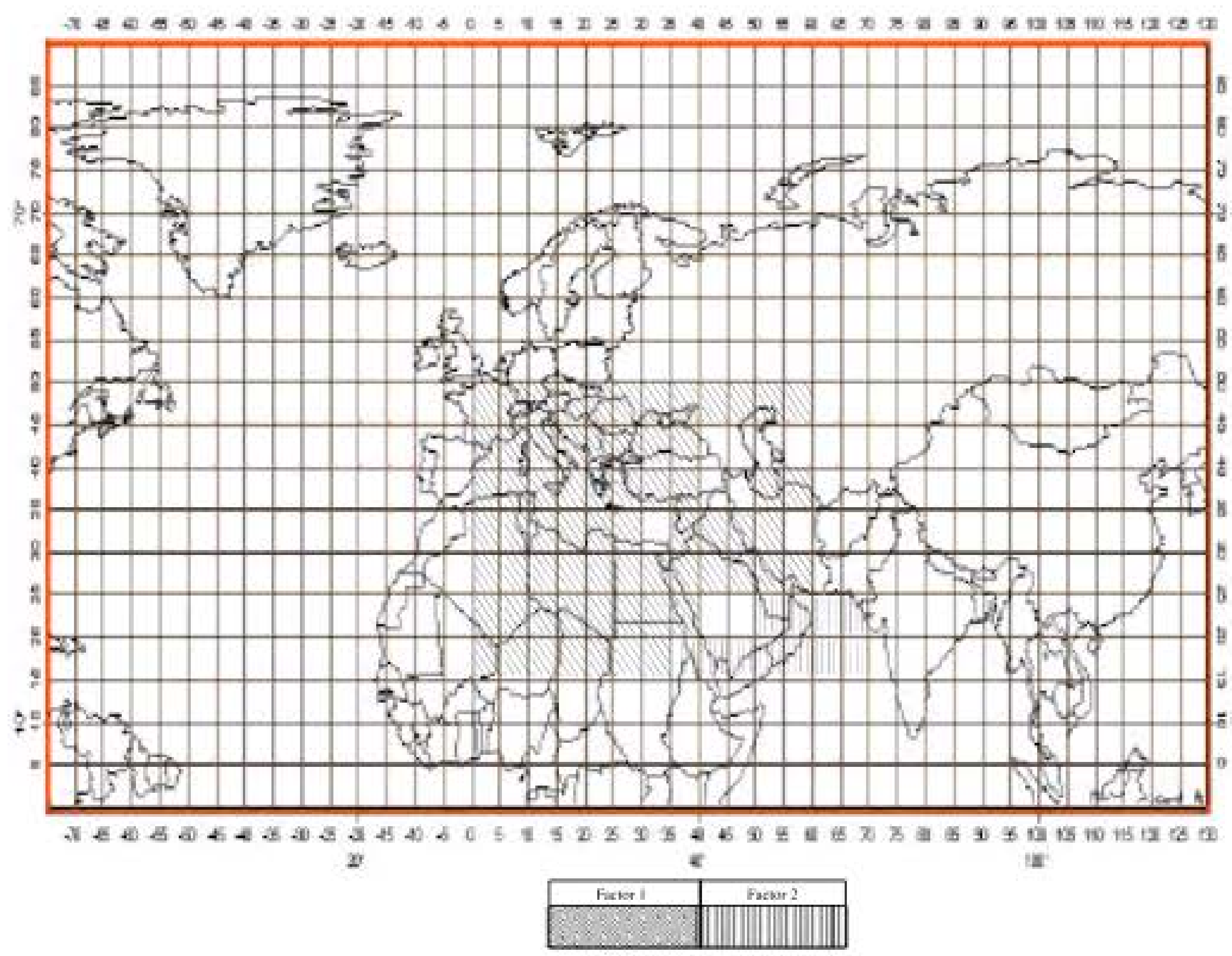

Fig. 3: The detected areas of relative humidity at 300 mb level in networks of 5×5 degree

of Persian Gulf and south of Red sea, The standardized sea surface temperature of Siberian network, The difference of temperature standardized between sea surface and the 1000 mb level of the Island

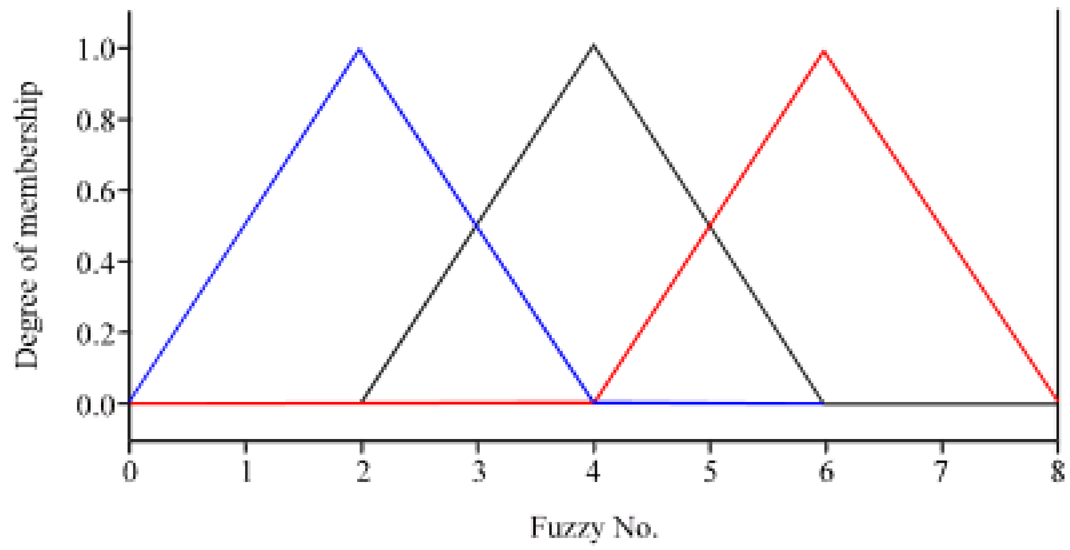

Fig. 4: Typical membership function with 3 results

network, The factor analysis of the relative humidity in the index area of factor 1 in a 5×5 degree networks (this region have shown in Fig. 3).

Fuzzy Logic

In classical models variables have real number values, the relationships are defined in terms of mathematical functions and the outputs are crisp numerical values (Center and Verma, 1998). In crisp sets, which are collection of objects with the same properties, the objects either belong to the set or not. In practice, the characteristics value for an object belonging to the set is coded as 1 and if it is outside the set then the coding is 0. The key idea in fuzzy logic is the allowance of partial belongings of any object to different subsets of the universal set instead of belonging to a single set completely. For instance, Fig. 4 shows a typical membership function which expresses the wordings as approximately 2, approximately 4 and approximately 6. Hence each one of these wordings is represented by a triangular function, which is referred to as the membership function. Any membership function indicates the partial belongingness of the value to implied sub-set such as approximately 2 with a membership value which assumes values between 0 and 1 inclusively (Center and Verma, 1998).

It is obvious that there are interferences between the numbers because of fuzzy linguistic word approximations. Likewise in fuzzy logic, values of variables are expressed by linguistic terms, the relationship is defined in terms of IF-THEN rules and the outputs are also fuzzy subsets which can be made crisp using defuzzification techniques. First the crisp values of system variables are fuzzified to express them in linguistic terms. Fuzzification is a method for determining the degree of membership that a value has to a particular fuzzy set. This is determined by evaluating the membership function of the fuzzy set for the value (Center and Verma, 1998).

Predicting of Annual Rainfall Using Mamdani Fuzzy Inference System

Fuzzy inference systems are non-linear models that describe the input–output relation of a real system using a set of fuzzy IF–THEN rules. Each fuzzy IF–THEN rule is a proposition of the form:

$$\text{Rule m: IF}(x_1 \text{ is } A_{1,m}) \text{ and } (X_2 \text{ is } A_{2,m}) \text{ and .....And } (X_k \text{ is } A_{k,m}) \text{ then Y is ......} \qquad (1)$$

Expressing the relation between K input variables x_1, x_2. . . x_k and the output y. The terms $A_{k,m}$ in the antecedents of the rules (i.e., the IF part of the rules) represent fuzzy sets used to partition the input space into overlapping regions (Zadeh, 1996). A fuzzy set is a generalization of the classical concept of set, in which membership defined as a question of degree rather than in a binary manner (either non-membership or full membership). Each fuzzy set $A_{k,m}$ in Eq. 1 is described by its membership function $A_{k,m}$, which evaluates the degree of membership of any value x_k in the fuzzy set $A_{k,m}$ through the corresponding membership value $A_{k,m}(x_k)$. The membership values $A_{k,m}(x_k)$ vary in the range (0, 1), where 0 indicates absolute non-membership and 1 indicates full membership of x_k in the fuzzy set $A_{k,m}$. The structure of the rule consequents (i.e. the THEN part of the rules) depends on the type of fuzzy inference system under consideration To state the relation between K, the input variable X_1, X_2, ..., X_k and the output is Y (Alexandra and Asaad, 2006).

In prior part of rules A_{km} shows the Fuzzy collection which are used for separating the entrant space in to the overlaps areas. A fuzzy system is a generalization of classic system which member ship function is introduced as a subject of degree in Binary form (each of no membership or perfect membership). The structure of result part (the part of rules) depends on type of the Fuzzy Inference system considered (Alexandra and Asaad, 2006).

Below stages was considered to collect the model of rainfall forecasting:

- Dividing the entrances and output into Fuzzy periods
- Making Fuzzy rules depend on the exist information
- Using the Fuzzy rules for predicting

The fuzzy membership function are collected in trapezoid from index of one tenth was used to collect the rain fuzzy membership functions. This index was prepared to prevent from deficiencies existing in normal present method in this thesis, DIP software was used to collect the fuzzy membership functions depend on the index of one tenth. Figure 5 and 6 show the selected fuzzy periods for rainfall and remote linkage controlling respectively. It is necessary to mention that this general division, was revised depend on the result sensitivity analysis of fuzzy model. In next stages, the final structure of fuzzy membership function was ascertained. Periods of selected rainfall depend on classification of the index of one tenths.

Fuzzy regions were divided in to five areas such as, very low, low, normal, high and very high. After the analysis of sensitivity for rain fuzzy division and above-mentioned signals, the general form of a collected fuzzy membership functions are assigned. Figure 7 shows the schematic of the fuzzy model diagram which is collected for rain forecasting.

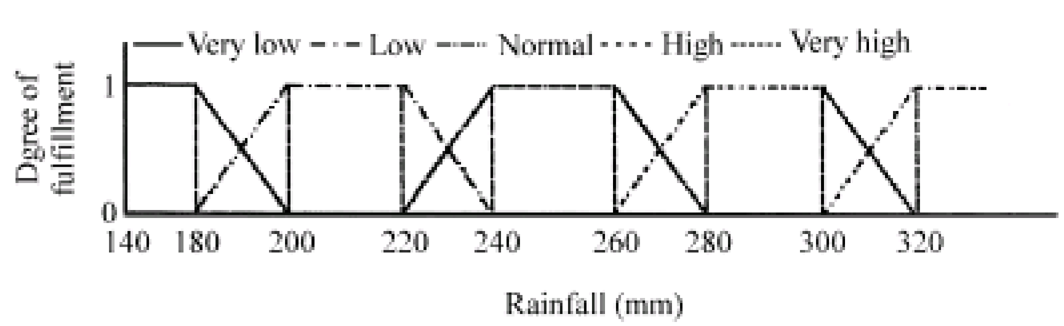

Fig. 5: The general form of fuzzy membership functions for rainfall

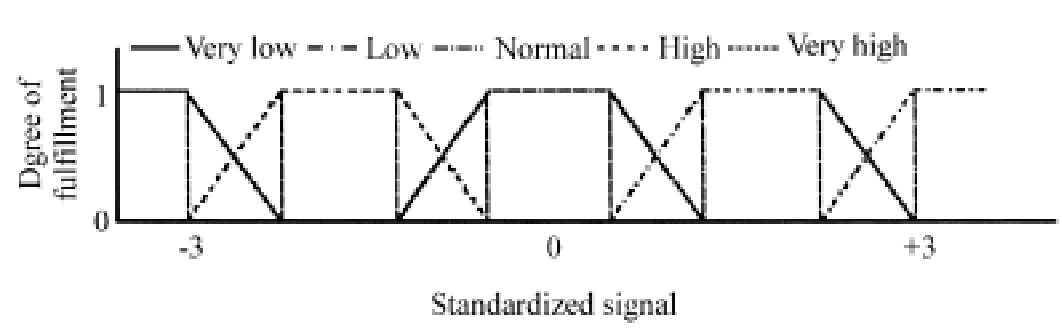

Fig. 6: The general form of fuzzy membership functions for meteorology signals

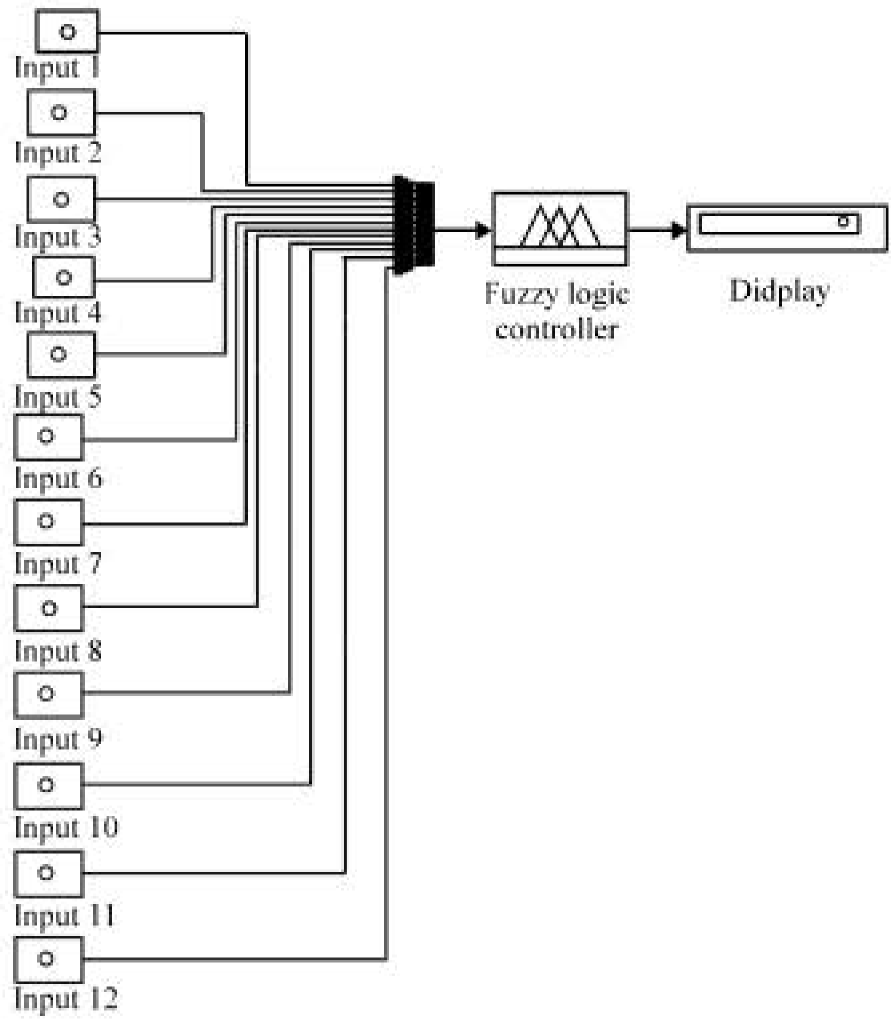

Fig. 7: The schematic of the fuzzy model diagram which is collected for the rain forecasting by use of conclusion fuzzy system in Mamdani way

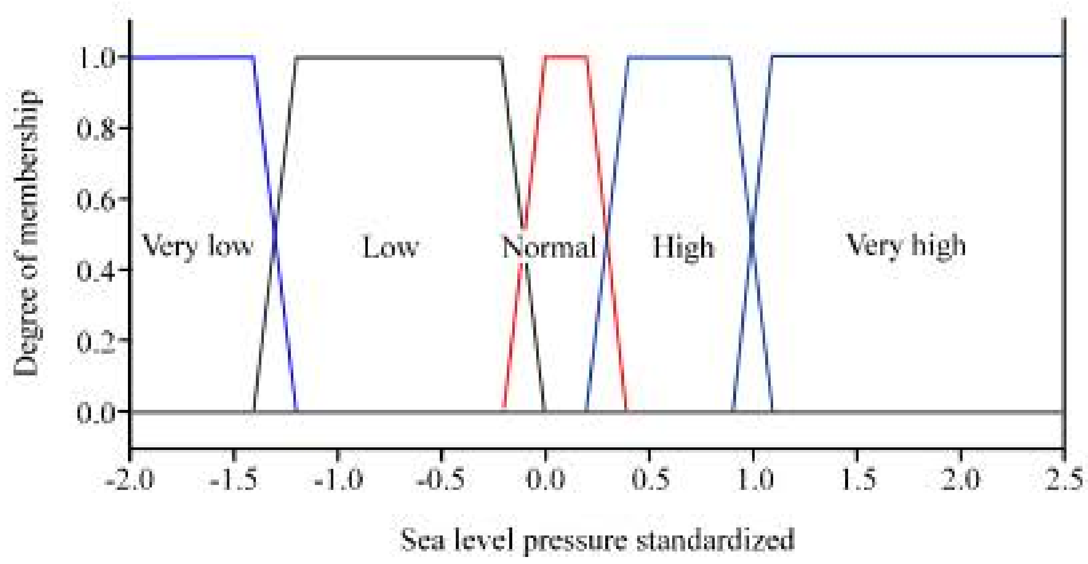

Fig. 8: Aden Gulf SLP standardized membership function

This model distributed the entrance data into two periods:

- Calibration of rule which in this study 1970-1992 are considered for rule making
- Forecasting period which in this study 1993- 2002 are considered for predicting

Depend on the information of 1970 - 1992; the fuzzy rules were made for predicting the rainfall during December to May. In the next stages, the rainfall predicted for years 1993 -2002.

As a result, Mamdani fuzzy inference system has used for seasonal rainfall forecasting. Also 13 input variables that are nominated in the section 1, have used. For FIS training, Membership Functions have been shown by Fig. 8-20.

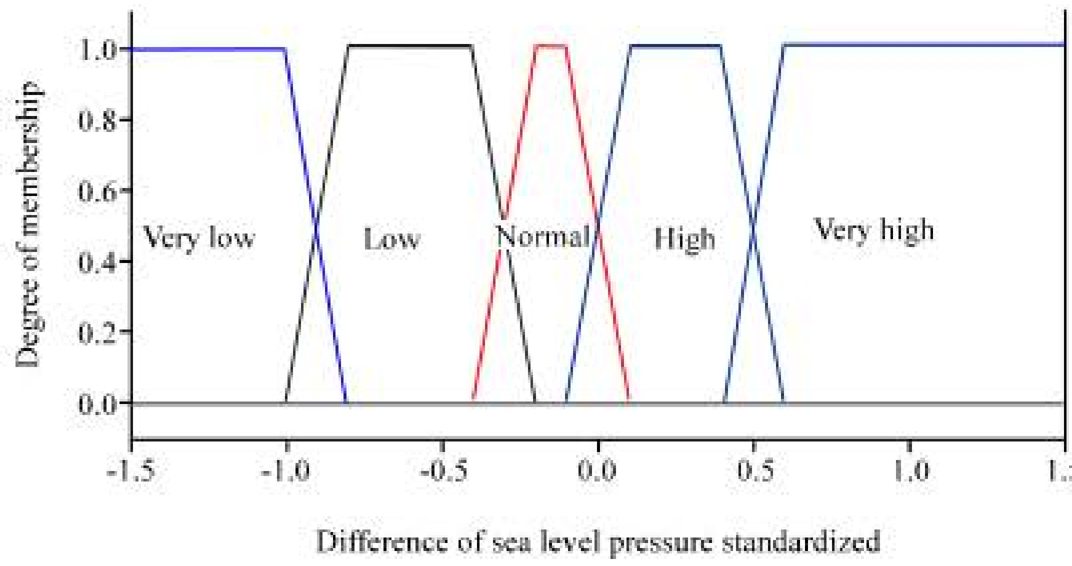

Fig. 9: Adriatic Sea and south Persian Gulf SLP standardized Difference membership function

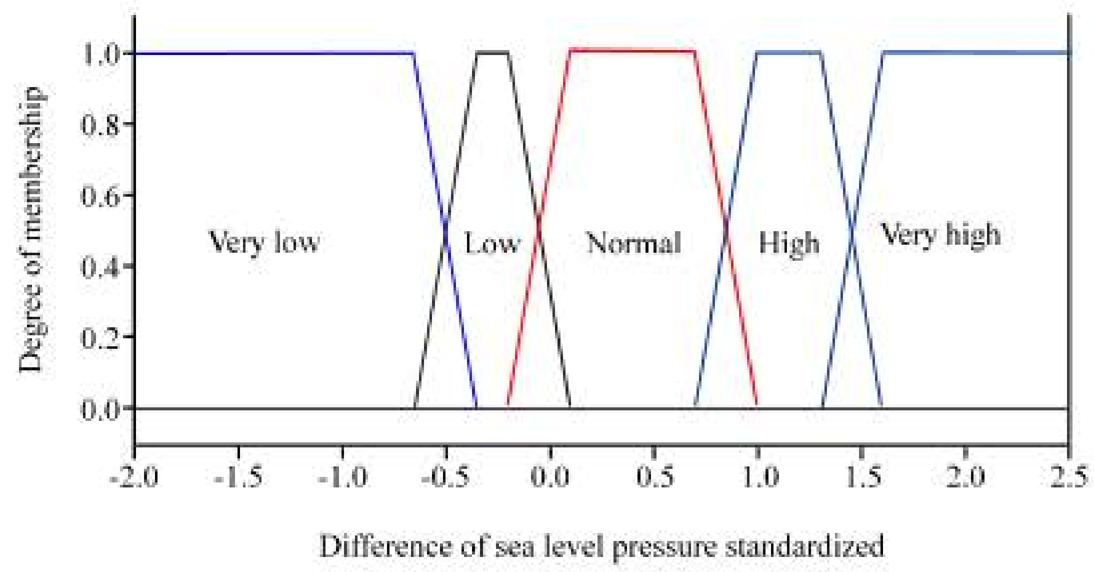

Fig. 10: Aral Lake and North Caspian Sea SLP standardized Difference membership function

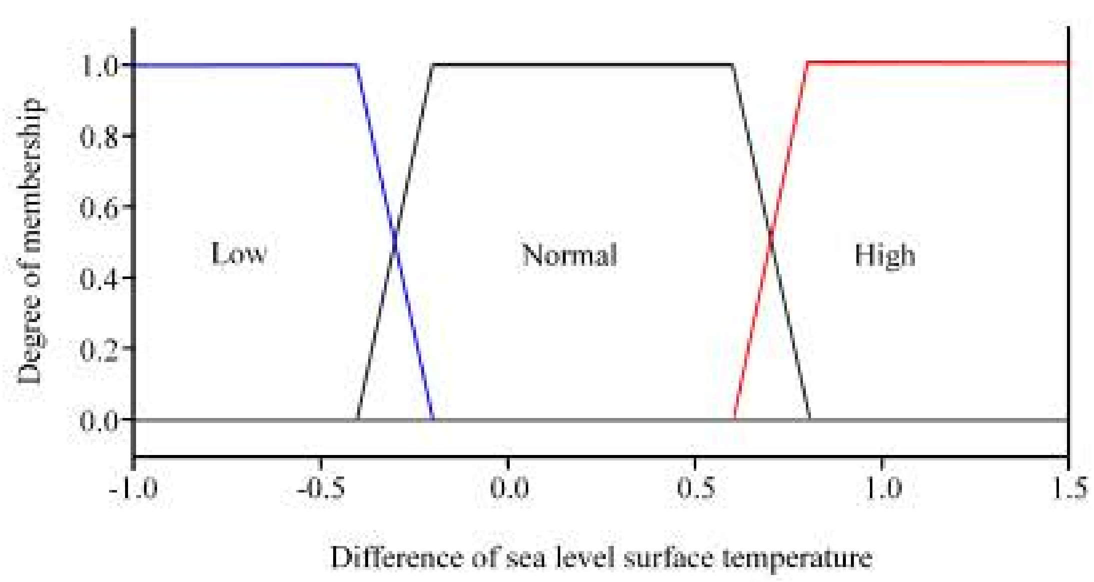

Fig. 11: Island grid SST standardized Difference membership function

The Result of the Mamdani Fuzzy Inference System

Table 1 shows the amount of observatory rain and predictive rain. It is necessary to mention that these results were calculated for 1993-2002 which were test period of the model.

It is necessary to remember that the amount of predictive rain in third column are obtained after de-fuzzition of model output achieved by non-fuzzition of central region therefore this amounts show the gravity of the output fuzzy series.

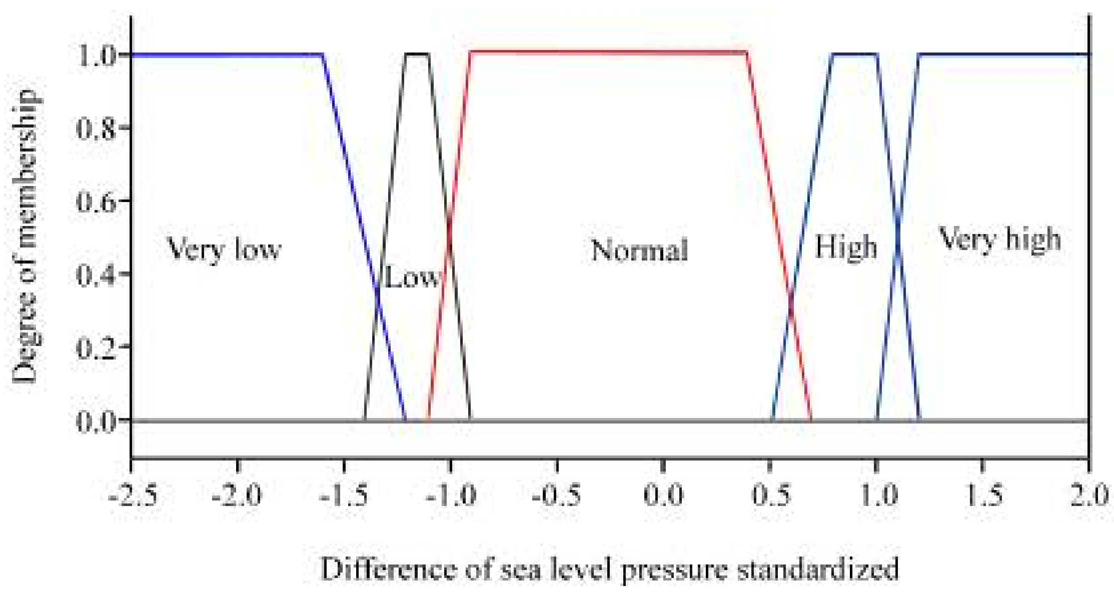

Fig. 12: North Red Sea SLP standardized membership function

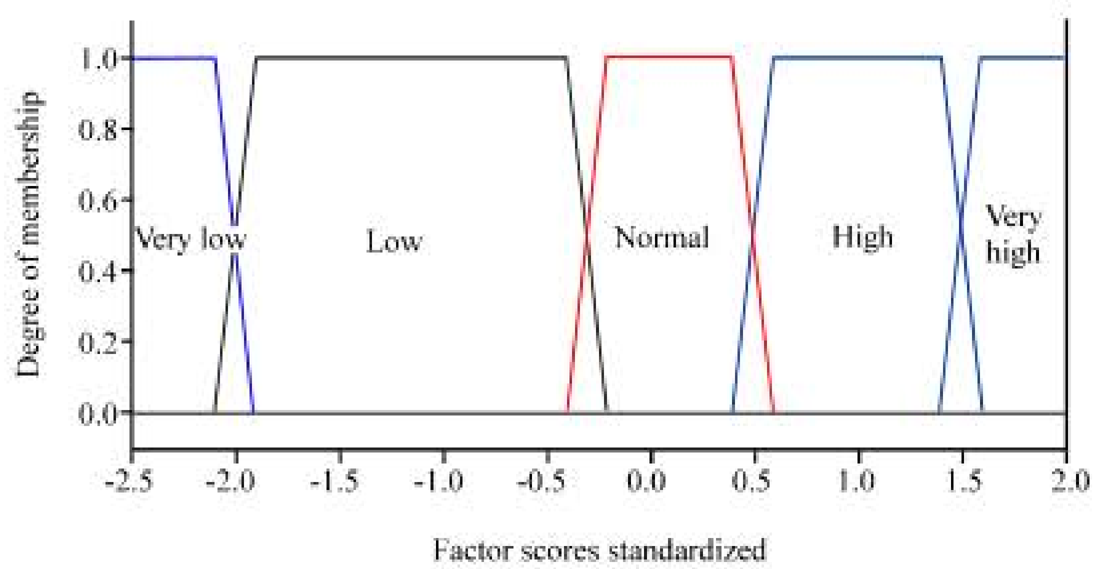

Fig. 13: Relative humidity standardized membership function

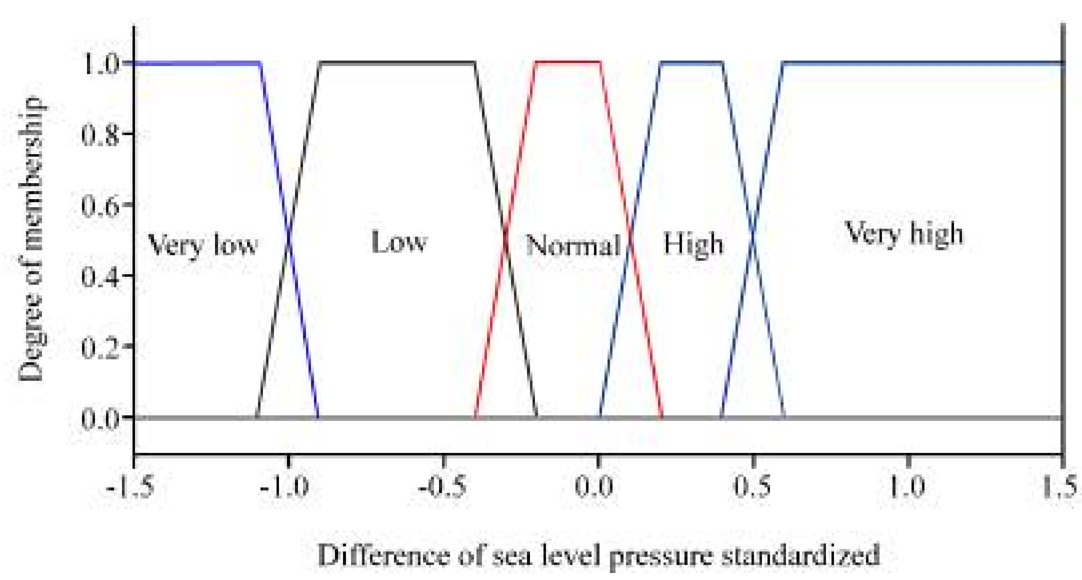

Fig. 14: South Persian Gulf and Oman Sea SLP standardized Difference membership function

The model results consideration shows the difference between the rain observed and predicted is in the acceptable range except of 1995, 2000, 2001 and this model can predict the rain with the acceptable error in 70% of the years. According to the observation, the model could not predict the rain of the years with low rainfall.

The reason of this matter is that these years were not repeated during forecasting model calibration and by this reasons the collective fuzzy rules did not include this events. It is necessary to

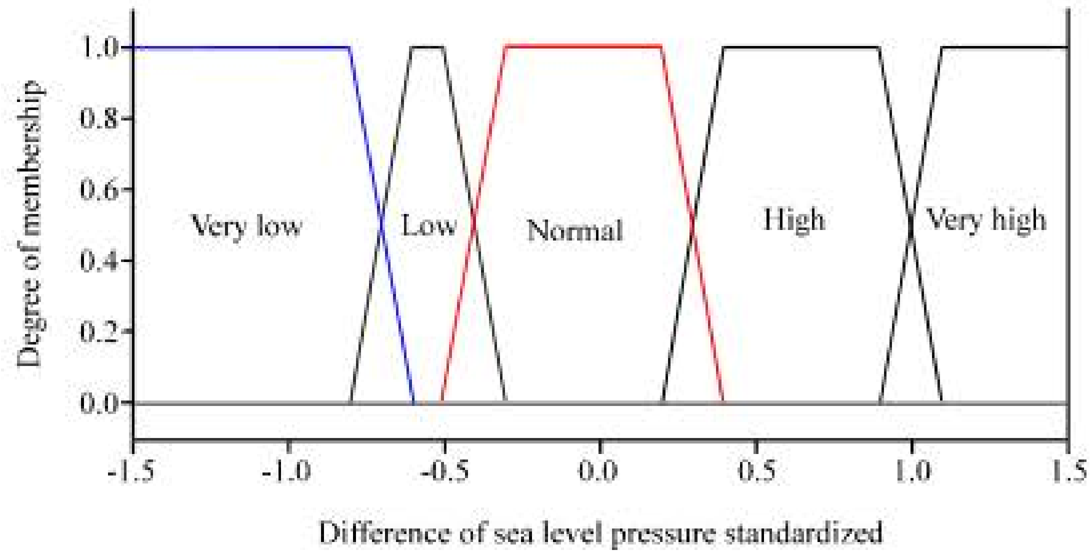

Fig. 15: South Persian Gulf and Arabic Sea SLP standardized Difference membership function

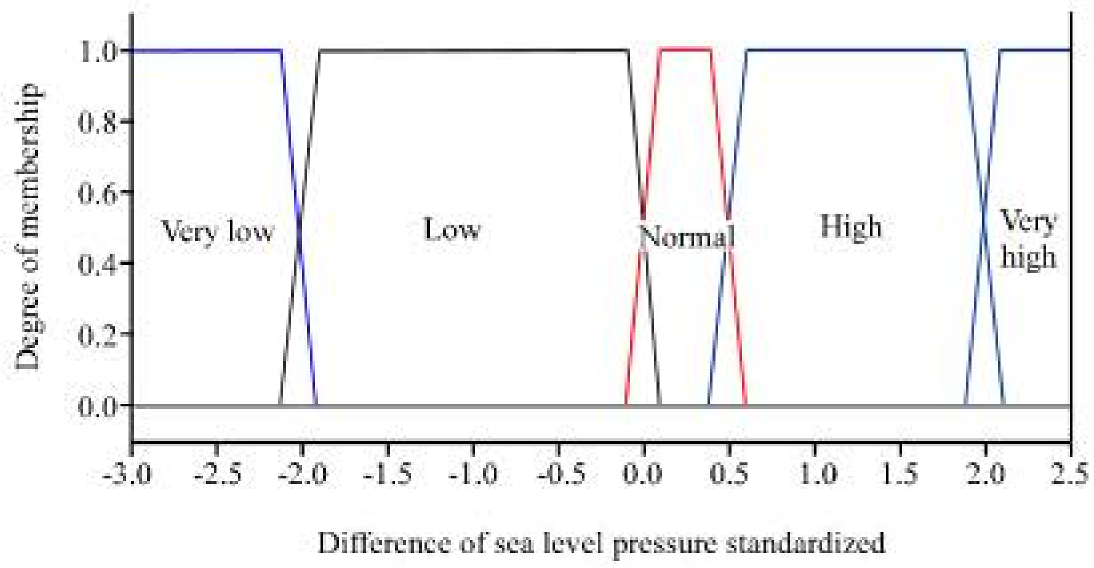

Fig. 16: South Persian Gulf and South Red Sea SLP standardized Difference membership function

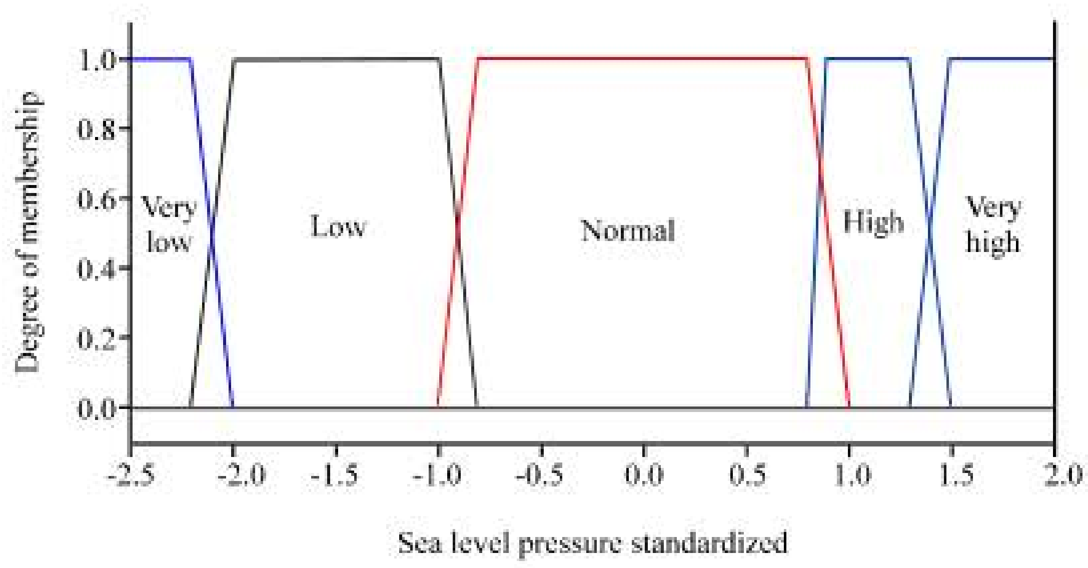

Fig. 17: South Persian Gulf SLP standardized membership function

Table 1: Seasonal Rainfall prediction using by FIS

Year	Predicted value	Observed value
1993	185.0	228.0
1994	210.0	158.1
1995	210.0	181.0
1996	210.0	210.0
1997	185.2	182.0
1998	210.0	247.5
1999	210.0	189.6
2000	210.0	106.4
2001	210.0	115.0
2002	210.0	197.2

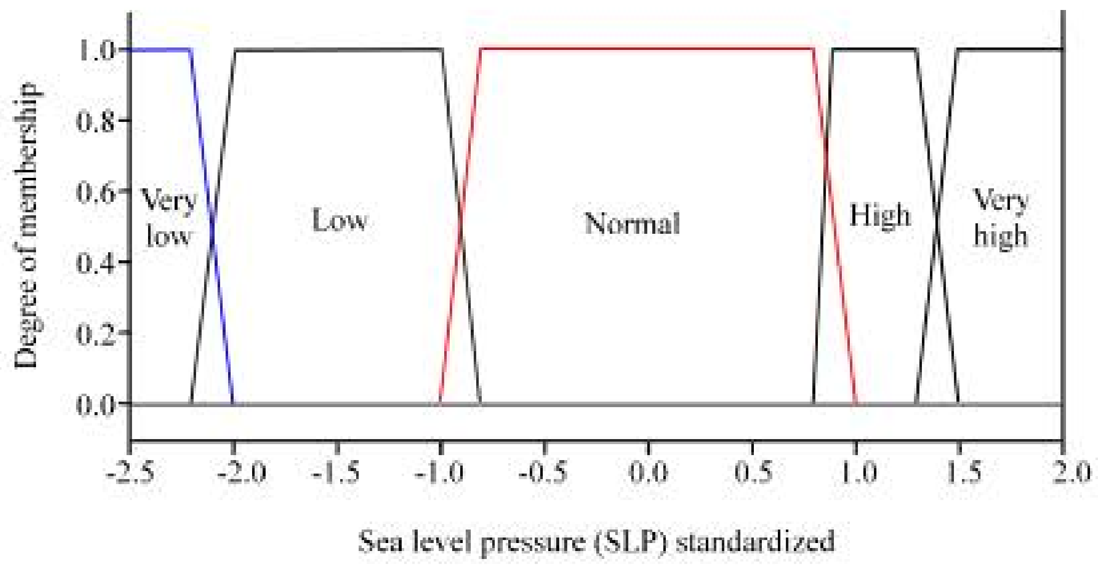

Fig. 18: South Red Sea SLP standardized membership function

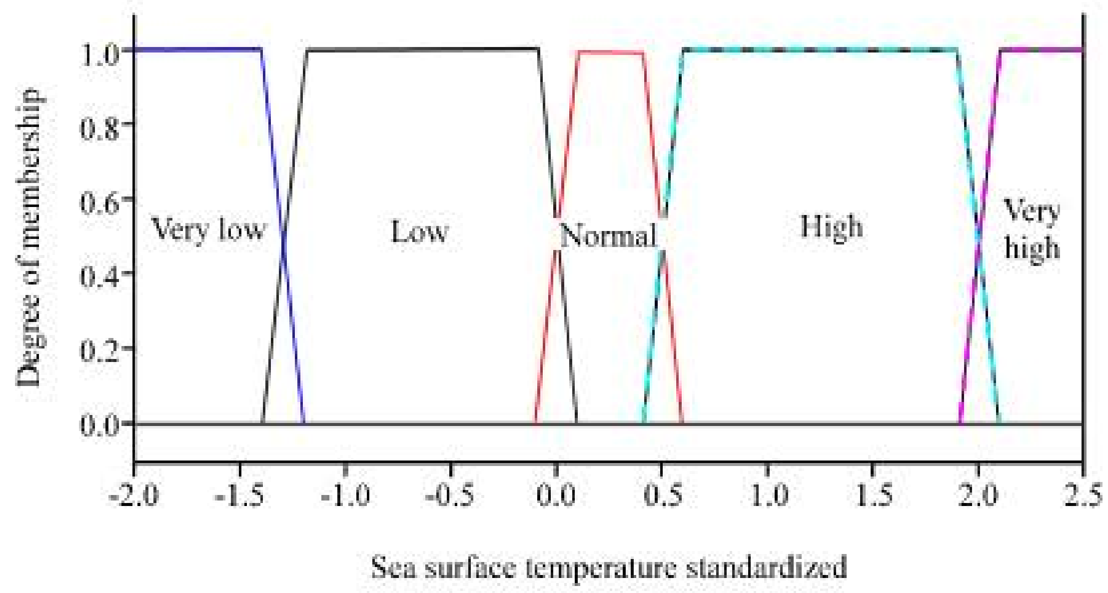

Fig. 19: Siberia SST standardized membership function

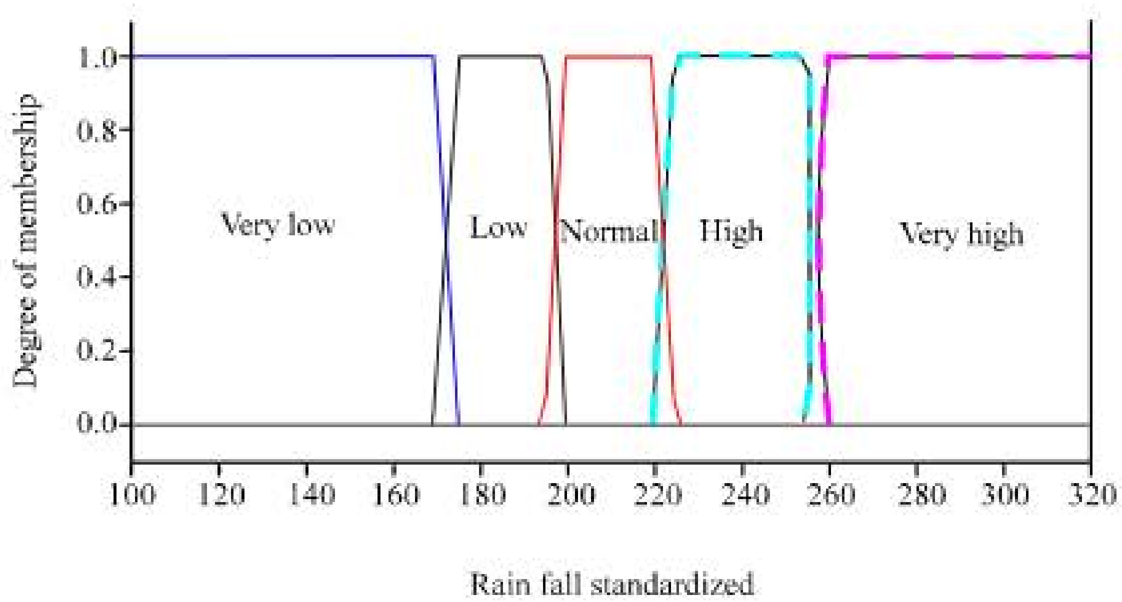

Fig. 20: Rainfall standardized membership function

remember that the lowest amount of rain was in rain time of 2000 and 2001.The chart of rain observed and predicted is shown by Fig. 21.

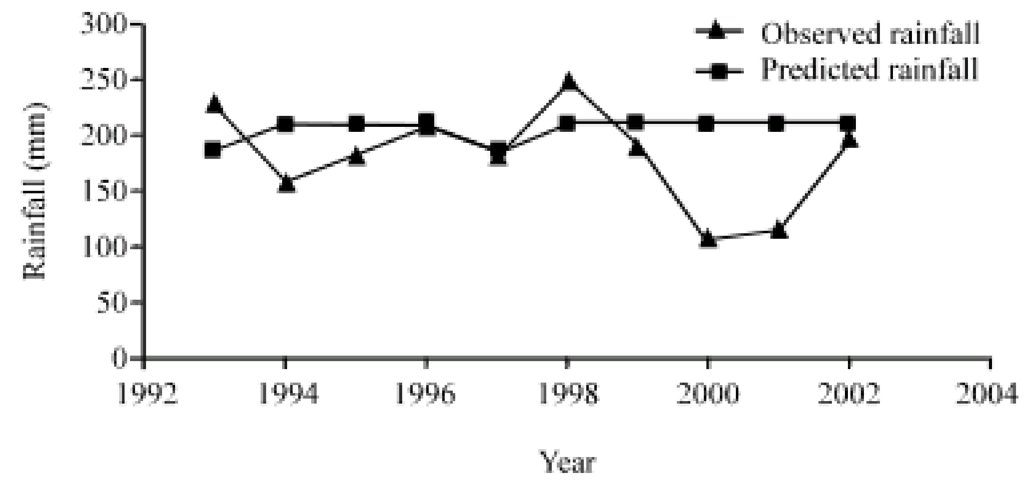

Fig. 21: Comparison of observatory rain and predictive rain in the area which was studied by MAMDANI fuzzy inference system

Root Mean Square Error for Fuzzy Model Was 52 mm

So, the fuzzy model was successful in the rainfall forecast. According to the results, the model was sensitive to statistical period and it is expected that the better results will be obtained by increasing the statistical periods.

DISCUSSION

Although the rainfall data from 1960 AD were recorded, there were many missing values in between and hence we had to restrict to periods for which a continuous time series was available. This was obtained for the period from 1970 to 2002. We divided the data from 1970-1993 as training set and data from 1993- 2002 as test set. In this study, we have used 6- month information (Dec. to May) of the each year in each of the 33 previous year for rainfall data and also we have used 6 month information (June to Nov.) of the each year in each of the 33 previous year for the predictors selected which would give good generalization properties.

We can infer from the above discussion that the variables used in the rainfall forecast model have been able to detect the distribution pattern of rainfall in the region and can act as predictors in rain forecast models. It must be noted that all the signals selected in this study conform to the cyclonic routes of the Middle East and Iran, which were studied by Alijani (2002). This is confirmed by the results of the research. A comparison of the results of the study with those of other researches such as Karamouz *et al*. (2005) in the western part of the country, or Mousavi Baygi *et al*. (2008) in the region of Khorasan including three provinces of Razavi, Northern and Southern Khorasans, indicates the high efficiency of such methods as neural networks, adaptive neuron-fuzzy networks in predicting the rainfall.

Thus, based on the information from the previous years, the model would predict the amount of rainfall to be expected in each 6-month of the each year an interval Dec. to May. Finally, the observed data and predicted data have plotted. The results showed that FIS model is promising and efficient and can successfully predict the amount of the rainfall in 70% of the years in the selected area.

CONCLUSIONS

In this study, we attempted to forecast the rainfall (six month ahead) based on Fuzzy Inference System techniques. As the RMSE values on test data are comparatively less, the prediction models are reliable. As evident from Fig. 21, there have been few deviations of the predicted rainfall value from the actual. As climate and rainfall predication involves tremendous amount of imprecision and uncertainty, soft computing technique might warrant the ideal prediction model. On the other hand, the proposed prediction models based on soft computing are easy to implement and produces desirable mapping function by training on the given data set. The model requires information only on the input variables for generating forecasts. In our experiments, we used only 23 years training data to evaluate the learning capability. The model performance could have been further improved by providing more training data. Moreover, the considered connectionist models are very robust, capable of handling the noisy and approximate data that are typical in weather data and therefore should be more reliable in worst situations. Choosing suitable parameters for the soft computing models is more or less a trial and error approach. Optimal results will depend on the selection of parameters.

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