Prediction of Rainfall for Ethiopian Upper Blue Nile Basin Using Soft Computing Models

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Abstract

Predicting rainfall for Ethiopian Upper Blue Nile Basin has several benefits for efficient resource planning and management including Renaissance Dam, agriculture, famine and disease control, rainwater catchment and ground water management. This paper predicts rainfall of Ethiopian Upper Blue Nile Basin to come up with an accurate model and prototype. Kiremt season rainfall and monthly rainfall predictions with different time lag were made using neural network, mamdani and sugeno adaptive neuro fuzzy models. A prototype was also developed that makes the predictions which incorporate many features, including capability to tune prediction rules enabling to catch up future unseen rainfall events. The result shows the soft computing models perform the prediction with relatively small error. The developed soft computing models show better skill than techniques used by Ethiopian National Meteorological Service Agency (ENMSA) and other previous studies which used statistical techniques. In addition, the outputs of this study are a very significant contribution to other researchers and experts in the rainfall prediction domain.

Keywords: Prediction; Renaissance Dam; Agriculture; Predictors; Soft Computing Models; Prediction Rules

1. Introduction

Ethiopia, which is located 3.0°-15°N, 33°-48°E, is a developing country striving to eradicate poverty. The Government of Ethiopia is formulating many policies and strategies to achieve this goal. Moreover, Ethiopia is struggling to achieve the Millennium Development Goals (MDGs) and its Growth and Transformation Plan (GTP). Currently the Ethiopian Government is undergoing the implementation of Ethiopian Renaissance Dam which will generate 6000 MW of electricity.

Ethiopian economy is agriculture lead. Famine is also the main problem which makes Ethiopian to have a negative image in the international arena. The problem with enough water provision for drinking and irrigation is also alleviated using ground water and surface water resources. Rain water catchment system is becoming popular in the northern part of the country to reduce shortage of water. Pre preparation for diseases like malaria is a must in rural areas. Rainfall is also used as a main affecting factor/predictor by several researches both locally and internationally. Hence, accurate prediction of rainfall is critically important for the success of the solutions provided by the government in all the areas mentioned above.

According to Diriba and Branston [1], Ethiopia has three climatological rainy seasons: June - September (called *kiremt*), October - January (*Bega*), and March - May (*Belg*). As pointed out by Paul and Rajagopalan [2], roughly 70% of annual precipitation in the Upper Blue Nile basin of Ethiopia is delivered during the *kiremt* season.

According to Paul and Rajagopalan [2] and Diro *et al.* [3], Ethiopian National Meteorological Service Agency (ENMSA) solely relies on analogue forecasts; statistical method based on analogue multivariate El Nino – Southern Oscillation (ENSO) index years whose output give probabilistic categorical forecasts of regional Ethiopian rainfall which is not consistently skillful for all regions and seasons. An interview with two senior experts from ENMSA also indicates that the agency is using the analogue technique dominantly for long term prediction. The findings from both papers indicate significant progress from ENMSA.

Accurate prediction of Ethiopian Upper Blue Nile (EUBN) Basin is a must to achieve the generation of

6000 MW energy in a consistent manner. Electricity will be generated in a consistent way both in rainy and non-rainy seasons if rainfall is predicted accurately. In addition, infrastructures found next to the dam can be protected from flooding. The analogue technique used by ENMSA is inappropriate to get these benefits because it provides probabilistic and categorical forecast which involve high expert judgments. As stated by Fallah-Ghalhary *et al*. [4] and El-Shafie *et al*. [5], accurate prediction of rainfall is a very challenging and complex issue.

This paper tries to alleviate this problem by modeling the variability of rainfall in Ethiopian Upper Blue Nile basin using soft computing models, specifically neural network and neuro fuzzy models. As stated by Abrahm *et al.* [6], soft computing techniques have the potential to predict complex, imprecise, uncertain and non-linear situations, such as rainfall, in a relatively accurate manner. Figure 1 shows the EUBN Basin. The main objective of this paper is to predict the *kiremt* season and monthly rainfall of EUBN Basin accurately and deterministically in time series using soft computing models and build a working prototype.

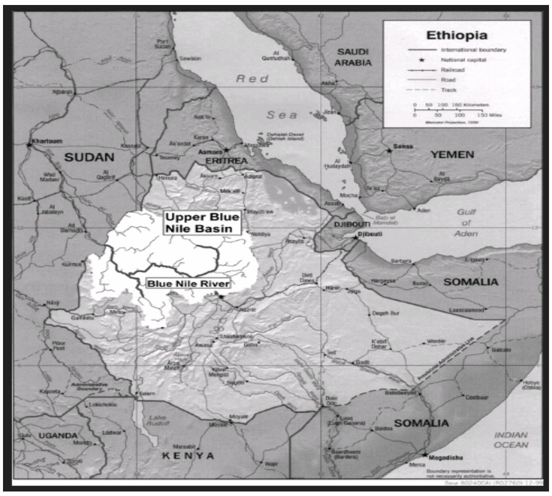

Figure 1: Ethiopian Upper Blue Nile Basin

2. Literature Review

Singhrattna *et al.* [7] and Ntale *et al.* [8] make use of two statistical modeling techniques for seasonal rainfall in Thailand and East Africa (excluding Ethiopia). Singhrattna *et al.* [7] utilized linear and non-linear regressions while Ntale *et al.* [8] utilized linear regression. Non-Linear regression better predicts rainfall than linear regression because rainfall has a non-linear nature. The output of the statistical techniques is a formula. But, it is difficult to modify or tune it to catch up future rainfall events.

Abraham *et al.* [6], Fallah-Ghalhary *et al*. [4], and El-Shafie *et al*. [5] pointed out that rainfall is a non-linear phenomenon. Neuro-fuzzy is a fusion of artificial neural network and fuzzy systems (fuzzy logic). Both neural network and fuzzy logic try to imitate the learning process of the human mind. Fuzzy logic contains fuzzy set theory and fuzzy if-then rules with reasoning capability. In fuzzy systems, knowledge is represented explicitly in if-then rule form but it is not an easy task to tune and refine these rules because it requires high expert judgment. Identification of fuzzy set is also a difficult task which requires high expert involvement.

In neural network, knowledge is gained by learning from data but there is no explicit way of knowledge representation, it is just coded as black box in the neural network. Abraham [11] and Robert and Henk [13] show that the drawbacks of fuzzy logic and neural network are complementary to each other. Hence, the drawbacks are eliminated by using neuro-fuzzy system which combines the transparent and interpretable if-then rule of fuzzy systems with the learning capability of neural network.

Abraham *et al.* [6] used soft computing techniques (including neural network and neuro-fuzzy model) and Multivariate Adaptive Regression Splines (MARS) to forecast annual rainfall at Kerala State, southern part of Indian Peninsula. El-Shafie *et al.* [5] use an ANFIS (i.e., sugeno) to model the prediction of rainfall for Klang River in Malaysia on a monthly basis. Fallah-Ghalhary *et al.* [4] used mamdani fuzzy inference systems for forecasting seasonal rainfall in Khorasan province in North-East of Iran.

As far as the Ethiopian context is concerned, the statistical linear regression techniques were very widely used rather than soft computing techniques such as neural network and neuro fuzzy model.

Diro *et al.* [3] made seasonal forecasts of the Ethiopian spring (*belg*) rainfall using Multiple Linear Regression (MLR) and Linear Discriminant Analysis (LDA). 35 years (1960-2003) of SST data were used. SST values at different time lag and different regions were used as predictors. The MLR gives deterministic outputs while the LDA gives probabilistic outputs. The result shows that the forecast shows better skill than analogue forecasts (which is used by ENMSA).

Diriba and Branston [1] examined the predictive potential for June-September (*kiremt*) rainfall in Ethiopia using statistical (multivariate linear regression) approach. It used rainfall data of 1970-2004. Their study tried to find relationship between ENSO, and other phenomena with *kiremt* rainfall of Ethiopia that predicts the rainfall prior to the rainy season (*kiremt*) onset. The predictors from March to May were used. The result shows that the Ethiopian *kiremt* rainfall is mainly governed by ENSO.

The paper by Paul and Rajagopalan [2] forecasts *kiremt* rainfall of Ethiopia. The authors stated that ENSO phenomenon is a main driver of inter-annual variability of seasonal precipitation in EUBN basin. They used one season lead predictors (from March to May) to forecast the rainfall in the next season (June to September). They used statistical regression technique - a non parametric local polynomial regression (which is non-linear), and the result shows significant skill better than ENMSA analogue technique.

Three points make the present paper different from others. First, soft computing techniques were utilized. Second, combination of different prediction approaches with different time lags were made to give high flexibility for decision makers. Third, prototype that predicts rainfall was developed which makes the work more real. An interview with two senior experts in ENMSA indicates that such prototype will help the prediction process of the agency.

3. Data Preprocessing

The data for predictors and predictand is collected from NCEP Reanalysis Derived Data provided by the NOAA/OAR/ESRL PSD, Boulder, Colorado, USA, from their web site data warehouse [9]. The monthly rainfall data used for this research was collected from the University of Delaware Precipitation and Air temperature V3.01 gridded at $0.5^0 \times 0.5^0$ resolutions.

University of Delaware rainfall Data was validated with CPC Merged Analysis of Precipitation (CMAP) Enhanced data. The two data sets are correlated with 0.98 coefficients. Paul and Rajagopalan [2] correlate the data (Climate Research Unit Data of University of East Anglia, UK) with University of Delaware rainfall Data with correlation coefficient of 0.79. This validates the consistency of University of Delaware data.

3.1 Rainfall Data

The collected rainfall data was subsetted from the global rainfall data. The subsetted spatial data was spatially averaged for the 68 cells, shown in Figure 2, by adding each pixel's data to get single average values that represent monthly rainfall value. This process was repeated temporally for each of the 1332 months that cover the years 1900 to 2010. The collected rainfall data has high quality and it is tested for outliers using Box Whisker plot which is referred as a useful plot by Stephenson [10]. As shown in Figure 3, the data is free of outliers.

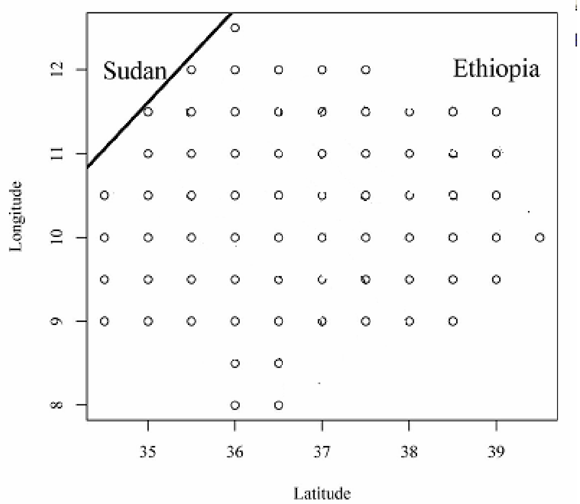

Figure 2: Sample points (grids) of EUBN Basin

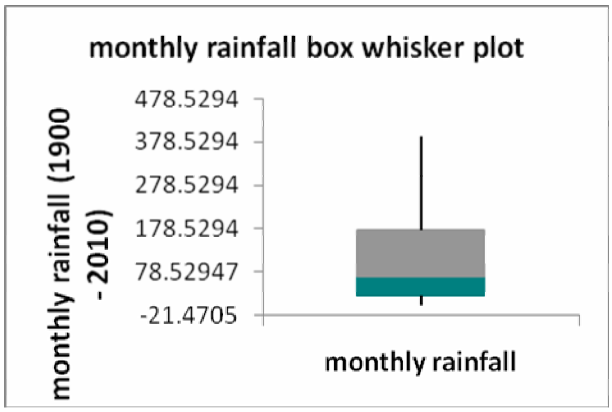

*Figure 3: B*ox Whisker plot for rainfall data.

3.2 Predictor Data

As stated in [1, 2], the *kiremt* rainfall of Ethiopia (including EUBN Basin) is primarily governed by ENSO. Hence, this research retains ENSO predictors to predict the *kiremt* rainfall of EUBN Basin. Five ENSO predictors were selected from the suite of potential large-scale predictors as in [2] to predict EUBN Basin rainfall: sea surface temperature (*sst)*, sea level pressure (*slp)*, geo potential height (*hgt)*, air temperature (*at)*, and *palmer drought severity index* (*pdsi*). However, Paul and Rajagopalan [2] recommend using *sm* instead of pdsi to get a more accurate result. Based on this fact, this research project maintains the first four predictors and makes use of *sm* instead of pdsi. *Sst* data was collected from NOAA extended reconstructed *sst* V3b at 2^0 x 2^0 grid data resolution from 1900 to 2010. *Slp*, *hgt* and *at* were collected from NOAA - CIRES 20th century reanalysis version 2 with 2^0 x 2^0 grid data resolution from 1900 to 2010. *Sm* data was collected from CPC derived NCEP - NCER reanalysis data with 0.5^0 x 0.5^0 grid data resolution from 1948 to 2010

Only data of those regions, out of the global coverage, that affect the EUBN basin rainfall should be used as predictor. Matlab Script that performs spatio-temporal correlation is written and used to identify these regions. Figure 4 shows sample spatio temporal correlation output for sst and Figure 5 shows the highly correlated regions for each predictor.

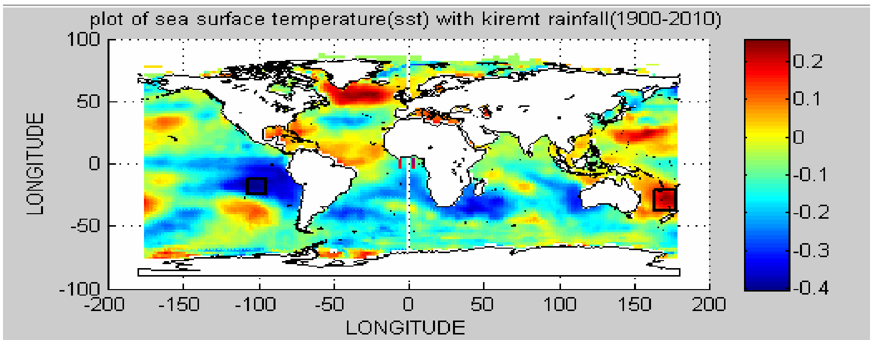

Figure 4: Spatio temporal correlation for sst

Table 1: Spatial coverage for predictors

Predictor Variable	*Spatial Region Covered*	*Correlation with UBN Rainfall*
Sea Surface Temperature(*sst*)	24.0^0 – 28.0S;168.0^0 E– 174.0E	+0.25
Sea Surface Temperature(*sst*)	14.0^0 – 18.0^0S;100.0^0 – 108.0^0W	- 0.4
Sea Level Pressure(*slp*)	60.0^0 – 64.0^0N;14.0^0 – 18.0^0W	+0.33
Sea Level Pressure(*slp*)	26.0^0 – 36.0^0S; 148.0^0 – 156.0^0E	-0.36
Geo Potential Height-500mb (*hgt*)	26.0^0 – 30.0^0N;80.0^0 – 88.0^0W	+0.33
Geo Potential Height-500mb (*hgt*)	36.0^0 – 38.0^0S;44.0^0 – 48.0^0E	-0.33
Air Temperature(at)	60.05^0 – 58.5^0N;144.4^0 – 148.1^0W	+0.31
Air Temperature(at)	21.65^0 – 25.45^0S;22.5^0 – 30.0^0W	-0.35
Soil moisture (*sm*)	39.25^0 – 36.25^0N;55.25^0 – 59.25^0E	+0.46

Sub setting out of the global coverage was done based on predictor's coverage. Then, the predictors' data was averaged for *belg* season (March to May) for 111 years (1900 to 2010). This data is used for *kiremt* rainfall prediction one season ahead.

Previous rainfall with different time lags as predictors and the predicting month rainfall as predictand were used for the other predictions i.e., monthly rainfall prediction one year ahead and one month ahead. This was done by further rearranging the 1332 records monthly rainfall data of 1900 to 2010 years. Moreover, the *kiremt* rainfall prediction eight months ahead was made by adding the predicted month rainfall of each month in *kiremt* season using monthly prediction one year ahead. Normalization was done automatically at modeling step.

4. Experimental Analysis and Modeling

Three soft computing models: Artificial neural network model, mamdani adaptive fuzzy inference model, and adaptive neuro-fuzzy (sugeno) inference model (also called ANFIS) were used to predict the EUBN Basin rainfall. Three different predictions were made using each model: *kiremt* rainfall prediction one season ahead, monthly rainfall prediction one year ahead, and monthly rainfall prediction one month ahead. The fourth prediction, *kiremt* rainfall eight month ahead, was inferred from monthly rainfall prediction one year ahead. These predictions give flexibility to decision makers. Making one prediction compensates for the other's drawbacks. To accomplish these jobs, several experiments were done for each processed data. The result for each kind of prediction with best accuracy is presented next. Now the data is ready for modeling. The experimentation was done using Matlab 2012a. Four separate data sets are ready for the first prediction, six separate data sets are ready for second prediction, and twelve separate data sets are ready for third prediction.

4.1 Kiremt Rainfall Prediction a Season Ahead

The mamdani adaptive neuro fuzzy model performs better for this prediction. At this prediction, the predictors are average ss, slp, at, hgt, and sm of previous season (March - May) and the predictand is *kiremt* rainfall. Indexed data (subtracting the less correlated region from the highly correlated one) with input membership function gaussmf and output membership function triangular, fuzzy c-mean clustering with 8 numbers of clusters gives better accuracy. The data division style is 53 records (1948 - 2000) and 10 records (2001-2010) for training and testing, respectively. Hybrid learning algorithm was used.

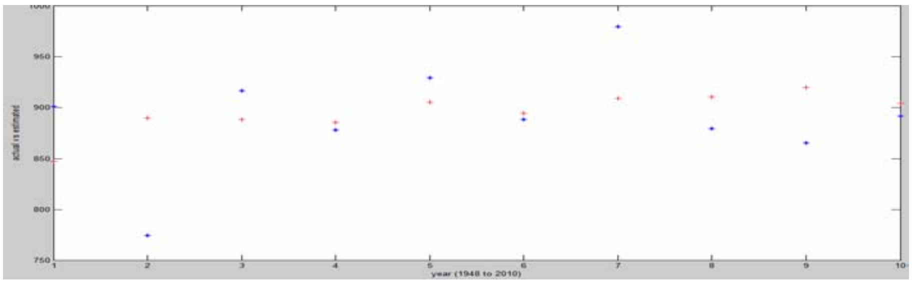

Figure 5: Plot of actual (blue) and predicted (red) value for the test range

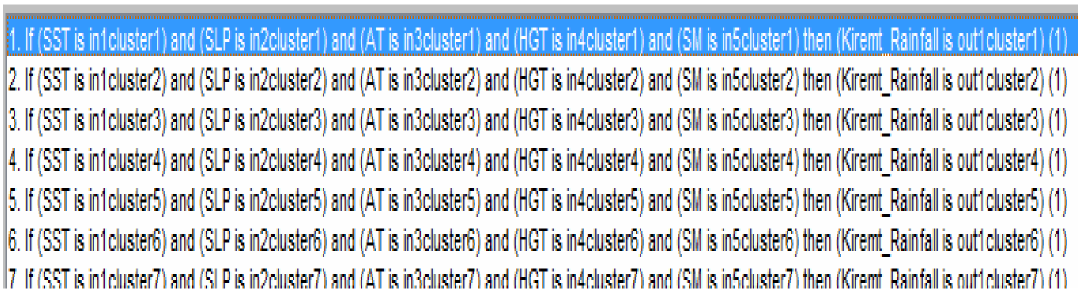
1. If (SST is in1cluster1) and (SLP is in2cluster1) and (AT is in3cluster1) and (HGT is in4cluster1) and (SM is in5cluster1) then (Kiremt_Rainfall is out1cluster1) (1)
2. If (SST is in1cluster2) and (SLP is in2cluster2) and (AT is in3cluster2) and (HGT is in4cluster2) and (SM is in5cluster2) then (Kiremt_Rainfall is out1cluster2) (1)
3. If (SST is in1cluster3) and (SLP is in2cluster3) and (AT is in3cluster3) and (HGT is in4cluster3) and (SM is in5cluster3) then (Kiremt_Rainfall is out1cluster3) (1)
4. If (SST is in1cluster4) and (SLP is in2cluster4) and (AT is in3cluster4) and (HGT is in4cluster4) and (SM is in5cluster4) then (Kiremt_Rainfall is out1cluster4) (1)
5. If (SST is in1cluster5) and (SLP is in2cluster5) and (AT is in3cluster5) and (HGT is in4cluster5) and (SM is in5cluster5) then (Kiremt_Rainfall is out1cluster5) (1)
6. If (SST is in1cluster6) and (SLP is in2cluster6) and (AT is in3cluster6) and (HGT is in4cluster6) and (SM is in5cluster6) then (Kiremt_Rainfall is out1cluster6) (1)
7. If (SST is in1cluster7) and (SLP is in2cluster7) and (AT is in3cluster7) and (HGT is in4cluster7) and (SM is in5cluster7) then (Kiremt_Rainfall is out1cluster7) (1)

Figure 6: Sample rule generated for mamdani *kiremt* rainfall prediction

4.2 Monthly Rainfall Prediction One Year Ahead

Neural Network performs better for this prediction. The predictors are the last twelve years' monthly rainfall data centered at the predicting month with two layers (one hidden and one output layer) and the following model specification: number of neurons in input layer is 12, number of neurons in hidden layer is 8 and number of neurons in output layer is 1. Levenberg-Marquardt learning algorithm was used with data division style 70% (832 records), 15% (178 records), and 15% (178 records) for training, validation and test, respectively.

4.3 Monthly Rainfall Prediction One Month Ahead

Again, neural Network performs better for this prediction. The predictors are the last twelve months' monthly rainfall data proceeding the predicting month with two layers (one hidden and one output layer) and the following model specification: number of neurons in input layer is 12, number of neurons in hidden layer is 8 and number of neurons in output layer is 1. Levenberg-Marquardt learning algorithm with data division style of 70% (924 records), 15% (198 records), and 15% (198 records) for training, validation and test, respectively

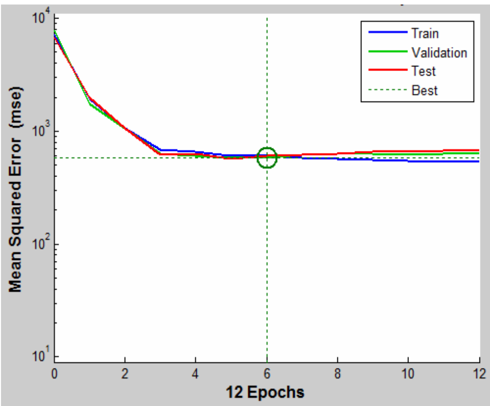

Figure 7: Performance plot for monthly rainfall prediction one year ahead

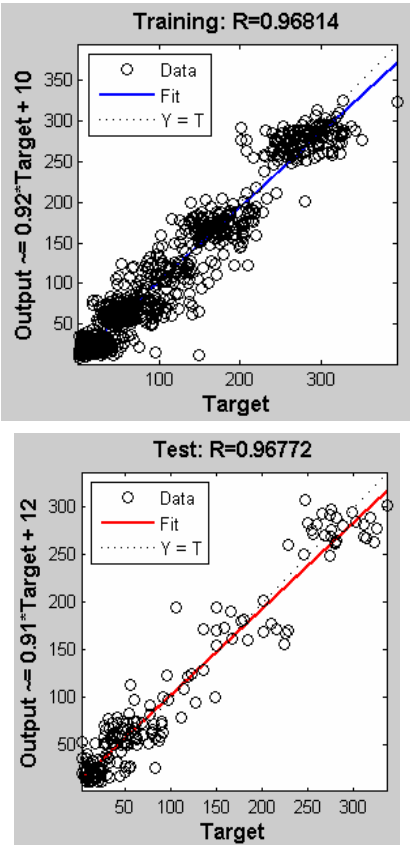

Figure 8: Regression plot for monthly rainfall prediction one year ahead

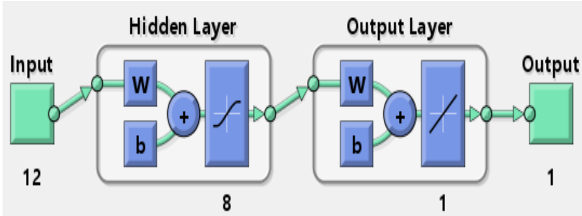

Figure 9: neural network architecture for monthly rainfall prediction one year ahead

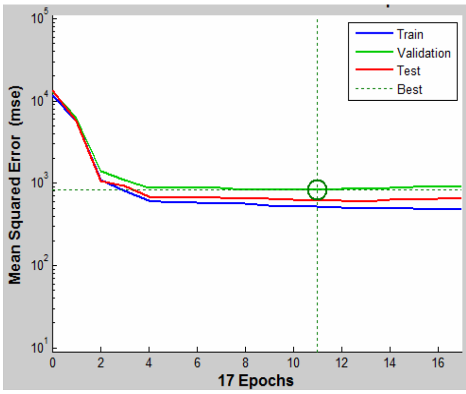

Figure 10: performance plot for monthly predictions one month ahead using neural network

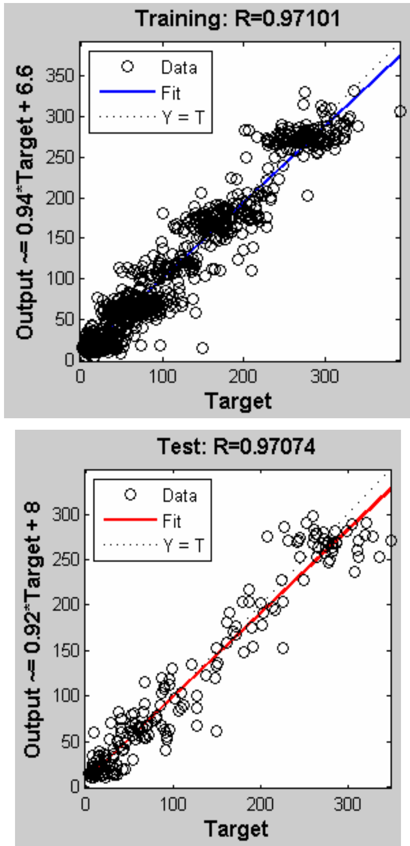

Figure 11: regression plot of training and testing for monthly predictions one month ahead

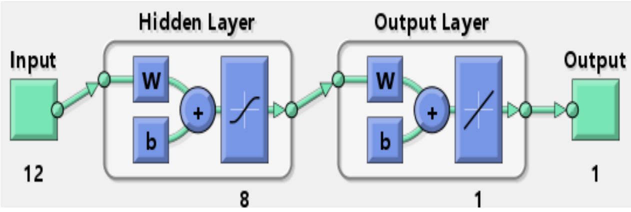

Figure 12: neural network architecture for monthly predictions one month ahead

4.4 Kiremt Rainfall Prediction Eight Month Ahead

This prediction was made by adding the predicted monthly *rainfall* values for each month in *kiremt* season (June, July, August, and September) using the neural network model built in Section 4.2.

5. Results and Discussion

Abraham [11] points out lack of common framework for comparing all soft computing models. Zhang *et al.* [12] defined accuracy as the forecasting error which is the difference between the actual (desired) and the predicted value. Zhang *et al.* [12] and Abraham [11] also stated that RMSE is the most frequently used accuracy measure in the literature. Table 2 provides model comparison for all models and predictions.

Table 2: Model comparisons using RMSE

Model Type		*RMSE (on test set) the four kinds of predictions in mm*			
		Kiremt a season ahead	*Monthly a year ahead*	*Monthly a month ahead*	*Kiremt prediction eight month ahead*
Neural network		78.6	24.5	24.7	98.0 mm
Neuro fuzzy	Sugeno	67.4	27.4	30.9	109.6 mm
	Mamdani	51.6	Similar with sugeno	Similar with sugeno	Similar with sugeon

Different techniques were used for model evaluation, validation, and visualization. Regarding neural network, model specification, RMSE, performance plots, regression plots, response plot, and model architectures were used. For neuro fuzzy model, model specification, RMSE, response plot, and sample rule were used.

This paper was designed to predict the seasonal (*kiremt* rainfall one season and eight months ahead) and monthly rainfall (one year and one month ahead) of EUBN Basin accurately in time series by using soft computing models. The *kiremt* rainfall is predicted one season ahead with RMSE = 51.6 mm on test data; the monthly rainfall one year ahead is predicted with RMSE = 24.5 mm on test data; the monthly rainfall one month ahead is predicted with RMSE = 24.7 mm; the *kiremt* rainfall eight month ahead is predicted with RMSE = 98.0 mm on test data. One of the important findings was the rules for all kinds of predictions using neuro fuzzy models. These rules are presented in simple IF-ELSE structures which can be edited and tuned by experts in rainfall prediction domain to make the prediction more accurate.

Paul and Rajagopalan [2] and Diro *et al.* [3] used Ranked Probability Skill Score (RPSS) values for model comparison with climatological forecast. RPSS values range from +1 to -∞. A value of +1 indicates that all the predicted outputs fall in the same category as the actual value. A value equals to zero indicates that the prediction skill is the same with the climatological forecast. The result shows that average RPSS = 0.90 for all years. Paul and Rajagopalan [2] found RPSS = 0.39 for all years covered in their study. RPSS was also calculated for extreme wet (greater than 90th percentile) and dry seasons (less than 10th percentile) separately. The result showed that RPSS = 1.0 for both extreme wet and dry seasons. paul and Rajagopalan [2] found RPSS = 0.86 and RPSS = 0.94 for extreme wet and dry seasons. The above results indicate that the output of this paper is better than that is [2] and significantly better than the climatological technique used by ENMSA. No previous work is found that predicts the monthly rainfall and *kiremt* rainfall eight month ahead for EUBN Basin. The performance plots and regression plots are also interesting and validate the prediction models.

6. Prototype Development

To make the output of this paper easily utilizable by experts, a prototype was built using Matlab. The prototype can make the four predictions using the three modeling techniques. Other features are also included in the prototype: an expert can view, edit, and add rules for neuro fuzzy models; view, plot, and edit membership functions; plot the fuzzy inference systems; plot surface plots for any two input and/or output variables; perform spatio-temporal correlations; and view neural network model architecture. Figure 13 shows sample snapshot of the prototype.

To evaluate the prototype, two experienced experts from Meteorological Forecasting and Early Warning Directorate of ENMSA were provided with the prototype and a simple questionnaire to gather their feedback. The response is very encouraging. The deterministic and modeling techniques are new to the Agency.

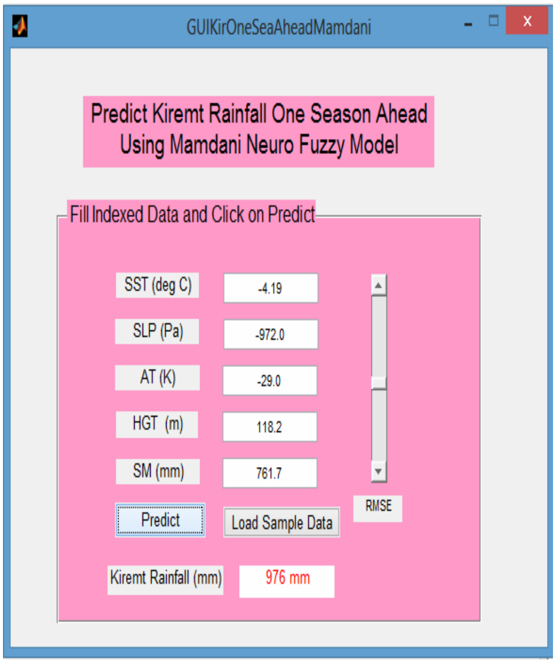

Figure 13: Snapshot for *kiremt* rainfall prediction a season ahead using mamdani model

7. Conclusion and Future Work

In this paper, first literature review was conducted which assesses what has been done and existing techniques. Then the collected data was converted to a format ready for modeling. In this part, four kinds of predictions and three soft computing modeling techniques were utilized. The outputs of the model were then converted to a simple and easy to use prototype.

The main objective of this paper was to predict the *kiremt* rainfall (one season and eight month ahead) and monthly rainfall (a year and a month ahead) of EUBN Basin accurately and deterministically in time series using soft computing models. The findings from the study showed that the result is successful and encouraging. The main findings of this paper are: the best predictors, and corresponding time lag and regions for these predictors, model evaluation outputs and the final model specification as the relatively best model, the editable and interpretable rules and membership functions, and the prototype that predicts EUBN Basin rainfall are a very significant contribution to other researchers and experts in rainfall prediction domain. In addition, the prediction accuracy is better than previous works and ENMSA especially in extreme dry and wet seasons which make it more useful.

This paper has several contributions, experts in different disciplines such as Renaissance Dam, agriculture, famine prevention and control, disease and flooding control and early warning, ground water and rain water catchment management can use it as the main decision support tool. It can also serve as a base for future studies and demonstrates the capability of soft computing models to predict rainfall.

Further investigation and experimentation incorporating climate changes, socio economic factors (like deforestation) and other climatic phenomena can be done to increase the accuracy of the prediction. Additional soft computing models and pixel by pixel prediction instead of average rainfall prediction can be incorporated. Prediction of start time and end time of rainfall can also be added to the current prediction approaches. In addition, the prototype can be enhanced in the future to make it complete.

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