



Rainfall Prediction and Cropping Pattern Recommendation Using Artificial Neural Network

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Abstract. Ethiopia's economy is primarily agricultural, with agriculture employing more than 85% of the country's population. In a country like Ethiopia, where agriculture is the main source of income, reliable rainfall data is critical for water resource management, disaster avoidance, and agricultural productivity. In a circumstance where the amount of rainfall varies from time to time, cropping pattern recommendation is also highly important. In this paper we perform report, and discuss results of rainfall prediction and cropping pattern recommendation specifically for Amhara region using different combination of metrological parameters. Our Radial Basis Function Neural Network (RBFNN) prediction demonstrates better performance than the techniques used by Ethiopian National Metrological service agency (ENMSA) and other statistical techniques. For the recommendation system we used Model based collaborative filtering technique; that is K-means algorithm. We used Mean Squared Error (MSE), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) and Sum of Squared Errors (SSE) evaluation metrics to evaluate our prediction results. Generally, we can say that this is the first work which combines rainfall prediction and cropping pattern recommendation.

Keywords: Rainfall prediction · Artificial neural networks · Recommendation systems · RBFNN · K-means

1 Introduction

Ethiopia's economy is chiefly agricultural, with more than 85% of the country's population employed in this sector. Many people believe that agriculture is the backbone of the Ethiopian economy, and that its success influences all other sectors and, as a result, the entire national economy. Agriculture contributes a lot to the Ethiopian economy in terms of export, employment, and sustenance, according to the Ministry of Finance and Economic Development (MoFED). Despite the production challenges, agriculture contributes 50% of GDP, 85% of employment (the rural population of Ethiopia), 90% of earning from export, and 70% of raw material requirements for the large and medium industries which are agro processing [1, 2].

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Crop production contributes for 60% of the agricultural sector's outputs in the country, while livestock accounts for 27% and other areas account for 13% of total agricultural value added. The sector is dominated by small-scale farmers who practice rain-fed mixed farming by employing traditional technology, adopting a low input and low output production system. The land tilled by the Ethiopian small-scale farmer accounts for 95% of the total area under agricultural use and these farmers are responsible more than 90% of the total agricultural output.

Given that the majority of Ethiopian farmers employ rain-fed mixed farming, rainfall data is critical for crop production, water management, and all other outdoor activities. The incident of extended dry period or heavy rain at the critical stages of the crop growth and development may lead to noteworthy reduction in the crop yield and hence affect the economy of the country. Actually, recently these problems are exacerbated by the impact of climate change in Ethiopia. This can be witnessed by the unpredictability of the rainy season and rain amount. This leads to a drought or flood that can impact large number of people in Ethiopia. Thus, an accurate and timely rainfall prediction and cropping pattern recommendation mechanisms could have a significant impact in the country's socioeconomic functioning in particular, food production.

This research paper aims to alleviate rainfall prediction and cropping pattern recommendation problems by modeling rainfall predictor using RBFNN and recommendation system by using model based clustering (K-means) algorithm.

2 Literature Review

2.1 ANN for Prediction

The use of ANN is a common data modeling approach that has been widely used to capture and depict complex input/output interactions in a variety of industries and research organizations. ANN for rainfall prediction have been used for a long time and have been proven to be more accurate than linear prediction models [3]. The pioneering work of applying ANN for rainfall prediction was done by French et al. [4], who used neural networks to predict two-dimensional rainfall one hour in advance. In 1999, Koizumi [5] using an ANN model that uses data from radar, satellite, and weather stations, as well as numerical products generated by the Japan Meteorological Agency (JMA) Asian spectral model, and used one-year data to train the model. The ANN abilities were found to be superior than the persistence forecast (after 3 h), linear regression forecasts, and numerical model precipitation prediction.

In 2000, Luk, Ball, and Sharma [6] to compare three different ANN models for rainfall prediction (Elman's partial recurrent neural network, multi-layer feedback neural network, and time-delay neural network) and concluded that this three networks can provide comparable performance results. E. Toth et al. [7] compared different forecasting models that use time series data for flood forecasting and found that artificial neural networks provide better results than

other models. Chang, Liang and Chen [8] in 2001 tried to develop a rainfall model using data collected from the Lanyoung River and found that the radial basis function neural network is very effective in forecasting floods three hours ahead. In 2007, Ozgur Kisi et al. [9] examined two widely used ANN methods, namely feedback back propagation and radial basis for prediction tasks. According to their research work, Radial basis ANN provides the superior prediction performance, which resulted in significantly lower error (MSE and RMSE) compared with the feed-forward back-propagation ANN model.

In general, previous studies have clearly shown that artificial neural networks are a good method and have great potential in predicting precipitation. Artificial neural networks can model without specifying hydro-logical processes, capture complex nonlinear input and output relationships, and solve them without using differential equations [4, 6, 10]. Also, even if the input data contains errors or is incomplete, ANN can learn and generalize from examples to produce meaningful solutions [6]. Existing artificial neural network models for rainfall prediction are primarily event-based; the input for these models is filtered/generated data, which only includes the rainy season (i.e. rain events, rainy days, or monthly rain data). So far, various researchers have used RBFNN to make accurate rainfall predictions and have obtained valuable results.

2.2 Recommendation Systems

In recent years, recommendation algorithms have become highly popular. It assists customers in locating information and making decisions when they lack the necessary knowledge to evaluate a certain item [11]. Recommendation systems are commonly utilized in e-commerce as a tool to assist users in searching through knowledge data that are relevant to their interests and preferences [12]. However, it is difficult to find literature related with recommendation systems regarding cropping pattern recommendation. So, we can say that this is first work on this area. As depicted in Fig. 1. there are different types of recommendation system techniques.

2.3 Crop Water Needs

The crop water need (ET crop) is the depth (or amount) of water required to compensate for evapotranspiration losses. In other words, it is the amount of water needed by the various crops to grow optimally. Crop water needs always refer to a crop grown under ideal conditions, such as a uniform crop that is actively growing, completely shading the ground, disease-free, and in good soil (including fertility and water). The crop thus reaches its full production potential under the given environment. [13].

Crop water requirements are mostly determined by the climate, crop type, and crop growth stage. The following are the key climatic elements that influence crop water requirements:

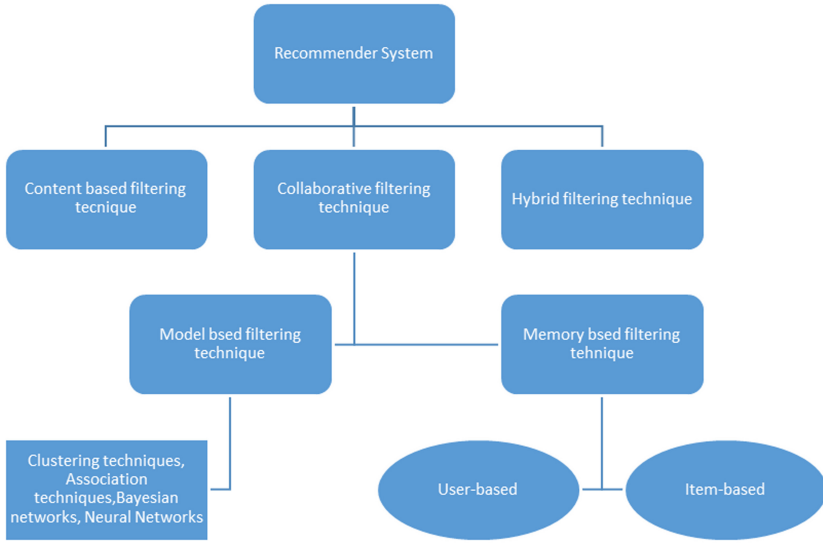


Fig. 1. Recommendation system techniques.

- Sunshine
- Temperature
- Humidity
- Wind speed

Table 1. Relationship between climatic factor and crop water need.

Climatic factor	Crop water needs	
	High	Low
Temperature	Hot	Cool
Humidity	Low (dry)	High (humid)
Wind speed	Windy	Little wind
Sun shine	Sunny (no clouds)	Cloudy (no sun)

As we can observe from Table 1, the highest crop water needs are thus found in areas which are hot, dry, windy and sunny. The lowest values are found when it is cool, humid and cloudy with little or no wind. Wheat, Maize, Sorghum and Barley are the major cereals which are produced by Ethiopian farmers. Table 2 will tabulate the water needs (mm/total growing period) and sensitivity to drought of these cereals for their total growing period.

Even though water needs of crops are influenced by sunshine, temperature, humidity and wind speed due to lack of information on those attributes, in this research we will consider only water consumption of the crop and their sensitivity to drought.

Table 2. Water needs and sensitivity to drought of different cereals.

Crop (cereal)	Water need (mm/total growing period)	Sensitivity to drought
Wheat	450–650	Low-Medium
Maize	500–800	Medium-High
Sorghum	450–650	Low
Barley	450–650	Low-Medium

3 Experimental Setup

3.1 Data

Currently large amounts of climate data of various types are becoming available for future research. There are different sources of climate data, ranging from single-site observations scattered across each country to climate model output. Each class of data has particular characteristics before it can be used or compared. A brief introduction to each type of data source was done [14].

The data source for this study is the Ethiopia national meteorology agency (NMA) data collected from weather stations found in West, North-East and South-East Amhara region. There are about one hundred fifty stations found in West, North-East and South-East Amhara Region (Gojjam, Gondor and Awi Zone, Semien Shewa). The stations record minimum temperature, maximum temperature, mean rainfall, sunshine and humidity.

The data obtained from weather stations are called Insitu data. Most of the stations are installed recently (Since 1999) and they do not have long period of time records. Some of the stations in capital cities and in some particular places are installed before 1980. However, they have high missing data and incomplete records. The study is limited to stations having complete record of monthly observations from 1980–2012. This gave a total of 15 recording stations. Among the 15 stations, 11 of them are selected for this study as representative weather conditions of Ethiopia.

The selected stations are taken from areas where there are dry and wet places that have different geographical variables to represent the weather conditions of Ethiopia. The selected stations and their geographical variables (Latitude (LAT), Longitude (LONG) and Elevation (ALT)) are shown in Table 3. For this study, we took monthly minimum temperature, maximum temperature, precipitation from the selected 11 places from 1980–2012.

3.2 Data Preprocessing

Data pre-processing is an important step in the data mining and machine learning process. The phrase “garbage in, garbage out” is particularly applicable to both of fields. Data-gathering methods are often loosely controlled, resulting in out-of-range values, impossible data combinations, missing values, etc. Analyzing data that has not been carefully screened for such problems can produce misleading results. Thus, the representation and quality of data is first and foremost before running an analysis [15].

Table 3. Geographical information of different metrological stations in Amhara region.

Station name	Altitude	Latitude	Longitude
AbaySheleko	1823.0	10°6' 46.8"	38°9' 25.2"
Aykel	2254.0	12°32' 24"	37°3' 32.4"
Bahir Dar	1800.000	11°35' 60"	37°21' 36"
Debre Birhan	2840.0	9°41'	39°32'
Debre Markos	2446.0	10°19' 33.6"	38°9' 25.2"
Debre Tabor	2612.0	11°52' 1.2"	37°59'42"
Debre Work	2508.0	10°39' 3.6"	38°9' 43.2"
Dessie	b/n2470 - 2550	11°8'	39°38'
Gondor	2128.0	12°36' 57.6"	37°27'32.4"
Kidamaja	1928.0	10°59' 56.4"	36°40' 44.4"
Metema	790.0	12°46' 30"	36°24' 50.4"

In general, the process of data preparation for a machine learning algorithm includes three steps:

- **Select data:** Consider what data is available, what data is missing and what data can be removed.
- **Preprocess Data:** Organize the selected data by formatting, cleaning and sampling from it.
- **Transform Data:** Transform preprocessed data ready for machine learning by engineering features using scaling, attribute decomposition and attribute aggregation.

There are different methods suggested in literature for treating missing values. Some of those methods include:

- **Ignore missed value:** This method usually done when class label is missed (assuming the task in classification).
- **Fill in the missed value manually:** This method is tedious, time consuming and infeasible.
- **Use a global constant to fill in the missing value:** This can be done if a new class is unknown.
- **Use the attributes' mean to fill in the missing value:** Replacing the missed values with the attributes' mean or mode (for numeric or nominal attributes, respectively).

In weather dataset, missing values are mostly due to equipment malfunction or users' error at the time of entry. Therefore, the appropriate method to fill the missing value in weather data is using the attributes' mean because all attributes in the weather dataset are numeric attributes and missing values of time series data has strong relation to its previous and next value in the series. In this research work we have used the attributes mean to fill the missing value.

Data transformation should be done to improve the speed, accuracy, efficiency, and performance of the model [16]. The performance of a neural network is often improved through data transformations. According to literature there are three existing data transformation methods.

- Linear transformation
- Statistical standardization and
- Mathematical function

Among the data transformation methods, the most commonly used one is scaling which is a type of linear transformation. Scaling is done to have a specific range, such as the range between -1 and 1 or 0 and 1, for the entire data set of a given station [17]. For this study we have used scaling technique to transform all the weather data sets (minimum temperature, maximum temperature, precipitation) to [xmin, xmax] scale.

$$Y = \frac{(Y_{max} - Y_{min}) * (X - X_{min})}{(X_{max} - X_{min}) + Y_{min}} \tag{1}$$

where Y is the scaled value, Mapminmax function processes matrices by normalizing the minimum and maximum values of each row to [xmin, xmax]. So, it processes data by mapping their values to minimum and maximum values (Fig. 2).

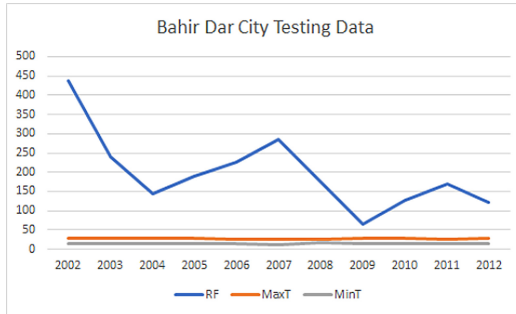


Fig. 2. Bahir Dar city testing data for June.

3.3 Setup the Dataset

Dividing the available sample dataset for training, and testing is common for prediction and classification in machine learning techniques. In [17] the selected data sets were randomly divided into two groups: 70% for training, 30% for testing after it had been first normalized into a certain range. In this study we have divided the data sets into training, and test set (70%, 30%) respectively. That means 22 years (1980–2001) of monthly data for training the neural network and 10 years (2002–2012) of monthly data for testing the prediction performance of our model (Fig. 3).

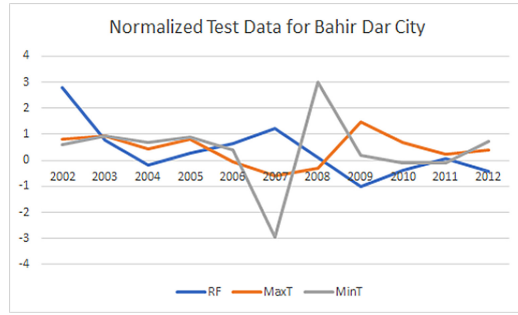


Fig. 3. Bahir Dar city normalized testing data for June.

3.4 Model Design

In this research work we developed two models:

- **Model-1 (Prediction model):** this model is prepared to predict the upcoming year rainfall amount of a given month by using the previous year’s similar month data as an input.
- **Model-2 (Recommendation model):** by accepting the predicted values from the previous model it will recommend what crop to plant.

The First model uses ANN architecture (RBFNN structure), while the second model uses K-means clustering (Fig. 4).

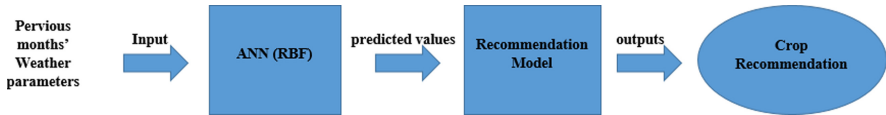


Fig. 4. General design of our proposed model.

Radial Basis Function Neural Network. Radial basis functions have been used as an important tool to solve problems which involve time series prediction and pattern recognition since late 1980s. An RBF network is basically an artificial neural network which uses radial basis function as activation function. Radial basis functions consist of three different layers: input layer, hidden layer and output layer. The hidden units in the network implement a radial basis function. While the output layer of the network is linear, the input layer of the network is non-linear.

In the time series modeling, the inputs are the data samples at certain time lapses and the output represents a signal value while in the pattern recognition, the input values represent the features of a point and output layer corresponds to the class label. The output is calculated by a linear combination. The weighted sum of the radial basis functions plus the bias according to the formula (Fig. 5).

$$Y(x_i) = \sum_{j=1}^n w_j \phi(\|x_i - c_i\| + w_o) \tag{2}$$

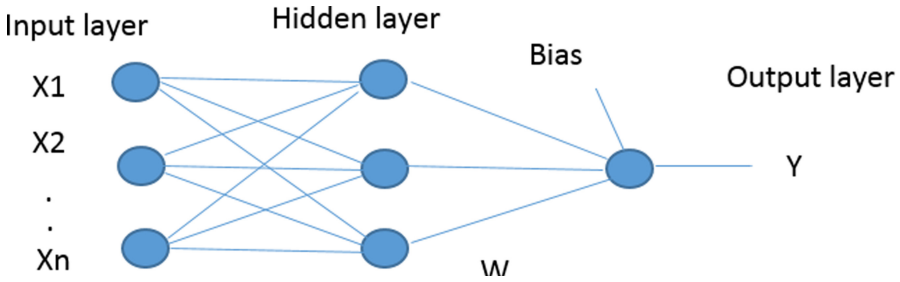


Fig. 5. RBFNN architecture.

Here the net input to the radbas transfer function is the vector distance between its weight vector w and the input vector x , multiplied by the bias b . The transfer function for a radial basis neuron is:

$$radbas(n) = exp(-n^2) \tag{3}$$

We design our RBFNN model with three inputs, twenty-two hidden and one output neurons.

We adjusted the RBFNN different parameters and select the best parameter values which gives better prediction results (P = 3; T = 1; GOAL = 0; SPREAD = 10; MN = 200; DF = 1;). Where P is input, T is the output, GOAL is Mean squared error goal, SPREAD - Spread of radial basis functions, MN - Maximum number of neurons, and DF - Number of neurons to add between displays.

K-means Clustering. Our recommendation system uses k-means clustering to recommend which crop to grow by accepting the predicted rainfall value of our RBF NN and the actual water needs of the selected crops. We used Orange3-3.6.0-Python34-win32 data mining tool for our K-means algorithm and Jaccard distance.

4 Experimental Results

Even though we conducted experiments for the four selected metrological stations namely Debre Birhan, Debre Markos, Gondar and Bahir Dar; for this research article we selected two cities only (Bahir Dar and Gondar). The results have been presented by using different evaluation metrics, graphs and tables.

4.1 Prediction Results

For the sake of saving some pages here we present the detailed prediction results for June month for both Cities (Bahir Dar and Gondar). Additionally MAE, SSE, MSE, and RMS results are presented for the three months (see Table 4).

Table 4. Prediction results using MAE, SSE, MSE, RMS for three months.

Months	Evaluation metrics			
	MAE	SSE	MSE	RMS
June	0.0098616201214	0.0048198015284	0.00043816377531	0.020932361914
July	0.3228689001455	10.61002822024	0.3228689001455	0.9821140565243
August	0.061528029425	0.38155200268	0.034686545698	0.18624324336

Prediction Results for Gondar City. In this section the detailed rainfall prediction results of Gondar city is presented. The results are depicted by Table 5 and Fig. 6.

Table 5. Prediction results for June month (Gondar).

Year	Actual values	Predicted values	Testing error (tE)
2002	197.40	197.397156684	0.00284331555940
2003	244.20	244.206224269	-0.00622426991512
2004	181.40	181.399202493	0.000797506273926
2005	137.50	137.566290411	-0.0662904111192
2006	98.70	98.7004967665	-0.000496766596697
2007	162.20	162.197409571	0.00259042812345
2008	228.50	228.498481883	0.00151811654302
2009	195.20	195.216542884	-0.0165428843431
2010	105.40	105.401297790	-0.00129779064215
2011	172.00	171.990342887	0.00965711205657
2012	160.90	160.900219220	-0.000219220163415

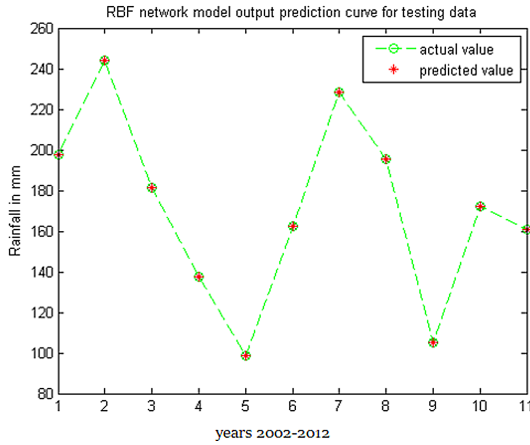


Fig. 6. Predicted results Vs actual value of June month from 2002–2012 (Gondar).

Prediction Results for Bahir Dar City. In this section the detailed rainfall prediction results of Bahir Dar city is presented. The results are depicted by Table 6 and Fig. 7.

Table 6. Prediction results for June month (Bahir Dar).

Year	Actual values	Predicted values	Testing error (tE)
2002	437.20	436.318262242423	0.881737757577184
2003	239.20	239.196520963533	0.00347903646749614
2004	144.30	144.288045159961	0.0119548400385838
2005	188.80	188.784253107786	0.0157468922142243
2006	225.50	225.502744965917	-0.00274496591691786
2007	285.60	286.475089324658	-0.875089324657836
2008	175.60	174.934988202164	0.665011797836257
2009	66.30	66.4235767290092	-0.123576729009173
2010	127.30	127.302742524422	-0.00274252442244460
2011	169.00	168.996294253586	0.00370574641419807
2012	122.00	121.990770264314	0.00922973568592056

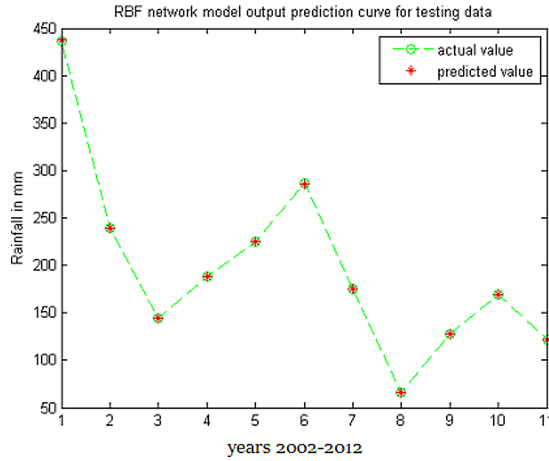


Fig. 7. Predicted results Vs actual value of June month from 2002–2012 (Bahir Dar).

4.2 Crop Recommendation Results

In this section we will present Crop recommendation results for Kiremt (Summer) Season. Because this is the main season that crops are grown in Ethiopia. Kiremt season consists of three months June, July and August. Table 7 shows the four seasons of Ethiopia and the months they constitute.

Table 7. Seasons and months of Ethiopia.

Season	Months
Kiremt or Meher (summer)	June, July, August
Belg (Autumn)	December, January, February
Bega (Winter)	December January, February
Tsedey(Spring)	March, April, May

Before we feed the output of our predictor model to the K-means recommendation system we have done three tasks.

- Sum-up the rainfall amount of each month in Kiremt season so as to get the aggregate amount of Rainfall of the season. Table 8 shows the aggregate results of Kiremt season from 2002–2012 for Gondar.
- Compute the average actual water needs of four crop types (Maize, Wheat, Sorghum and Barley). The actual water needs of crops and their sensitivity to drought is shown in Table 2.
- Scale the average actual water needs of crops based on their sensitivity to drought and the maximum and minimum amount of predicted rain fall values.

Means we use their sensitivity to drought as a scaling factor and predicted minimum rainfall and maximum rainfall as Domain. Table 9 shows the results of the above three tasks.

Table 8. Aggregate Rain Fall amount of Kiremt season from 2002–2012 (Gondar).

Year	Months	Predicted values	Season's total
2002	June	197.397156684	757.593482
	July	312.587723749	
	August	247.608601540	
2003	June	244.206224269	843.6054331
	July	318.701244177	
	August	280.697964651	
2004	June	181.399202493	871.9308527
	July	378.237761989	
	August	312.293888222	
2005	June	137.566290411	711.9952592
	July	300.8461206104	
	August	273.582848227	
2006	June	98.7004967665	695.497506
	July	291.497530851	
	August	305.299478341	
2007	June	162.19740957	857.9784652
	July	340.701462835	
	August	355.079592796	
2008	June	228.498481883	895.5232072
	July	365.533522626	
	August	301.491202686	
2009	June	195.216542884	788.6067698
	July	292.994018351	
	August	300.396208539	
2010	June	105.401297790	697.0017577
	July	266.607393999	
	August	324.993065879	
2011	June	171.990342887	670.8525965
	July	230.864035820	
	August	267.998217825	
2012	June	160.900219220	735.8973744
	July	296.397829111	
	August	278.599326048	

After we get the results of Scaled Rainfall amount for each crop we organize our data for clustering algorithm in the manner depicted on Table 10 and feed this data to the K-means Algorithm.

The last three rows of the table shows the scaled water needs of crops, while the remaining part of the table is the aggregated predicted value of Kiremt season for the respective years. Finally, we fed this data to Kmeans algorithm and found results shown in Fig. 8.

Table 9. Scaled rainfall amount for crops.

Crop type	Actual water need	Average water need	Sensitivity to drought	Scaling factor	Scaled RF amount
Wheat	450–650	550	Low-Medium	1.4	770
Maize	500–800	650	Medium-High	1.5	975
Sorghum	450–650	550	Low	1.3	715
Barley	450–650	550	Low-Medium	1.4	770

Table 10. Scaled water needs of crops and predicted values of Rainfall (Gondar).

Year/Crop Type	Amount of RF
2002	757.593482
2003	843.6054331
2004	871.9308527
2005	711.9952592
2006	695.497506
2007	857.9784652
2008	895.5232072
2009	788.6067698
2010	697.0017577
2011	670.8525965
2012	735.8973744
Wheat/Barley	770
Maize	975
Sorghum	715

As we can observe from Fig. 8 our recommendation system clusters the given data into three distinct groups C1 (sorghum), C2 (Wheat/Barley), C3 (Maize).

Analysis of the Results. In this section we will present the analysis based on the output of our recommendation system. According to our recommendation system farmers live in Gondar and nearby Gondar shall sow (see Table 11)

- Sorghum in 2005, 2006, 2010 and 2011.
- Wheat or Barley in 2002, 2009 and 2012.
- Maize in 2003, 2004, 2007 and 2008.

	Cluster	Year/Crop Type	RainFall/Centroids
1	C2	2002	757.5934820
2	C3	2003	843.6054331
3	C3	2004	871.9308527
4	C1	2005	711.9952592
5	C1	2006	695.4975060
6	C3	2007	857.9784652
7	C3	2008	895.5232072
8	C2	2009	788.6067698
9	C1	2010	697.0017577
10	C1	2011	670.8525965
11	C2	2012	735.8973744
12	C2	Wheat/Barly	770.0000000
13	C3	Maize	975.0000000
14	C1	Sorghum	715.0000000

Fig. 8. Recommendation results (Gondar).

Table 11. Analysis of recommendation results.

Clusters	Predicted rainfall	Year
C1 (sorghum)	715.0000000	
	711.9952592	2005
	695.4975060	2006
	697.0017577	2010
	670.8525965	2011
C2 (Wheat/Barley)	770.0000000	
	757.5934820	2002
	788.6067698	2009
	735.8973744	2012
C3 (Maize)	975.0000000	
	843.6054331	2003
	871.9308527	2004
	857.9784652	2007
	895.5232072	2008

5 Conclusion

Global climate fluctuations and their impacts on economic development have been a worldwide concern during the past several decades. The problem is more acute in developing countries in Africa, Asia, and Latin America, where alternat-

ing severe, droughts and floods have been persistent causes of severe economic hardships. To help mitigate the impacts of extreme weather and climate fluctuations requires routine timely and accurate monitoring and prediction. Especially countries like Ethiopia suffers from drought to many years, so rainfall prediction and cropping pattern recommendation systems can be used to alleviate this problem. The objective of this research was to develop such system and evaluate its performance.

In this research paper we presented our research results by using different graphs and tables. The results were presented for Bahir Dar and Gondar cities only for the sake of saving pages. But we also have conducted experiments for others cities and Woredas in Amhara region. The obtained results show that if we deploy such systems in the real life it will be helpful to increase the productivity of farmers and mitigate drought problems that are frequently occurring in our country.

As indicated in experimental results section, the prediction results were very good; means there is only a fractional point difference from the actual values. So, from this we can conclude that RBFNN is very good in predicting time series values. Generally, we can say that this is the first work which combines rain fall prediction and cropping patter recommendation.

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