INTELLIGENT PREDICTION OF AGRICULTURAL DROUGHT USING CLASSIFICATION ALGORITHMS

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Abstract
The application of computer science has led to advancements in various sectors of economies including agricultural production, manufacturing and marketing. Computer algorithms have been used for prediction. There has been immense interest and research on meteorological prediction aimed at addressing drought. This has been achieved through the development of various drought indices. Some researchers have studied drought prediction by applying computer science solutions. However, critical issues related to agricultural drought have not been well addressed. This study looked at issues related to agricultural droughts, with the aim of developing an efficient and intelligent agricultural drought prediction system. By using a case study approach and knowledge discovery data mining process this study was preceded by literature review, followed by analysis of daily 1978-2008 meteorological and annual 1976-2006 maize produce data in Voi Taita-Taveta (Coast province, Kenya). The design and implementation of an agricultural drought prediction system for meteorological data preprocessing, classification algorithms for training and testing as well as prediction and post processing of predictions to various agricultural drought aspects is accomplished. To overcome the problem of geographical differences the solution allows choice of area latitude during the preprocessing. To come up with the agricultural drought meteorological data relationships, the study was forced on the two different datasets. Meteorological data is on daily basis while maize produce data is on annual basis. The datasets difference constraint was overcome by performing analysis of metrological data on monthly, seasonal and yearly basis so as to properly relate the two data sets. Further to overcome the limitation of data incompatibility the analysis of each dataset was done independently. Literature review on drought occurrences verified the results of associated maize produce and meteorological data analysis. Maize was used as a study crop since it is the staple food and also most sensitive to agricultural drought compared to other seasonal crops. The solution was evaluated by comparison of predicted to actual 2009 data and Kenya Meteorological Department (KMD) records. The evaluation of our study results indicated consistency with the KMD 2009 outlook. The report concludes that the application of classification algorithms together with past meteorological data can lead to accurate predictions of future agricultural drought.

Keywords: Data mining, knowledge discovery, classification algorithm, intelligent prediction, agricultural drought, nearest neighbor classification

1 Introduction

As reported by Apollo (2002) stated that agriculture is very important in Kenya as 75% of the country's population is dependent on agriculture for food and income; however, only about one third of the total land area of Kenya is agriculturally productive. Two thirds of the Kenya land is semi-arid to arid, and characterized by low, unreliable and poorly distributed rainfall. Patrick and Rosemary (2006) indicated that over 80% of the Kenyan population live in the rural areas and derive their livelihoods, directly or indirectly from agriculture. The development of agriculture is important for poverty reduction since most of the vulnerable groups like pastoralists, the landless, and subsistence farmers, also depend on agriculture as their main source of livelihoods. Southtravels (2010) report shows Kenya has climatic and ecological extremes with altitude varying from sea level to over 5000 meters in the highlands. Rainfall occurs seasonally throughout most parts of Kenya. Most parts of Kenya are subject to periodic droughts or delays in the start of the rainy seasons. Rainfall ranges from mean annual of less than 250 mm in arid and semi-arid lands to mean annual of greater than 2000 mm in high potential areas. Catholic Relief Services (2011) stated that failure of seasonal rains in Kenya is coupled with increased food prices leading to emergency food assistance from United Nations and Government of Kenya. Recurring agricultural drought leaves millions with little or nothing to eat. Agricultural drought is the major constraint of Kenyan agriculture sector severely affecting seasonal crops. As Kenya relies heavily on rain-fed agriculture, agricultural drought prediction can play a vital role, as it can provide necessary parameters to use in planning for agricultural drought mitigation measures. There is lack of regular information, education and social mobilization in strategic sectors to mitigate the agricultural drought related shocks. ICT tools continue to produce significant transformations in several sectors of the economy including agriculture. This research purpose was to take these transformations a notch higher; by developing an intelligent agricultural drought prediction system that integrates historical data on droughts, maize production and climate data. The first step towards this research was based on investigations to ensure that there are relevant truths regarding precipitation patterns and agricultural droughts prospects. The design was preceded by the analysis of two sets of historical data; 1) maize production and 2) weather data. The aim was to identify agricultural drought patterns on historical data and use the results for the prediction of future agricultural droughts. The prediction was to provide information on agricultural drought occurrences onset/offset, intensity magnitude and the impact on maize crop.

2 Literature Review

Apollo, B. (2002) indicated that two thirds of the Kenya land area is arid and semi arid (ASALs), and characterized by low, unreliable and poorly distributed rainfall. Patrick and Rosemary(2006) acknowledged that the development of agriculture is also important for poverty reduction since most of the vulnerable groups like pastoralists, the landless, and subsistence farmers, also depend on agriculture as their main source of livelihoods. Drought is a serious problems that significantly affect millions of people in the ASALs and it occurs when the rainfall and soil moisture are inadequate to meet the water requirements of crops. In a study conducted by London school of hygiene & tropical medicine, (1986) on predicting famine researchers observed rain and crop data as well as human behavioral patterns with regard to famine. The researchers regarded human responses to drought such as migration, livestock sales, loans, and increase in grain prices as useful famine indicators. In Tanzania Ladislaus B. et al (2010), studied rainfall prediction using environmental indicators through appraisals, interviews, focus groups used to collect data while SPSS was used for analysis. Their study reported that local environmental indicators and astronomical factors pathology are widely used in the region to forecast rainfall. In China Gong Z, (2010), studied agricultural drought prediction. By analyzing the occurrence trend of agricultural drought by using grey catastrophic forecast models the study reported that serious drought can occur in 2012. The study offered decision basis for disaster prevention and risk reduction. Staff of Cook island department of Water Works, (2003) study aimed at monitoring of evolving drought conditions used 70 years daily rain data to develop a drought index that compared current condition and previous drought. The study allowed monitory of evolving drought condition as well as development of drought management plans. In China, Lin Zhu, (2008) studied monitoring drought losses and drought influence on agriculture. The researcher used soil moisture and daily metrological data were used as input to Borel Ecosystem productivity simulator (BEPS) to assess agricultural drought. The findings were that assimilated remotely sensed soil moisture in BEPS model improved the way of monitoring drought losses and drought influence on agriculture. In Kenya the European Commission, (2009) predicted drought using Food sec crop yield model. In their study they established crop yield, calculated FAO crop evapotranspiration. They also incorporated Land cover weighed normalized difference vegetative index (WNDVI). In San Francisco Celso, (2009), studied drought forecasting. The study analyzed rainfall frequencies using data from 248 rain gauges (1938-2005). SPI was determined using ANN feed feedfoward and back propagation algorithm. The findings showed that the result of ANN is suitable for drought forecast. In Iran Dostrani (2010) study aimed at comparing ANN and ANFIS in precipitation prediction. Dostrani study realized ANN efficient in rain prediction. Xin (2010) in Puyang studied predicting agricultural drought. Xin study used 1880-2005 rain data to analyze agricultural drought. By applying fuzzy sets analysis on the condition of crops and valid rain history, result of fuzzy clustering obtained. Drought years extracted from fuzzy clustering results. Time series used to predict next drought year. Ashock (2006), study in Kenya and Zambia aimed at translating seasonal forecast to agricultural terms. Ashock study used crop simulation model to translate seasonal forecast to agricultural terms. The results offered support to farmer's climate risk management. Bob(2007), in China studied rainfall prediction by direct determination of surface soil moisture using microwave observation. In Bob study data was acquired and analyzed over several test sites. The study was validated by conducted large field experiments. Niu S. (2006), Predicted agricultural drought in paddy fields using remotely sensed data. Niu study used and found NDVI to be reasonable in detecting agricultural drought.

The study was limited by insufficient data as fuzzy was done in non cropping time. Kozyra (2009) study evaluate metrological conditions causing drought using the differentiate between precipitation & evapotranspiration to evaluate metrological conditions causing drought. Tsegaye (2007) study in USA identified historical patterns for drought using VegOut Model that integrated Climate Ocean, satellite indicators; used regression trees to identify historical patterns for drought intensely and vegetation. SPI and PDSI were used to represent climate vulnerability. Tadesse study was evaluated using 2006 drought year. Unlike previous studies this paper contributes on prior work by considering drought literature, crop production history and weather data history together with classification algorithms. Apart from providing historical agricultural drought analysis our work provides future projections with limit of twelve months agricultural drought predictions. Unlike previous studies this research emphasis is on prediction of agricultural drought using both historical and projected meteorological conditions. This study provides user friendly output concerning the impact of agricultural drought on maize crop.

3 Methodology

3.1 Study Area

Taita-Taveta district was a case study area where this study applied the Knowledge Discovery and Data mining (KDD) process steps. There being no much study done on agricultural droughts prediction in Kenya and further agricultural drought prediction problem being rather complicated to analytically explain, the case study approach was the best to yield a rich picture of the situation, which can well be further subjected to comparative analysis. The study area chosen is classified as an arid and semi arid (ASAL) district in Kenya. Case study method enabled close examination of the data within the agricultural drought context. As indicated in the Taita-Taveta District profile, (2010) out of the total area of 17,128.3 Km^2 covered by the district 24 per cent is range land suitable for ranching and dry land farming, while only 12 per cent is available for rain-fed agriculture. Of the 2,055.4 km^2

arable land, 74 per cent is low potential agriculture land, receiving an annual mean rainfall of 650mm. The district lies between 2° 46' north to 4° 10' north and longitudes 37° 36' east to 30°14' east. The average temperature in the district is 23˚C. The district is divided into three major topographical zones. These are the upper zone, lower zone and volcanic foothills. The District experiences two rain seasons the long rains between the months of March and May and the short rains between November and December. The rainfall distribution is uneven in the district, with the highlands receiving higher rainfall than the lowland areas. The lowland areas, which are mainly ASAL, are only suitable for planting crops with short maturing period like sorghum, cowpeas, green grams, cashew nuts, sunflower, millet and dry land hybrid maize varieties. According to Kenya Seed Company, (2010) Maize crop is the most planted crop during the rain seasons. Pwani hybrids maize (PH1 and PH4) which are resistant and tolerant to moisture stress, are considered as the most common varieties of maize that are grown in the area.

3.2 Data and Computations

To understand the application domain, a period of 1979 to 2008 daily Voi KMD historical dataset on minimum/maximum temperatures and precipitations and annual Kenyan Ministry of Agriculture 1976 to 2006 maize production dataset from Taita-Taveta district was obtained. The selection of samples of the datasets to use in analysis was done based on picking of data range without much of missing data. For the maize production dataset yearly production in tons and area cultivated in hectares were used as independent variables to determine production per hectare. In the meteorological dataset monthly average temperatures and monthly total precipitation were used as study variables to establish monthly, seasonal and annual precipitation conditions during the various years in the dataset (Graph 3 and Graph 4). Monthly normal maize crop water requirements were determined using existing FAO crop growth models while drought and non drought years were selected using literature review and their production compared to ratios of precipitation using the formulas below:-

$$EtCrop = p.Kc.(0.46Tmean + 8)$$

$$where$$

$$Tmean == (\sum_{day=1}^{day=n} \min Temp + \sum_{day=1}^{day=n} \max Temp)/2n$$

$$T\min = (\sum_{day=1}^{day=n} \min Temp)/n$$

$$T\max = (\sum_{day=1}^{day=n} \max Temp)/n$$

$$\therefore EtCrop = p \times kc \times (0.46(\sum_{day=1}^{day=n} \min Temp + \sum_{day=1}^{day=n} \max Temp)/2n + 8)$$

$$for\_all\_years, all\_months,$$
$$prec\_ratio, month\_i = (total\_prec\_month\_i)/(EtCrop)$$

Climatologically precipitation predictions for 2009 were computed using (1978-2008) precipitation data in 1 up to 10 year steps and analysis were done using spreadsheet and graphs.

$$sample\_size = totalYears / sampleStep$$

$$while\_n >= sample\_size,$$
$$do$$
$$sample\_years = get\_data\_year(n - sampe\_size),$$
$$n = n - sample\_size.$$
$$precipitation\_year(n+1), month\_i = (\sum_{1}^{sample\_size} sample\_year(\sum_{day=1}^{day=n} month\_i\_prec)) / sample\_size$$

$$for\_year(n+1), all\_months,$$
$$prec\_ratio, month\_i = (total\_prec\_month\_i)/(EtCrop)$$

4 Results

Table 1 shows analysis of precipitation during selected drought years. During the drought years the ratio of actual precipitation to normal water required went below 0.5 in one or both the seasons. Table 2 shows analysis of precipitation during selected non drought years. During the non drought years the ratio of actual precipitation to normal water required was above 0.5 in one or both the seasons. Climatologically precipitation prediction analysis results for year 2009 are shown in graph 1 with realization that 10 year step sampling is the most appropriate. Based on the analysis results the solution was designed using process logic and data flow diagrams and implemented using both Java programming language and Weka knowledge discovery software. FAO formulas were incorporated in the preprocessing module. The implementation involved preprocessing output consisting of two sets of files as follows; Training file with attributes year, month, scaled precipitation values and class index (1979-2008) and Prediction file with attributes year, month, scaled precipitation values (2009). The Weka knowledge flow processing module produced output with attributes Year, Month, Scaled precipitation values (range: 0 to 1), Precipitation class values, Index class (range: -2 to 2). Three classifiers (Isotonic Regression, K-nearest neighbor classifier, and Regression By Discretization) were considered appropriate in working with the preprocessed training and testing sets since the classifiers could come up with desired output classes on processing. Classifiers comparisons were done by performing 10 fold cross validation and comparing the performance to the actual classes as shown in table 3 and graph 5. The root relative squared error on running the three classifiers is shown in graph 6.

5 Discussions

The results on data preprocessing with comparison of 2009 prediction sets on various sample step years are depicted in graph 2. The outputs classes of classifiers were evaluated with actual classes for year 2009 as shown in graph 3. The output of the Weka knowledge flow (figure 3) formed the input to post processing module that manipulated processed data to user understandable form (figure 5). The end results of 2009 agricultural drought predictions are evaluated through comparison to actual precipitation situation in 2009 (figure 6). The consistency of solution was evaluated to Kenya Meteorological Department 2009 seasonal precipitation forecasts and actual 2009 precipitation records. KMD analyses and model outputs, with reference to the outlook for Long Rains (March-May) 2009 season as shown in figure 7 (a) and 7 (b) indicated that most parts of Coast Province (Lamu, Tana River, Voi, Taita Taveta, etc) were expected to receive generally depressed rainfall (near-normal rainfall tending to below normal). In the KMD outlook for 2009 Short Rains season (October-November-December) the areas forecasted to receive above-normal rainfall (enhanced rainfall) included the Coast Province especially (Mombasa, Kilifi, Malindi, Msabaha, Lamu, Voi, Taveta). The KMD MAM 2009 rainfall records indicated that the coastal districts recorded the most depressed rainfall. Most stations along the coastal strip recorded very low rainfall amounts during the month of May despite the fact that this is normally the peak rainfall month in the region during the Long Rains season. Localized and short-lived intense rainfall occurred in Voi and contributed significantly to the seasonal rainfall totals. Voi was pounded by a heavy downpour on 8th April 2009 resulting in 131.3mm on that single day (our study predicts an index of 2 for April 2009). Similar to our study results where March had a zero index while May had a negative index (-1.5), the KMD records show that in March 2009 rainfall was near normal while in May 2009 the rainfall was very poor. The OND 2009 short-rains season coincided with weak El-Niño conditions. As a consequence, Voi station experienced fairly enhanced rainfall amounts (Oct -1.5, Nov 1.5, Dec 1.5). The KMD forecasts for 2009 and actual 2009 KMD records are consistent with our study outcomes.

6 Conclusion

The results of this research show an improvement from previous researchers as the solution contributes to agricultural drought prediction with an emphasis specifically on agricultural drought for maize crop. The use of case study in analysis of data allowed design of a solution that is possible to run using data from other regions as well as investigations different seasonal crops. This paper demonstrated that the technique of combining meteorological data, crop production data, literature review on drought, FAO crop models, together with classification algorithms can be a feasible way of predicting agricultural drought and evaluate its impact on agriculture. The agricultural drought prediction output results obtained showed that the nearest neighbor classifier is a suitable tool for training precipitation data for agricultural drought output classes. As part of machine learning the IBk classifier results accomplished intelligence through the knowledge discovery and data mining process as aimed in the study main objective. Evaluation of results indicated a close relation in agricultural drought predictions with the outlook provided by KMD. The recommended future work is designing a solution that can cater for predictions in multiple regions for multiple crops at the same time; in Kenya for instance all districts can be represented and in each agricultural drought impacts evaluated for various seasonal crops. Possible adjustments of our solution output parameters socioeconomic measures on agricultural droughts anticipations can be suggested e.g. early warning allowing for government provision on importing calculated quantities of produce for crops believed to suffer an agricultural drought

References

Ashok, M. *et al*, 2006. Linking Seasonal Climate Forecasts with Crop Simulation to Optimize Maize Management, CCSP Workshop: Climate Science in Support of Decision Making, 14-16 November 2005 Crystal Gateway Marriott Arlington, Virginia 14-16 November 2005.

Dastorani, M. *et al* (2010). Application of ANN and ANFIS Models on Dryland Precipitation Prediction (Case Study: Yazd in Central Iran). *Journal of Applied Sciences,* **10**: pp 2387-2394.

Gong, Z. *et al*, (2010). Risk Prediction of Agricultural Drought in China. 2010 Seventh International Conference on Fuzzy Systems and Knowledge Discovery (FSKD 2010).

Kenya Meteorological Department, Agrometeorological bulletin, Issue No. 27/2009.

Kozyra, J. *et al* (2009). Institute Of Soil Science and Plant Cultivation National Research Institute, International Symposium, Climate change and Adaptation Options in Agriculture, Viena, June, 22-23 2009.

Ladislaus, B. *et al*, (2010). Indigenous knowledge in seasonal rainfall prediction in Tanzania: A case of the South-western Highland of Tanzania, Journal of Geography and Regional Planning Vol. 3(4), pp. 66-72, April 2010.

Lin Z. , Jing, M. Chen, Qiming Qin, Mei Huang, Lianxi Wang, Jianping Li, Bao Cao: Assimilating Remote Sensing based Soil Moisture in an Ecosystem Model (BEPS) for Agricultural Drought Assessment. IGARSS (5) 2008*:* 437-440.

Niu Shulian, Susaki Junichi, 2006. Detection of Agricultural Drought in Paddy Fields Using NDVI from MODIS Data. *A Case Study in Burirum Province, Thailand.*

Patrick O. Alila and Rosemary Atieno, 2006. Agricultural Policy in Kenya: Issues and Processes, *A paper for the Future Agricultures Consortium workshop, Institute of Development Studies, 20-22 March 2006.*

Reutemann P., (2007). WEKA KnowledgeFlow Tutorial for Version 3-5-7, University of Waikato 2007.

Tsegaye, T. and Brian, W. (2007). The Vegetation Outlook (VegOut): A New Tool for Providing Outlooks of General Vegetation Conditions Using Data Mining Techniques. ICDM Workshops 2007: 667-672

Z. (Bob) Su, Y. Chen, M. Menenti, J. Sobrino, Z.-L. Li, W. Verhoef, L. Wang, Y. Ma, L. Wan, Y. He, Q.H. Liu, C. Li, J. WEN, R. van der Velde, M. van Helvoirt, W. Lin1, X. Shan, (2007). Drought Monitoring and Prediction over China, **In**: Proceedings of the 2008 Dragon symposium, Dragon programme, final results, 2004-2007, Beijing, China 21-25 April 2008.

Orodho A. B, (2002). Department of Range Management, Faculty of Agriculture and Animal Production, University of Nairobi, Kenya.
http://www.fao.org/ag/AGP/AGPC/doc/counprof/Kenya.htm#1*, accessed on 14th February 2011*

Catholic Relief Services, 2011. http://crs.org/kenya/ongoing-hunger-crisis, *accessed 14th February 2011*

Kenya Seed Company, 2010. http://www.kenyaseed.com/maize.html, *accessed on 14th February 2011.*

Taita Taveta District profile, 2010.
www.aridland.go.ke/semi_profiles/taita_taveta_profile.pdf, *accessed on 25th January 2011, 25th January 2011*

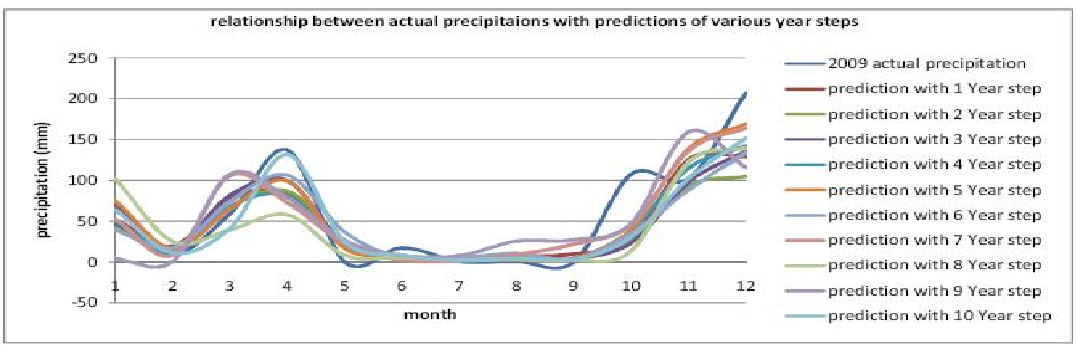
Appendix I: Tables, Figures and Graphs

Drought Year	Season 1 (mm)	Season 2 (mm)	Annual (mm)	Annual production (tones)	Area planted (hectares)	Production per hectare (tones)	Ratio of precipitation to normal (season 1)	Ratio of precipitation to normal (season 2)
1996	206.4	234	440.4	2538	4230	0.6	0.456637168	0.517699115
2005	158.7	88.1	246.8	3798	17464	0.217476	0.351106195	0.194911504

Table 1: Precipitation ratios and production per hectare during selected drought years

Non Drought Year	Season 1 (mm)	Season 2 (mm)	Annual (mm)	Annual production (tones)	Area planted (hectares)	Production per hectare	Ratio of precipitation to normal	Ratio of precipitation to normal (season2)
1981	355.1	356.8	711.9	22615	16509	1.369859	0.785619469	0.789380531
1982	182.7	424.6	607.3	8946	8082	1.106904	0.40420354	0.939380531
1986	151.5	387.1	538.6	12556	7715	1.627479	0.335176991	0.856415929
1991	380.9	139.9	520.8	8146	4007	2.032942	0.842699115	0.309513274
1997	217.3	495	712.3	7765	6488	1.196825	0.480752212	1.095132743

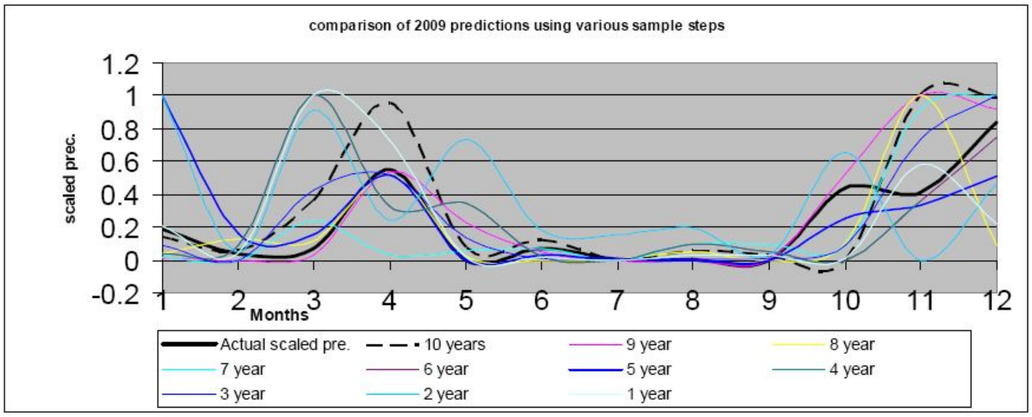
Table 2: Precipitation ratios and production per hectare during selected non drought years



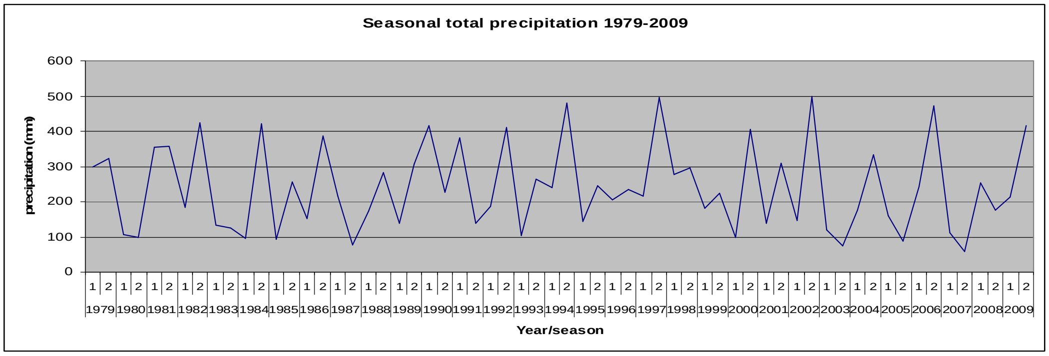
Graph 1: Climatologically 2009 precipitation predictions using 1 up to 10 sample years steps

Month	Actual class	Class predicted by classifiers					
		Ibk		Isotonic Regression		Regression By Discretization	
		5 Step	10 Step	5 Step	10 Step	5 Step	10 Step
Jan	-0.5	2	-1	2	-1	2	-1
Feb	-1.5	-1	-1.5	-0.5	-1.5	-0.5	-1.5
Mar	-1.5	-0.5	0	-0.5	0	-0.5	0
Apr	0.5	0	2	0.5	2	0.5	2
May	-2	-1.5	-1.5	-2	-1.5	-2	-1.5
Jun	-1.5	-1.5	-1.5	-1.5	-1	-1.5	-1
Jul	-1.5	-2	-2	-1.5	-1.5	-1.5	-1.5
Aug	-1.5	-1.5	-1.5	-2	-1.5	-2	-1.5
Sep	-2	-1.5	-1.5	-2	-1.5	-2	-1.5
Oct	0	0	-1.5	-0.5	-2	-0.5	-2
Nov	0	0	1.5	0	2	0	2
Dec	1.5	0.5	1.5	0.5	2	0.5	2
Error of the predicted values		0.0027		0.0027		0.0108	
Root relative squared error		3.7048%		3.7127%		7.4096%	
Time taken to train/build model		0 seconds		0.03 seconds		0.05 seconds	

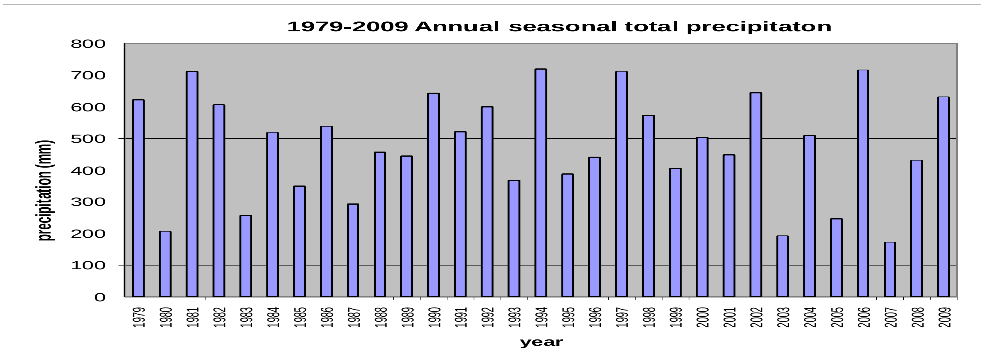
Table 3: Comparison of year 2009 actual classes to classes predicted by various classifiers



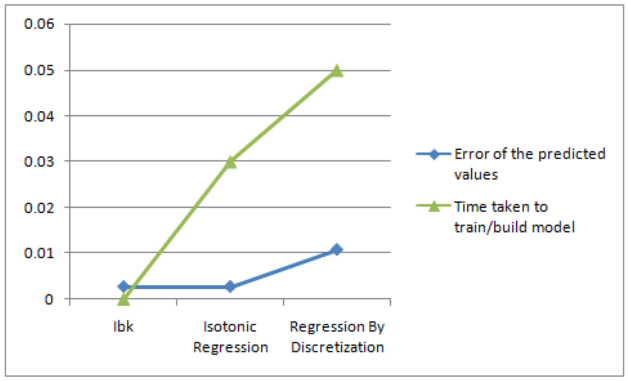
Graph 2: Comparison of various output predictions sets to year 2009 actual precipitation set



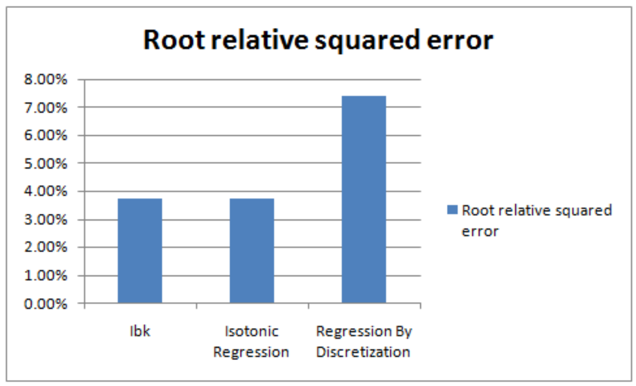
Graph 3: 1979 -2009 seasonal total precipitations (Data Source: KMD)



Graph 4: 1979 -2009 Annual seasonal total precipitation (Data Source: KMD)



Graph 5: Comparison of the classifiers using error on prediction and time taken to build model



Graph 6: Comparison of the classifiers root relative squared errors on running

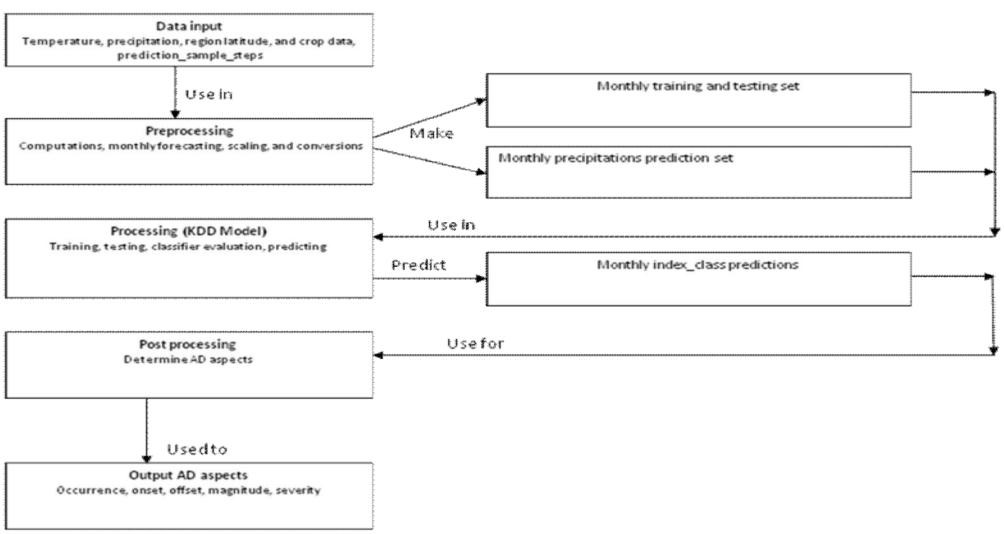


Figure 1: The Process Flow

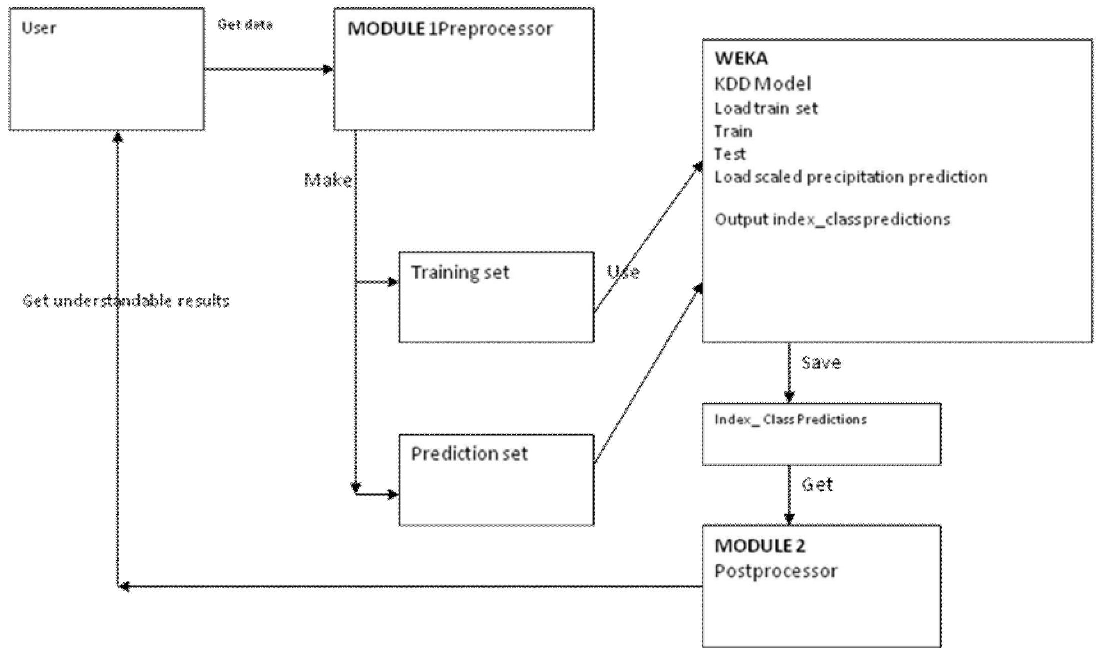


Figure 2: how the system works

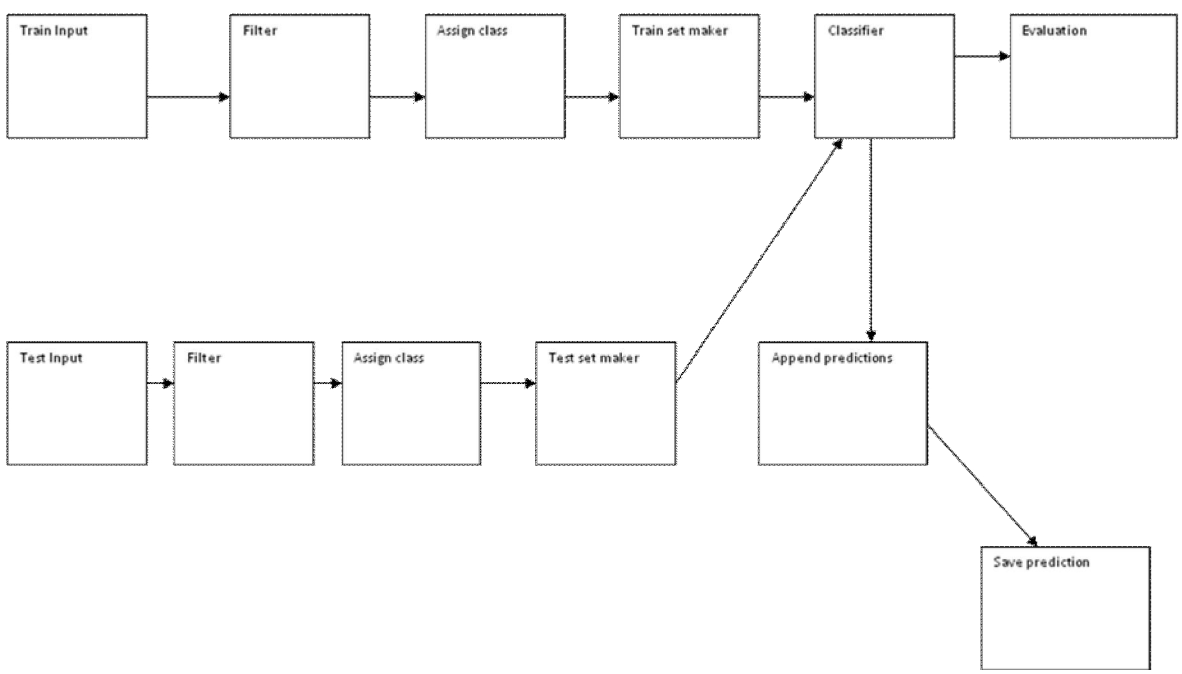


Figure 3: WEKA processes

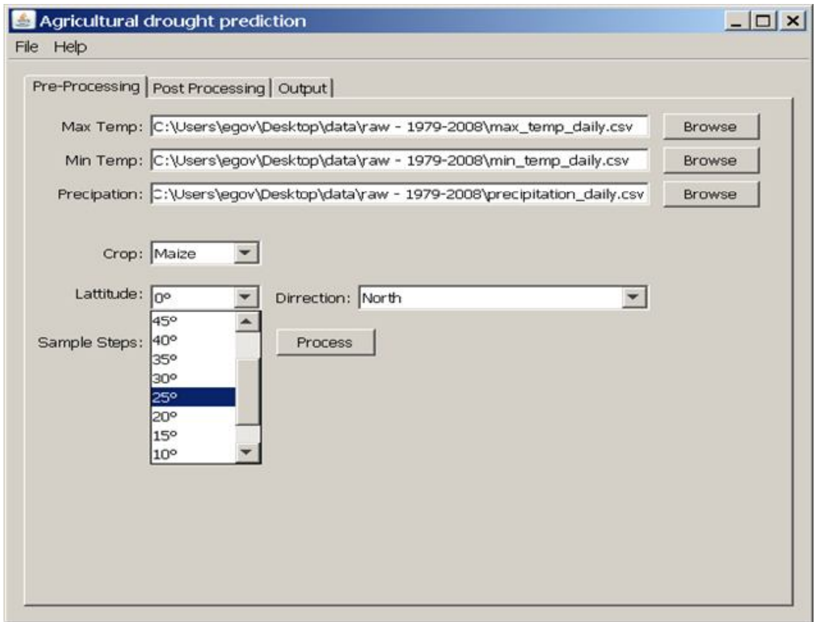


Figure 4: input interface for data preprocessing module

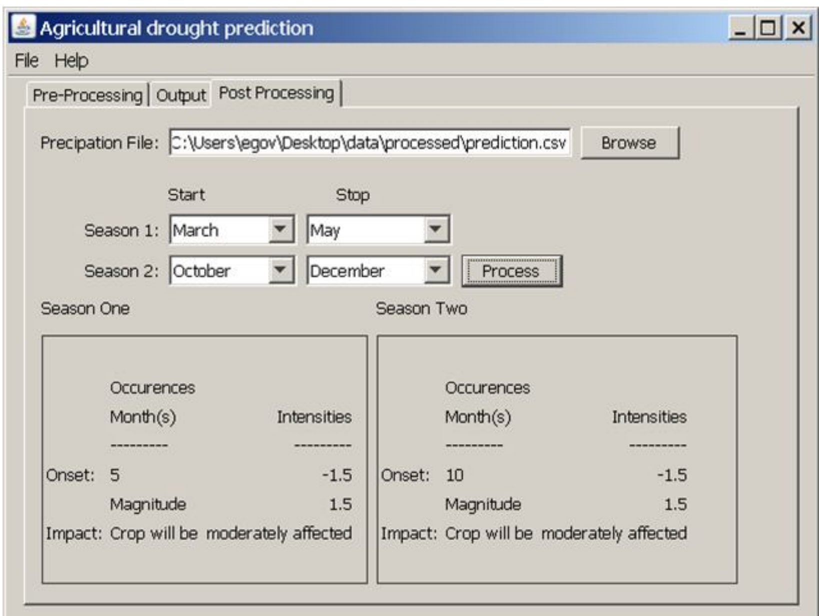


Figure 5: Output of agricultural drought predictions for season 1 and season 2

Crop	Initial stage	(days)	Crop dev. Stage	(days)	Mid-season stage	(days)	Late season	(days)	Season average
Cotton	0.45	(30)	0.75	(50)	1.15	(55)	0.75	(45)	0.82
Maize	0.40	(20)	0.80	(35)	1.15	(40)	0.70	(30)	0.82
Millet	0.35	(15)	0.70	(25)	1.10	(40)	0.65	(25)	0.79
Sorghum	0.35	(20)	0.75	(30)	1.10	(40)	0.65	(30)	0.78
Grain/small	0.35	(20)	0.75	(30)	1.10	(60)	0.65	(40)	0.78
Legumes	0.45	(15)	0.75	(25)	1.10	(35)	0.50	(15)	0.79
Groundnuts	0.45	(25)	0.75	(35)	1.05	(45)	0.70	(25)	0,79

Table 4: Crop factors, kc, for the most commonly grown crops

Latitude:	Month											
North	Jan	Feb	Mar	Apr	May	Jun	July	Aug	Sept	Oct	Nov	Dec
South	July	Aug	Sept	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	June
60°	.15	.20	.26	.32	.38	.41	.40	.34	.28	.22	.17	.13
55°	.17	.21	.26	.32	.36	.39	.38	.33	.28	.23	.18	.16
50°	.19	.23	.27	.31	.34	.36	.35	.32	.28	.24	.20	.18
45°	.20	.23	.27	.30	.34	.35	.34	.32	.28	.24	.21	.20
40°	.22	.24	.27	.30	.32	.34	.33	.31	.28	.25	.22	.21
35°	.23	.25	.27	.29	.31	.32	.32	.30	.28	.25	.23	.22
30°	.24	.25	.27	.29	.31	.32	.31	.30	.28	.26	.24	.23
25°	.24	.26	.27	.29	.30	.31	.31	.29	.28	.26	.25	.24
20°	.25	.26	.27	.28	.29	.30	.30	.29	.28	.26	.25	.25
15°	.26	.26	.27	.28	.29	.29	.29	.28	.28	.27	.26	.25
10°	.26	.27	.27	.28	.28	.29	.29	.28	.28	.27	.26	.26
5°	.27	.27	.27	.28	.28	.28	.28	.28	.28	.27	.27	.27
0°	.27	.27	.27	.27	.27	.27	.27	.27	.27	.27	.27	.27

Table 5: p values for various longitudes/latitudes in degrees north/south

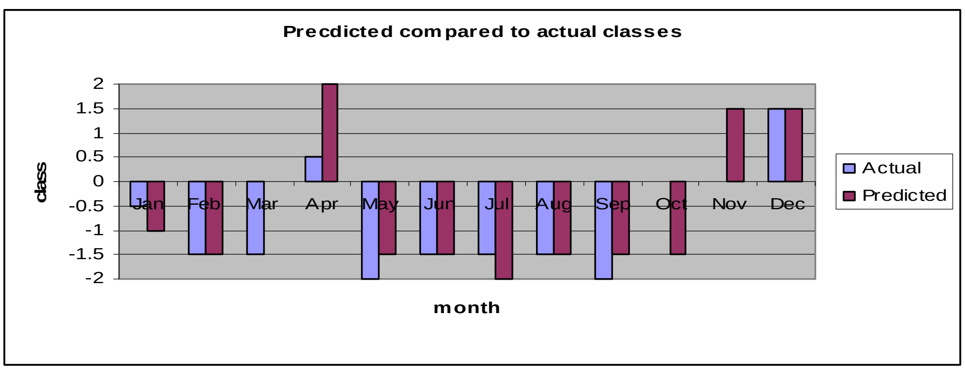


Figure 6: ibk classifier year 2009 predictions compared actual

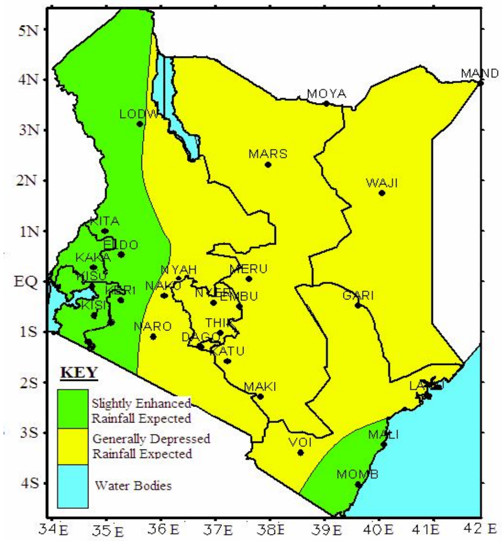


Figure 7 (a): KMD Mar-Apr-May 2009 Forecast

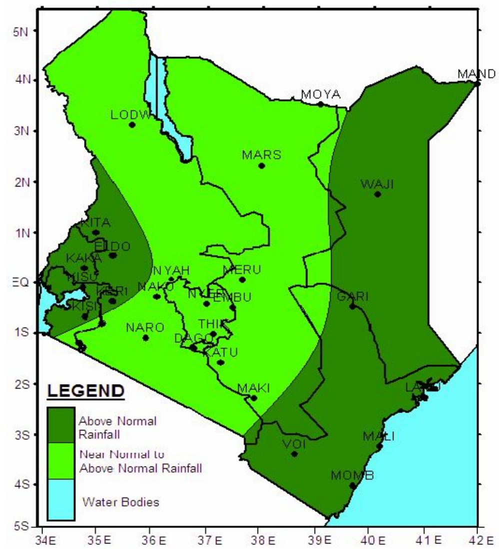


Figure 7 (b): KMD Oct-Nov-Dec 2009 Forecast