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ABSTRACT

Sorghum *(Sorghum bicolor)* is an important African cereal crop and is listed among Africa's lost crops but is now gaining popularity as other cereals are declining in production due to climatic change. To promote food security, many researchers and policy makers are shifting the focus on production of sorghum. In Kenya, sorghum is primarily grown in ASALs whose suitability is climatic factors but the extent is not known. This paper modeled the potential sorghum suitable areas of current and the years 2050 and 2080 climatic periods. The sorghum location data were downloaded from GENESYS and Kenya Agricultural Research Institute while climate data was from world climate database website. Analysis was done using Maxent and DIVA-GIS softwares. The model generated an excellent AUC of 0.97 and the suitable areas in the future are shown to expand in both 2050 and 2080 climatic periods though not in same magnitude. The main variables contributing more than 10 % of change in suitability areas in decreasing order are precipitation of wettest period, temperature seasonality (STD * 100), precipitation of warmest quarter, and precipitation of driest month. The generated information will guide the policy makers and stakeholders in making informed decisions with regard to the efforts of re-introduction and promotion of sorghum production in ASALs.

Introduction

Sorghum and several other cereal crops are important for food security in sub-Saharan Africa. Crop production in Kenya has been steadily declining FAO (2013). Such declines in maize production have been linked with unpredictable rainfall and drought, considered to be consequences of climate change (Meehl *et al*., 2007). This has led to efforts for development of new cereal germplasms that have high water use efficiency and tolerant to drought, which can withstand the effects of climate change (Twomlow *et al.* 2008). The newly introduced sorghum is performing well at 1.57 metric tons per acre in Kitui Kenya (Esipisu, 2013) and is complementing other failing cereals under the influence of climate change (FAO 2013).

Sorghum is relatively tolerant to drought (FAO 2013; KARI 2013) making it a primary candidate for cultivation in arid and semi-arid lands (ASALs) that are highly vulnerable to climate change. Sorghum is currently gaining popularity in Kenya due to its adaptability to different climates, failure of other crops, and its new industrial uses in alcohol production. Many researchers and policy makers are shifting their efforts towards production of sorghum both at small-scale and large-scale levels. In Kitui Kenya, farmers can only many to supply 2,080 metric tons against a demand of 40,000 metric tons from East African Breweries Limited (Esipisu, 2013). A large germplasm collection for sorghum comprising of more than 42,000 accessions has been developed (Huang 2004). As stakeholders take up the production of sorghum, it is important to map areas that are climatically suitable for sorghum at present and future cultivation of this crop.

A number of studies have been done on spatial species distribution modeling, either using one method, or a comparison of different methods. Pearson and Dawson (2003) in their studies recommended the use of Climate Envelope Modeling (CEM) in species distribution studies. Climate Envelope Modeling (CEM) and spatial analysis tools were be used in estimating the current and future distribution of sorghum growing areas. The model uses geo-referenced growing areas and nineteen climatic variables (Philips *et al.* 2006). Other researchers have used the Geographical Information System (GIS) in their studies and have recommended its application in similar studies (Chen 2001; Christensen *et al.* 2004; Zonneveld *et al.* 2009). This is because GIS applications are easy to use, integrate a lot of information and do complex analysis. Outputs of GIS are maps showing sorghum suitability growing areas under different climates. In view of the anticipated climatic variations, this paper modeled potential areas of growing sorghum currently, and the projection for the years 2050 and 2080. The generated information is useful in determining how climate change will affect the suitability of ASALs for sorghum production, and regions that require special focus.

Methodology

Data Sources and Processing

Data were sourced from different published materials. The sorghum location data were sourced from GENESYS website www.genesys-pgr.org and published material from Kenya Agricultural Research Institute website (www.kari.org). From this data, eighty two geo-referenced points were selected in sorghum ASALs areas. The current, the years 2050 and 2080 climate data with a resolution of 5 km were downloaded from

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Global Climate data website (www.worldclim.org). The future climate data is under CCM3 A2 carbon dioxide emission scenario and contain annual precipitation, minimum and maximum temperature. Using DIA-GIS, climate data was used to generate other sixteen climate variables all grouped as bioclim variables. The bioclim variables are coded as BIO1 = Annual mean temperature, BIO2 = Mean diurnal range (max temp – min temp) (monthly average), BIO3 = Isothermality (BIO1/BIO7) * 100, BIO4 = Temperature seasonality (Coefficient of variation), BIO5 = Max Temperature of warmest period, BIO6 = Min temperature of coldest period, BIO7 = Temperature annual range (BIO5-BIO6), BIO8 = Mean temperature of wettest quarter, BIO9 = Mean temperature of driest quarter, BIO10 = Mean temperature of warmest quarter, BIO11 = mean temperature of coldest quarter, BIO12 = Annual precipitation, BIO13 = Precipitation of wettest period, BIO14 = Precipitation of driest period, BIO15 = Precipitation seasonality (Coefficient of variation), BIO16 = Precipitation of wettest quarter, BIO17 = Precipitation of driest quarter, BIO18 = Precipitation of warmest quarter and BIO19 = Precipitation of coldest quarter.

Sorghum Potential Growing Areas Modeling

Data required for modeling potential growing areas was prepared in excel and DIVA-GIS and model built in Maxent. The climate envelopes were then mapped and categorized as low suitability (25-50%), medium suitability (50-75%) and high suitability (over 75%) areas. Maps of more than 25% suitability were generated for all the climatic periods. The robustness of the developed model was validated using cross tabulation one of the methods available in the Maxent software. The changes in suitability growing areas were sought and mapped using DIVA – GIS in the categories stated for each climatic period.

Results and Discussion

All the 19 bioclim variables were used in the model with 50 of the location data used for training and 10040 used to determine the Maxent distribution (background points and presence points). Figure 1A is the omission rate and predicted area as a function of the cumulative threshold which is calculated on the training presence records, on the test records. The closer the Omission on training samples line is to the Predicted omission, the more accurate the generated model. In work done by Zonneveld *et al.* (2009) the location data used for *Pinus kesiya* and *P. merkusii* were 46 and 50 respectively. Scheldeman *et al.* (2010) on their research on the influence of presence points in model concluded that after 50 species presence point, the prediction of potential distribution stabilizes. In a comparison of modeling methods, region and taxa, Elith *et al.* (2006) reported a general progression of performance (least to best performing) from BIOCLIM to DOMAINE and Maxent. Area Under Curve (AUC) of the Receiver Operating Characteristic (ROC) curve figure 1B, is a parameter used to evaluate the predictive ability of the generated model. It measures the likelihood that a randomly selected presence point is located in a raster cell with a higher probability value for species occurrence than a randomly selected absence point.

The generated model's AUC for training data was 0.97 an excellent model as per Araújo *et al.* (2005) guidelines with a random prediction AUC of 0.5. Apart from Maxent being substantially superior to GARP (Genetic Algorithm for Rule-Set Prediction), Phillips *et al.* (2004) concluded that it also has a natural probabilistic interpretation and can be easily understood by non-experts. The same conclusion was arrived at by Philips *et al.* (2005) in the study of species geographic distribution modeling. Their results showed that both Maxent and GARP were significantly better than random when tested for omission and ROC analysis. They further concluded that Maxent showed better discrimination of suitable and unsuitable areas of the species in the analysis of AUC.

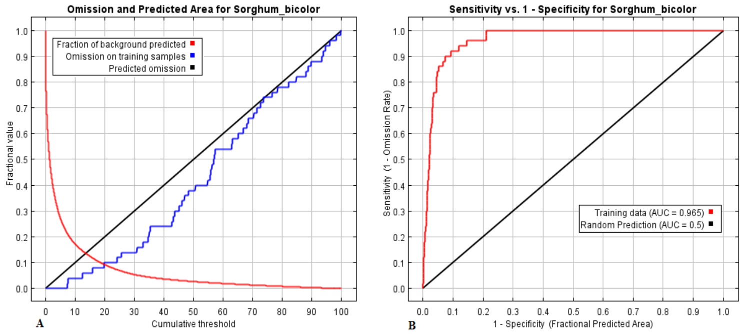

Figure 1: The receiver operating characteristic (ROC) curve for sorghum

Change of variables with climate

The contributions of bioclim variables to the model were different with the highest at 37.0% and lowest being four variables at 0.0%. The four variables contributing more than 10% to the model table 1 were BIO13- Precipitation of Wettest Period (month) (37.0%), BIO4 - Temperature Seasonality (STD * 100) (21.6%), BIO – 18 Precipitation of Warmest Quarter (14.8%) and BIO – 14 Precipitation of Driest Month (13.6%). The Kenya's ASALs figure 2 comprises a total of 27 districts of which 10 are classified as arid and 17 as semi-arid lands (GOK, 2013).

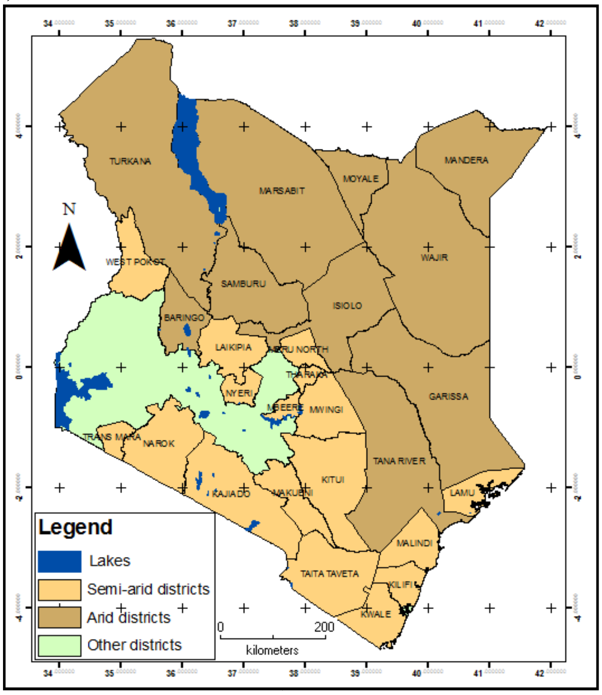

Figure 2: Kenya arid and semi-arid lands districts

Within the Kenya's ASALs, the four main bioclim variables changes are summarized in table 1. The values of all the location points used in the model were averaged for each variable and differences sought in each climatic period. All the four variables are predicted to be reducing at different magnitudes in the future climatic periods where sorghum is currently growing.

Table 1: Change in the key environmental variables in current sorghum location points contributing more than 10% in sorghum suitability growing areas

Variable code	Variable title	Percent contribution	Current values	2050 Changes	2080 Changes
BIO13	Precipitation of wettest	37.0	125.84	0.54	-21.18

	period				
BIO4	Temperature seasonality (STD * 100)	21.6	187.28	-1.76	-23.88
BIO18	Precipitation of warmest quarter	14.8	4.05	-0.21	-0.35
BIO14	Precipitation of driest month	13.6	236.09	-1.34	-5.39

Spatial analysis was also performed for the four main bioclim variables figures 3 and 4 and their variations with climatic periods described. The results showed that the different variables change differently in the future climatic periods with some to the positive and others to the negative.

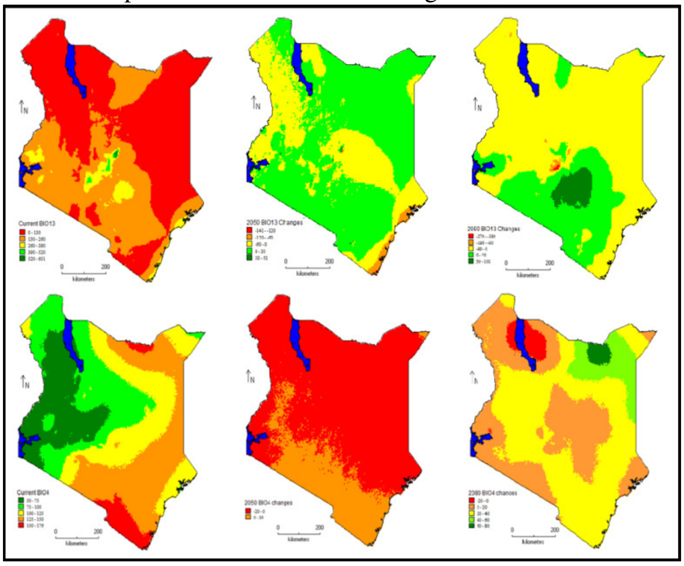

Figure 3: The current and changes in 2050 and 2080 climatic periods of BIO13 and BIO4 variables

The variable BIO13 measures precipitation in the wettest month of the year which in large parts of ASALs range from 0 mm – 260 mm in the current climatic period. In 2050 climate BIO13 changes will be from a low of -141mm to a high of 61mm. Many parts of north western, eastern and coastal regions will experience changes in precipitation of slightly less than 0 mm to -141 mm. In addition, the rest of the ASAL region will receive precipitation slightly more than 0 mm to a maximum of 61 mm. There will be a reduction of as much as -270 mm and an increase of 100 mm in precipitation in the 2080 climate scenario. In this climatic period, much of the western, northern, north-eastern and coastal regions will experience precipitation variance of between 0 mm and -270 mm. An improvement in precipitation of 0 mm – 100 mm will only be received in the eastern and lower eastern regions. Majority of the ASAL districts will experience an increase in BIO13 from slightly more than 0 mm to 30 mm in 2050 climate while a reduction of between -90 mm to 0 mm will be observed in 2080 climate.

The variable, BIO4 (temperature seasonality*100) is a measure of temperature variation over the course of the year. This variable in the current climate range from a low of 50 in western and north-western regions then increases gradually to the eastern and southern parts of the Kenya to a value of 176. Its 2050 climate values divide the country into southern and northern parts with maximum values of 20 and minimum of -20 respectively. The BIO18 (precipitation of warmest quarter) measures precipitation in the four hottest months. Much of the ASALs especially the north-western and coastal areas will experiences declines ranging from 0 mm to -80mm while the north-eastern parts changes are between 0 mm to 216 mm. Furthermore, the warmest quarter precipitation in 2080 climate will continue to decline in the ASALs. Much of these regions will experience decline of between 0 mm to -255 mm with a few areas receiving extra precipitation by up to 115 mm.

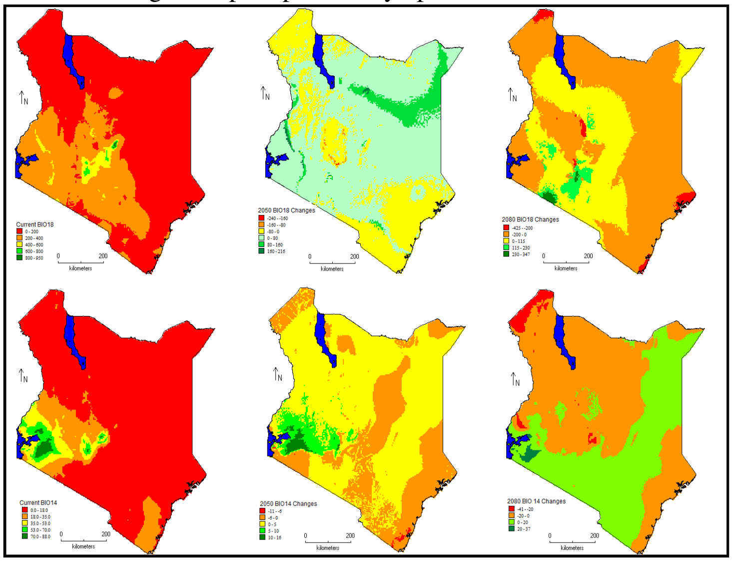

Figure 4: The current and changes in 2050 and 2080 climatic periods of BIO18 and BIO14 variables

The BIO14 variable (precipitation of driest month) is a measure of precipitation in the driest month with the entire ASALs having a value of between 0 mm – 18.0 mm with some areas in the south coast receiving up to 35.0 mm per month. Majority of ASALs in 2050 climate will experience changes of between -6.0 mm and 5.0 mm with a few areas in the south coast less precipitation by 11.0 mm. The scenario in the 2080 climate indicate that the coastal, northern and north-western parts will receive reduced precipitation by as much as -41.0 mm with the eastern and north-eastern regions having an increased rainfall by up to 20.0 mm per month.

A lot of researches concerning climate change and its impacts with varied conclusions have been undertaken. KNMI (2006) used 12 models to investigate changes in precipitation using runs forced with Special Report Emission Scenario (SRES) A1B scenario. The research arrived at a conclusion of elevated precipitation under global warming in Kenya. KNMI (2007) indicated that there will be variations in climate observed in Kenya by the year 2100. The report contains different precipitations variations from different models and emission scenarios. In the North Western, northern and coastal districts an improvement is projected in the year 2100 short rain events. Ward (2007) used DOMAIN, MAXENT and BIOCLIM to model the potential geographic distribution of six invasive ant species in New Zealand. The research concluded that unlike DIMAIN and MAXENT, BIOCLIM performed poorly with low AUC and higher omission errors. Similar studies have also been undertaken by CIAT (2011) on climate influence on tea growing areas in Kenya. This study observed that there will be a decrease in suitable tea growing areas in Kericho and Nandi regions and expansion of the same in Central Kenya districts by the years 2020 and 2050. Kigen *et al.* (2013) who studied climate change impact on the Grevy's zebra niche concluded that there will be a significant niche expansion in under the year 2080 climatic period. The model's AUC was 0.984 and the key variables contributing more than 2% were Isothermality, Precipitation of Coldest Quarter, Annual mean temperature, Annual Precipitation, Min Temperature of Coldest Period and Precipitation of Wettest Quarter. A study in South East Asia on the impacts of climate on pine distribution used Maxent and DIVA GIS software concluded that the spatial distribution of pine will change with climate by the year 2050. The pine populations especially in China, Cambodia and Thailand are under threat Zonneveld *et al*. (2009). They further discovered that areas with potential new pine niche cover Malay Archipelago. The key environmental variables in the output model were annual temperature, maximum temperature, temperature seasonality, annual precipitation and precipitation in the driest quarter.

Modeled sorghum growing suitability areas

The modeled Kenya's current sorghum growing areas of more than 25% (low) suitability in the ASALs covers mainly the semi arid districts of Kajiado, Makueni, Kitui, Mwingi, Tharaka and Meru North. Other ASAL districts with minimal suitable areas are in the coastal region comprising Lamu, Tana River, Kilifi, Kwale and Taita Taveta. Also included in the current model are some high potential neighboring districts. These current modeled suitability areas are in agreement with genesis spatial data published in (GENESYS, 2013). The same areas are also published by (Wortmann *et al.,* 2006; KARI 2013; Esipisu, 2013; Muui *et al.* 2013) as Kenya's sorghum growing areas. The future 2050 and 2080 climate suitability areas figure 5 indicated an expansion in the suitable sorghum growing areas. The expansion of suitable regions in 2050 climatic period will cover not only the semi-arid districts as the current distribution but also new areas as Malindi, Kilifi, Kwale and the entire Lamu districts. The new growing areas of arid lands are Tana River, Lamu, Garissa, Wajir, Marsabit and Turkana. The sorghum suitable growing areas will shrink in 2080 climate with major changes in area of coverage and level of suitability. All the districts show a reduction in level and coverage of suitability exception of Marsabit and Trans Mara districts with positive changes.

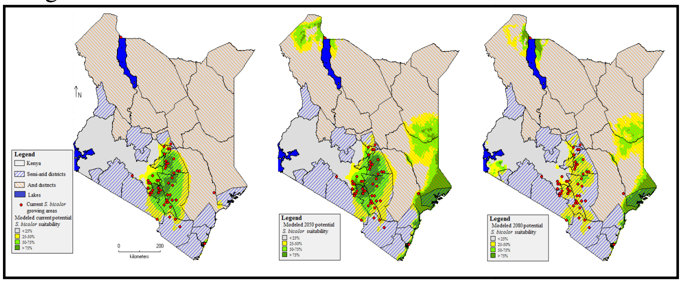

Figure 5: The modeled current, 2050 and 2080 *S. bicolor* potential growing areas in ASALs of Kenya

These results are consistent with (GENESYS 2013; KARI 2013) and descriptions in Muui (2013). Similar studies have been done by Zonneveld *et al*. (2009) and Kigen *et al.* (2013) on the impacts of climate on pine and Grevy's zebra niche respectively. They both concluded that the climate variables affected the distribution of pine and zebra both negatively and positively in their areas of study. The percentage area variations with climatic periods in each level of suitability are summarized in table 2. The current suitability areas were used for basis of comparison changes in suitability areas in the future climatic periods. The 2050 climate will have a net increase in all the levels of suitability with low suitability area increasing by 130%.

Table 2: Changes in sorghum suitability growing areas (square kilometers)

Suitability	Current area	2050% change	2080 % change
Low	27,700	130	168
Medium	33,275	79	-17
High	11,500	267	71

In addition, medium suitability increased by 79% and over high suitability area changing positively by 267%. The 2080 climate effected sorghum suitability areas negatively by various degrees. There is an increase of 168% in areas of low suitability with medium suitability decreasing by 17% the high suitability areas expanded by 71%. Parry *et al.* (2003) used models to estimate change in world percent cereal changes in different climatic periods. Their results showed that under SRES A1FI emission scenario, percent cereal yield changes in Kenya range from 2.5 in 2020, -2.5 in 2050 and -30 in 2080.

Conclusion and recommendations

Sorghum crop is gaining popularity in Kenya due to climate variability as other cereals are failing and its new application in the brewing industry. With the changing climate, modeling has indicated the potential changes in sorghum suitable growing areas thereby providing useful information for policy makers. The study recommends incorporation of models to achieve sustainable development and utilization of Kenyan ASALs.

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