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Modelling Climate-based changes of sugarcane growing areas in Western Kenya

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Abstract:

Sugar cane *(Saccharum* spp. hybrids*)* is an important cash crop for Kenya's sugar industry contributing significantly to the country's economy through farming and employment. Its production in Kenya is both irrigation and weather dependent. In Western Kenya, it is a major economic activity heavily dependent by more than 50% of the population. To plan for sustainable development of the counties in western Kenya, it is important to understand how the anticipated climate change will influence this cash crop. This paper modeled the potential sugarcane growing areas of current and the year 2050 climatic periods. The sugarcane location data were extracted using fishnet from published materials while climate data was obtained from world climate database website. Data analysis and modeling was done using Maxent and DIVA-GIS softwares. The model generated an excellent Area Under Curve of 0.996 and more than 0.6 suitability level areas increased by 167.21% in 2050 climatic period. The main variables contributing more than 5% of change in suitability areas are Precipitation of Driest Period (42%), Precipitation of Coldest Quarter (28.8%), Isothermality (13.3%) and Precipitation of Wettest Quarter (8.1%). The generated information will guide the policy makers and stakeholders in making informed decisions with regard to the efforts of promotion of sugarcane production in western Kenya Counties.

KEY WORDS: Sugarcane, Maxent, DIVA-GIS, modeling

1 INTRODUCTION

Sugarcane *(Saccharum* spp. hybrids*)* is the driver of Kenya's sugar industry and is identified by Vision 2030 (GoK, 2007) which is largely confined in the western region. It has been cultivated in Kibos, Siaya County since 1902 and expanded to western Kenya region in the mid 1960s and early 1980s (Luckman, 1959). The Sugar Industry Strategic Plan of 2010-2014 (GoK, 2009) indicated that other factories constructed comprise Muhoroni (1966), Chemelil (1968), Mumias (1973), Nzoia (1978), and South Nyanza (1979), West Kenya (1981), Soin Sugar Factory (2006) and Kibos Sugar and Allied Industries (2007). In 2008, cane variety CO 945 occupied 35.72% of the total area under cane while Varieties CO 421, CO 617 and N14 occupied 28.4%, 13.29%, 10.95% of the total area respectively and Kenya Sugar Research Foundation developed four new cane varieties (KEN 82-062, KEN 82-472, EAK 73-335 and D8484) in 2007 Gok (2009).

Sugarcane growing in Kenya by 2008 covered an area of 1694.21 km^2 producing a total of 5,165,786 tons of sugarcane (Gok, 2009). The sugarcane growing areas are between 1300 – 1700 meters above sea level with a mean annual rainfall of 1200 – 1900 mm and an average temperature of 20^0C

(Jamoza, 2005). These climatic conditions are changing and are anticipated to change more in the future (IPCC, 2014). The predicted climate change in these regions shows an elevated annual average temperature and a decrease in rainfall amounts (KNMI, 2007) and spatial modelling will give insights into the resulting vegetation change.

A number of studies have been done on spatial species distribution modeling, using either one method or a comparison of different methods. Many studies conducted on climate change and its impacts on plant and animal communities have produced varied conclusions. KNMI (2006) used 12 models to investigate changes in precipitation using runs forced with Special Report Emission Scenario (SRES) A1B scenario. The research concluded that Kenya would experience elevated precipitation under global warming. KNMI (2007) indicated that there will be variations in climate observed in Kenya by the year 2100. The report contains different precipitation variations from different models and emission scenarios. In the north-western, northern and coastal regions an improvement in precipitation is projected in the year 2100 short rain events. Similar studies have been undertaken by CIAT (2011) who focused on climate change 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 regions 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 habitat expansion in the year 2080 climatic period. A study in South East Asia on the impacts of climate change on pine distribution using 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) with potential new areas covering the Malay Archipelago. The Maxent and DIVA GIS software models the spatial suitability of selected crops, plants and animals based on a given criteria of controlling variables such as climate, soils and altitude. Maxent apart from selecting the suitable areas also allocates the suitability level ranging from 0 (unsuitable) – 1 (maximum suitability) while DIVA GIS functionality is primarily display and area calculation.

Many researchers (Pearson and Dawson, 2003; Chen, 2001; Christensen *et al.*, 2007 and Zonneveld *et al.*, 2009) recommended the use of Climate Envelope Modeling (CEM) in species distribution studies. Climate Envelope Modeling (CEM) and spatial analysis tools were used in estimating the current and 2050 sugarcane growing areas. The outputs of the model are maps showing sugarcane growing areas under different climates therefore providing new information to aid informed decision making. In view of the anticipated climatic variations, this paper modeled potential areas of growing sugarcane currently, and the projection for the year 2050 with an objective of identifying areas to grow this crop. The generated information is useful in determining how climate change will affect the suitability of sugarcane production thus influencing economic development decisions in Kenya's western counties.

2 METHODOLOGY

2.1 Data Sources and Processing

Data were sourced from different published materials. The sugarcane location data were sourced from Survey of Kenya (1985). From these spatial data, 169 geo-referenced points in decimal degrees were generated in the sugarcane growing areas to be used for modeling. The current and the year 2050 climate data with a resolution of 5 km were downloaded from Global Climate data website (www.worldclim.org). The future climate data is under CCM3 A2 carbon dioxide emission scenario and contain annual precipitation, and minimum and maximum temperature. Using DIVA-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 (maximum temperature– minimum temperature) (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.

2.2 Modeling the Current and Future Sugarcane Potential Growing Areas

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 0-0.2, 0.2-0.3, 0.3-0.5 and 0.5-0.7 and 0.7-1 suitability areas. The robustness of the developed model was validated using cross tabulation a method available in the Maxent software. The changes in suitability growing areas were sought and mapped using DIVA – GIS for the two climatic periods.

3 RESULTS AND DISCUSSION

All the 19 bioclim variables were used in the model with 67 of the location data used for training and 10061 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 and 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) in their research on the influence of presence points in a model concluded that after 50 species presence point, the prediction of potential distribution stabilized. Comparing modeling methods, regions and taxa, (Elith *et al.*, 2006) reported a general progression of performance (least to best performing) from BIOCLIM to DOMAIN and Maxent. Area Under Curve (AUC) of the Receiver Operating Characteristic (ROC) curve (Figure 1B), is 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.

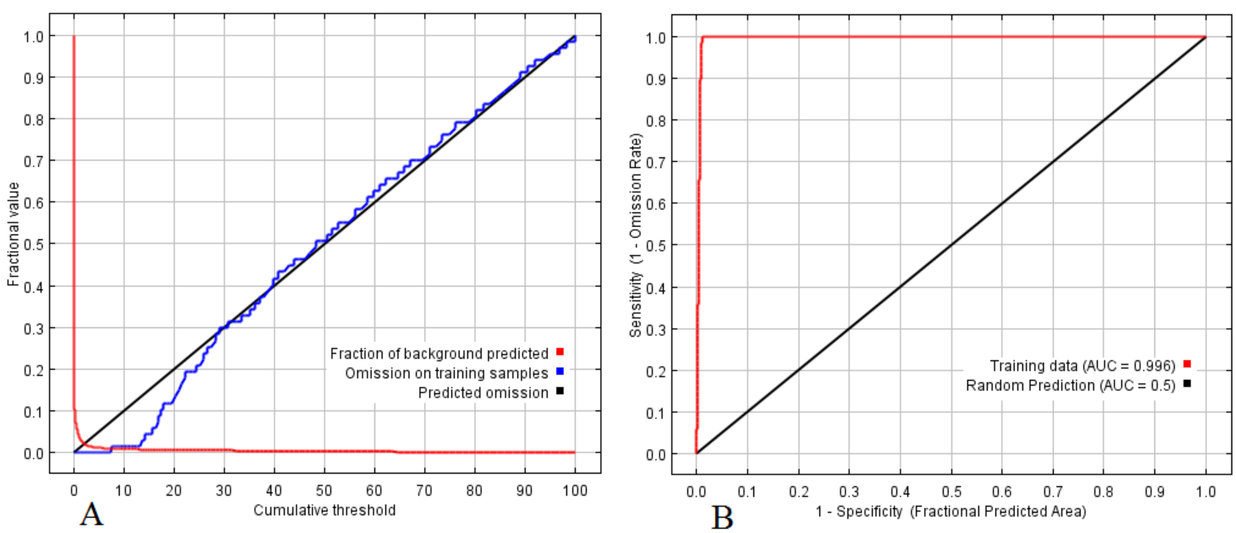

Figure 1: The omission and predicted area (A) and sensitivity vs specificity (B) for sugarcane

The generated model's AUC for training data was 0.996, 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.*, 2005) concluded that it also has a natural probabilistic interpretation and can be easily understood by non-experts. Their results showed that Maxent and GARP were significantly better than random prediction 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.

3.1 Change of Variables with Climate

The bioclim variables were dissimilar in the two climatic periods under study with differing contribution levels. The bioclim variables contributions were highest at 43% with the lowest being four variables at 0.0%. The four variables contributing more than 8% to the model (Table 1) were BIO14 (43%), BIO19 (28.8%), BIO3 (13.3%) and BIO16 (8.1%). The values of the 67 location points used in the model were averaged for each variable and differences sought in each climatic period and presented in per cent change. Three of the variables are predicted to be reducing by between -11.74- -0.64% except BIO16 which increased by 1.58%.

Table 1: Change in the key environmental variables in current sugarcane location points contributing more than 8 % in sugarcane suitability growing areas

Variable code	Variable title	Percent contribution	Current values	2050 values	2050 % change
BIO14	Precipitation of driest period	43.0	50.10	44.22	-11.74
BIO19	Precipitation of coldest quarter	28.8	442.82	414.61	-6.37
BIO3	Isothermality	13.3	86.90	86.34	-0.64
BIO16	Precipitation of wettest quarter	8.1	648.40	658.62	1.58

Figure 2 is the response curves of the four bioclim variables. It shows how the environmental variable affects the Maxent prediction. They demonstrate the logistic prediction change as each environmental variable is varied, keeping all other environmental variables at their average sample value Phillips *et al.*, (2005). The BIO14 ranged from -10 – 100mm with an inverse logistic output of above 0.9 – 0. The variable BIO14 ranged from 37 - 67 mm in the current climatic period and predicted to be 32 – 62 mm in 2050 climate. The BIO19 logistic output peaked at 500 with a value of 0.65 in a range of -100 – 700. This variable in the current climate ranges from 349 – 525 mm and between 310 – 505mm in 2050 climate. BIO3 displayed a sharply increasing trend after 80mm and peaking at 90mm with a logistic output of 0.65. Its values range from 85.66 – 88.11 and 83.79 – 88.17 in the current and future climatic periods respectively. The precipitation of wettest quarter (BIO16) ranged from 0-1200mm with a maximum of 1200mm at a logistic output of about 0.68. The bioclim has values ranging from 561 – 705 in the current climate and 566 – 732 in the 2050 future climate.

3.2 Modeled Sugarcane Growing Suitability Areas

The modeled sugarcane growing areas in square kilometers of more than 0.2 suitability level were mapped (figure 3). In both climatic periods, the areas with more than 0.6 suitability levels are restricted within Kakamega and Bungoma counties. The current modeled areas of between 0.4 – 0.6 are largely found in Kakamega and Bungoma expanding to Busia and Vihiga in 2050 climatic period though the total area reduced. The suitability levels of 0.2-0.4 cover all the counties with a general expansion to new areas on the eastern part side of the western counties in 2050. These current modeled suitability areas are in agreement with information published by (Survey of Kenya 1985; Jamazo 2005; GoK 2009) as Kenya's sugarcane growing areas. The sugarcane suitable growing areas are predicted by the model to change in 2050 climate in different magnitudes with the highest being an expansion by 167.21% in the more than 0.6 suitability level.

Spatial modeling research have been done by (Zonneveld *et al.*, 2009; Kigen *et al.*, 2013) on the impacts of climate on pine and Grevy's zebra niche respectively. Others include CIAT (2011), working on the impacts of climate on tea and Pearson (2003), working on the impacts of climate change on the distribution of species. They all concluded that the climate variables are predicted to influence the species under study. The changes in areas under different suitability levels in the different climatic periods are summarized in table 2.

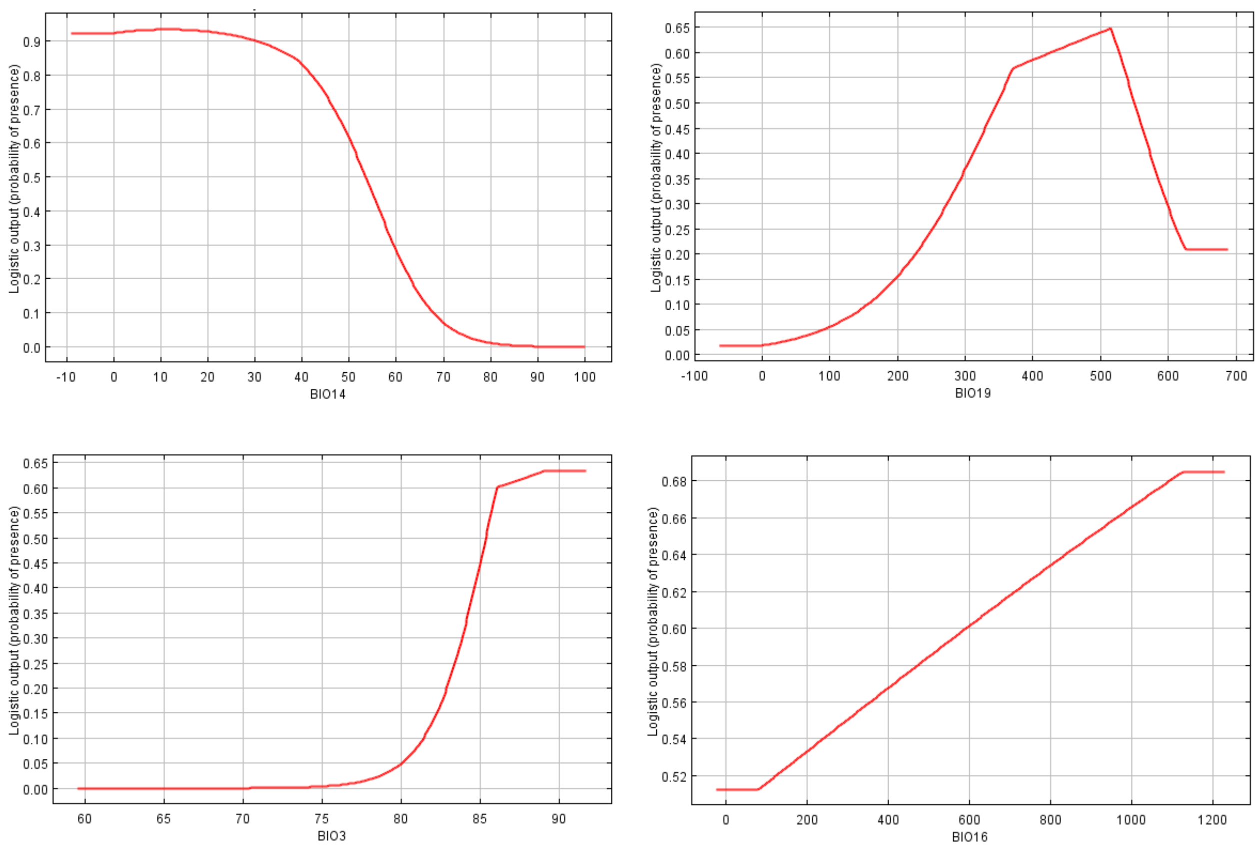

Figure 2: The logistic response curves of the bioclim variables on Maxent prediction

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

Suitability level	2015 area (km^2)	2050 area (km^2)	Area (km) % change
0.2-0.4	2600	4075	56.73
0.4-0.6	2900	1800	-37.93
0.6-1	1525	4075	167.21

The percentage change of sugarcane growing areas for the future climatic period was calculated based on the current growing area. The 2050 climate will have an expansion effect of 56.73 and 167.21% in the 0.2-0.4 and 0.6-1 sugarcane growing suitability levels respectively. The 0.4-0.6 suitability level is predicted to reduce by -37.93% to cover an area of 1800 km^2 from 2900 km^2. Parry *et al.*, (2003) used models to estimate change in world percent cereal changes in different climatic periods. Their results showed that under SRES A2 emission scenario, percent cereal yield changes in Kenya range from 2.5 in 2020, -2.5 in 2050 and -30 in 2080.

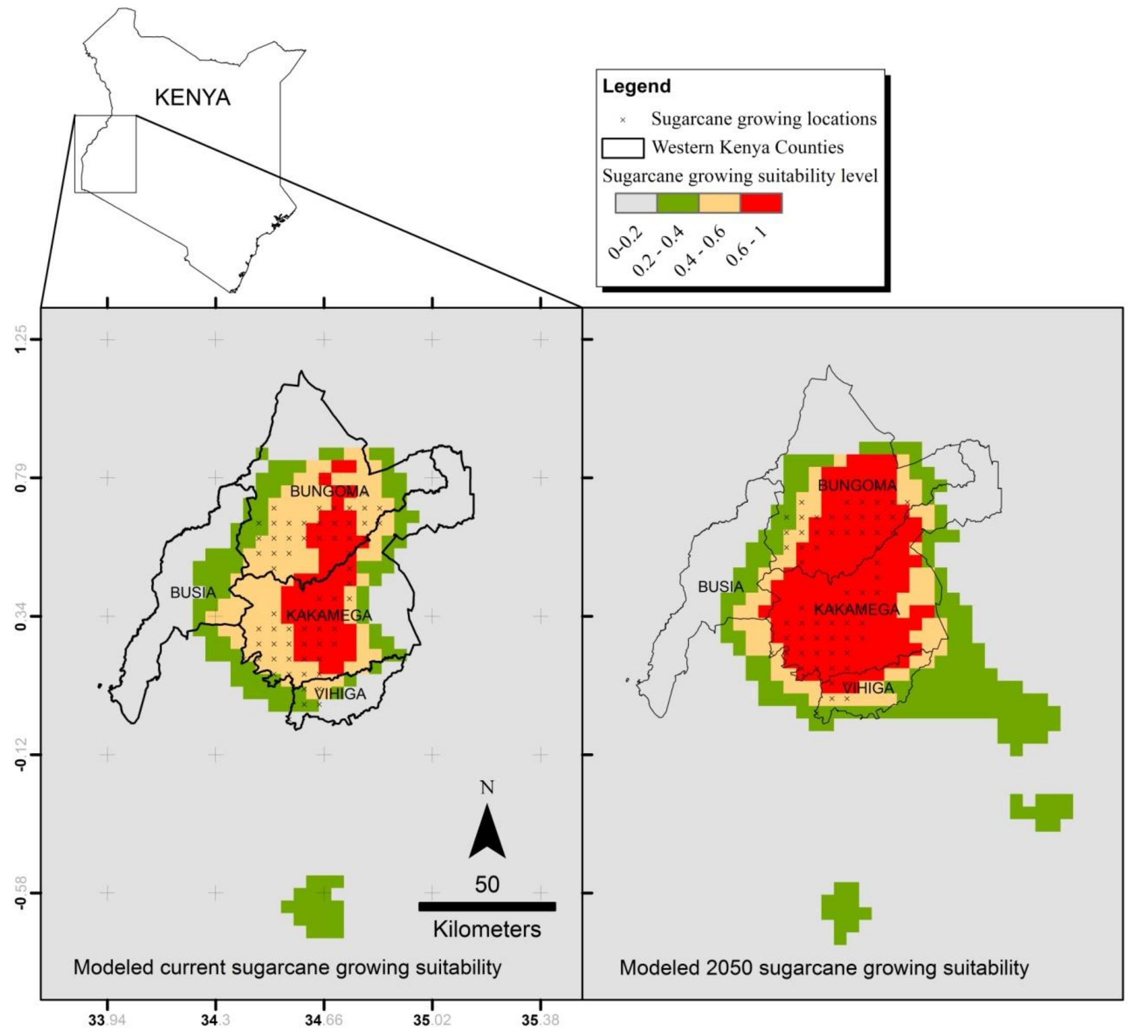

Figure 3: The modeled current and 2050 sugarcane potential growing areas in western Kenya

4 CONCLUSION AND RECOMMENDATIONS

The 2050 predicted climate will have a positive effect in western Kenya sugarcane growing areas. The information from the model is useful in the management of sugar industry in Kenya and the policy makers should take appropriate action. The study recommends inclusion of other factors controlling sugarcane growing and use of more refined bioclim data.

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