Vulnerability of Maize Production to Climate Change in Maize Producing Counties of Rift Valley Kenya: The Indicator Approach

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Abstract

Efforts towards attainment of sustainable economic growth and food security in Kenya are under increasing threats due the adverse effects of climate change. This study therefore, sought to assess the vulnerability of maize production to climate change in major maize producing counties of Kenya's Rift Valley region, using the indicator approach. Climate data including monthly rainfall, maximum and minimum temperature was obtained from Kenya Meteorological Department. The Sen's Slope Estimator was used to determine the rate of change of rainfall and temperature (1981-2010), which constituted the exposure indicators. The Standardized Precipitation Index (SPI) was used to determine the frequency of extreme climate events that formed part of exposure variables. As for the socioeconomic and biophysical data sets, sensitivity indicators included demographic and ecological sensitivity variables while adaptive capacity variables encopmassed social capital, literacy rate, financial capital and physical capital. Sensitivity and adaptive capacity data was obtained from Kenya Bureau of Statistics, Ministry of agriculture and Fisheries and Tegemeo Institute of Agricultural Policy and Development. After normalization, Principal Component Analysis (PCA) was used to assign weights to the indicators. Subsequently, the normalized values of each variable were multiplied with their respective weights as obtained from PCA and later aggregated to obtain Exposure, sensitivity, adaptive capacity and vulnerability indices

Trans Nzoia had the least exposure index (0.19) and second highest adaptive capacity(2.59) which made it record the lowest vulnerability index of -0.212. Narok recorded the highest vulnerability index of 1.51 with the peak exposure (1.03) and least adaptive capacity (-2.28). Nakuru had the second highest vulnerability index (0.35) while Uasin Gishu recorded the second least vulnerability index (-0.12). Generally, counties with considerable socioeconomic development recorded high adaptive capacity which reduced their vulnerability significantly. Hence, in order to cushion most vulnerable maize producing counties, climate change policies and strategies should prioritize adaptive capacity enhancement through socio economic development initiatives such as irrigation, rural infrastructural development and educational programs.

Key words: *Vulnerability Assessment, Climate Change, Indicator Approach*

1.0 INTRODUCTION

Over the last three decades, the earth's surface has successively been warming up at the highest rate compared to the preceding decades since 1850. The Fifth Assessment Report by Intergovernmental Panel on Climate Change (IPCC), shows that the global averaged land and ocean surface temperature increased by 0.85°C (0.65°C - 1.06°C) from 1880 to 2012 (Pachauri *et al.*, 2014). In comparison to the base period between 1986 and 2005, the increase in global mean surface temperature by the end of the century has been projected to be in the range of 0.3^0C to 4.8^0C (Pachauri *et al.*, 2014).

Climate change is largely driven by the increasing emission of greenhouse gases (GHGs) that emanate from anthropogenic activities (Parry, 2007; Stocker *et al.*, 2013). Although there are concerted efforts to reduce the emission of GHGs, global temperatures are still expected to continue increasing and therefore there is urgent need to explore mechanisms for adapting to the continuing change in climate, specifically for developing countries which face the biggest brunt of the adverse impacts of climate change (Ahumada-Cervantes *et al.*, 2015).

The high temperatures and increased frequency of extreme weather events due to climate change, are bound to jeopardize agricultural production and as a result compromise food security in Africa(Conway, 2009). Climate change will significantly reduce cereal crop yields in Africa by increasing water stress, decreasing the length of the growing season and escalating the frequency of pest, disease and weeds prevalence(Niang *et al.*, 2014). Since 1960, the mean temperatures in Kenya have increased by about 1^0C, representing approximately 0.21^0C increase per decade. Warming has increased by 0.29^0C during the hotter months (December-January-February) and by 0.25^0C during the cooler months (June-July-August). Observations show that rainfall has increased during the short rainy season (October-November-December), while the long rainy season (March-April-May) has recorded decreased rainfall and also become less reliable(Parry *et al.*, 2012). Various studies have been carried out to assess the impact of climate change on maize production in which revealed that rising temperatures during the long rainy season (March to May) shortened crop growth stage and reduced maize yields, hence revenue from maize decreased(Wandaka, 2013). Maize production is expected to decrease by 23% by 2100 based on simulations from climate scenarios(Wandaka, 2013).

Maize is Kenya's staple food and accounts for more than one third of the caloric intake for the population(Ariga *et al.*, 2010; Wandaka, 2013). As a result, the availability of locally produced maize considerably determines Kenya's food security both nationally and at the household level. It is predicted that by the year 2020, yields resulting from rain fed maize farming will decline by half(Ojwang *et al.*, 2010).The negative impacts of climate change have significantly reduced maize production locally and hence jeopardized Kenya's policy on food(Mati, 2000).

The importance of vulnerability assessments in shaping adaptation to impacts of climate change has been underscored in recent studies conducted worldwide(Heltberg & Bonch-Osmolovskiy, 2011; Monterroso *et al.*, 2014). The studies have shown that mapping of vulnerability and its components constitutes an integral part in providing information to policy makers and stakeholders so as to appropriately envisage the impacts of climate change and support effective risk management and spatial planning(Preston *et al.*, 2011;López-Carr *et al.*, 2014). Therefore, formulation of policies and strategies to adapt to and mitigate adverse impacts of climate change on maize production should be founded on the basis of scientific vulnerability assessments.

Of the few studies done on vulnerability to climate change in Kenya (Mwangi & Mutua, 2015; Opiyo *et al.*, 2014; Yohe *et al.*, 2006), none has focussed on maize production. This study therefore, seeks to bridge this gap by assessing the vulnerability of maize production to climate change in the Rift Valley's major maize growing counties using the indicator approach.

1.1 Vulnerability Context

In this study, the definition given by IPCC was adopted as a basis for vulnerability assessment. According to IPCC's Third Assessment Report, vulnerability is defined as the degree to which a system is susceptible to or unable to cope with adverse effects of climate change including climate variability and extremes (McCarthy, 2001). Vulnerability is a function of exposure, sensitivity and adaptive capacity. The nature and extent to which climatic variations affect a system is called exposure(Parry, 2007). The degree of beneficial or adverse impacts of climate change on a system is referred to as sensitivity(Parry, 2007). Adaptive capacity refers to the capability of a system to adjust in order minimize probable harm, take advantage or cope with consequences of climate change, variability and extremes(Parry, 2007).

This study used the integrated approach which is an aggregate of biophysical and socio-economic approaches because it is best suited for policy making process(Rama Rao *et al.,* 2016 ; Deressa *et al.*, 2009).The indicator method was used for vulnerability assessment in this study because it selected a set of potential indicators and then merged them analytically, so as to show the degree of vulnerability and nature of vulnerability in a form that is comprehensible(Leichenko & O'brien, 2002).

2 MATERIALS AND METHODS

2.1 Area of study

The study was conducted within the major maize producing counties of the Rift Valley region of Kenya comprising Uasin Gishu, Trans Nzoia, Narok, and Nakuru Counties(Figure 1).

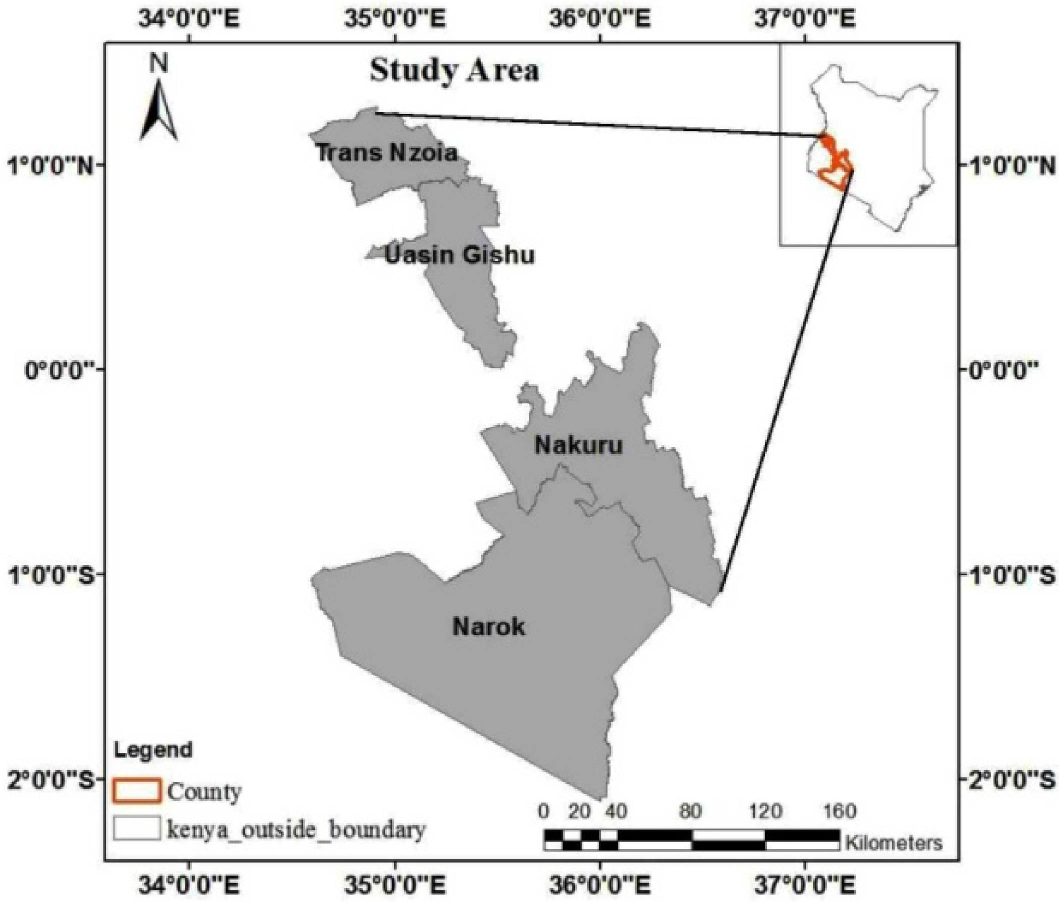

Figure 1: Map of Study area

Uasin Gishu County lies between longitudes 34^0 50’’ East and 35^0 37” West and latitudes 00^0 03” South and 00 55” North and has a total area 3,327 km^2 (Osundwa *et al.*, 2013). Its altitude ranges between 1500 metres and 2700 metres. The mean annual rainfall of the county ranges from 624.9mm to 1560.4mm. The dry spells commence in November and end in February. Temperatures range from 8.4^0 C to 26.1^0C with a mean of 18^0C (Korir, 2011). The main crops grown in the county are maize, sunflower, wheat, pyrethrum, potatoes and barley. The population of the county stood at 894,179 in during the 2009 Census (Korir, 2011; Osundwa *et al.*, 2013; Uasin Gishu County Government, 2013).

Trans Nzoia County has an area of 2,467 km^2 and an average altitude of 1800 metres. Its coordinates lie between latitude 00 38'' and 10^0 18'' North of the equator and longitudes 34^0 38" and 35^0 23" East. The county receives a mean annual rainfall of 1,296.1mm and a mean temperature of 18.6^0C. Maize production is the main farming activity and accounts for the greatest acreage of arable land. By the year 2009, the total population of Tran Nzoia was 818, 757 (Mungo, 2014; Trans Nzoia County Government, 2013).

Nakuru County has an area coverage of 7,495.1 km^2 and an altitude of 2,000 metres (Nakuru County Government, 2013). It lies between longitude 35^0 28'' and 35^0 36'' East and latitude 0^0 13'' and $1^0$10'' south (Sangori, 2012) . The county experiences high temperatures of 29^0C (December-January-February) and low temperatures of 12^0C (June-July). Most farmers in the county grow wheat, maize and horticultural crops (Dennis, 2010). By the year 2009, the population of the county was 1,603,325 people (Nakuru County Government, 2013)

Narok County lies between latitudes 0^0 50'' and 1^0 50'' South and longitude 34^0 28'' and 36^0 25'' East and has an area coverage of 17,944 km^2 . Its average elevation is 1827 metres above sea level. The population of the county in the year 2012 was estimated to be 850,920. Generally the county receives a mean annual rainfall ranging from 500mm to 1800mm with temperatures ranging from 12^0C to 28^0C. Crops that are mainly grown in the county include barley, wheat, maize, beans, and Irish potatoes. Out of these crops, the highest revenues are realized from maize and wheat that are widely grown by most of the farmers in the county (Narok County Government, 2017)

2.2 Data types and sources

Vulnerability indicators were chosen considering: suitability of the indicator in terms of its theoretical basis in the framework of vulnerability, definite direction of influence between the indicator and vulnerability and its ability to measure what it should measure adequately, and easy access to data on the indicator(Gbetibouo *et al.*, 2010).Monthly temperature and rainfall data during the baseline period(1981-2010) for Eldoret, Kitale, Nakuru and Narok meteorological stations representing Uasin Gishu, Trans Nzoia, Nakuru and Narok Counties respectively, were obtained from the Kenya Meteorological Department.

The study also used data on socioeconomic and biophysical indicators; exposure indicators including rates of change of rainfall, minimum and maximum temperature, frequency of droughts and floods; sensitivity indicators comprising ecological sensitivity (the percentage dependency on rain- fed agriculture, total annual maize production, maize yields per hectare and agricultural area under maize production) and demographic sensitivity (density of rural population, percentage of farmers who practice maize farming and people living under poverty line); adaptive capacity indicators including social capital (share of farmers in farm organisations), literacy rate, financial capital (percentage of farmers who saved money, off farm income, farm income, holding size farm land, farm assets, net house hold income, remittances and access to credit) and physical capital (distance to motorable roads, distance to National Cereals and Produce Board(NCPB) depot, distance to tarmac road , distance to farm produce market, use of chemical fertilizers, rate of irrigation and use of improved seeds). The data on sensitivity and adaptive capacity was obtained from Kenya Bureau of Statistics, Ministry of agriculture and Fisheries and Tegemeo Institute of Agricultural Policy and Development.

2.3 Methodology

2.3.1 Determination of rates of change of meteorological parameters

The rates of change of temperature and rainfall were computed using the non-parametric method developed by Sen in 1968(Drápela & Drápelová, 2011; Gocic & Trajkovic, 2013). Based on this methodology, a linear model can be illustrated using equation 1

$$f(t) = Qt + K \qquad \{1\}$$

Where Q is the slope

K is the constant

In order to estimate the slope, Q, a computation of slopes for all data pairs was carried out using equation 2.

$$Q_i = \frac{x_j - x_k}{j - k} \qquad \{2\}$$

Where $i=1,2 \ldots N,\ j>k$

For n values of x, the number of slopes that would estimate Q_i was given by equation 3.

$$N = \frac{n(n-1)}{2} \qquad \{3\}$$

Where N, is the number of slopes required and n is the total number of data sets.

The N values of Q_i were ranked in ascending order of magnitude and the slope median (Sen's slope estimator) calculated based on the criteria in equation 4.

$$Q = \begin{cases} Q_{\frac{N}{2}} & if N\ is odd \\ \frac{1}{2}\left(Q_{N/2} + Q_{N+2/2}\right) & if N\ is\ even \end{cases} \qquad \{4\}$$

The rate of change of rainfall and temperature were used as exposure variables in the computation of exposure and vulnerability indices. Standard precipitation Index was used to analyse observed rainfall data of each station so as to get the frequency of droughts and events that were anomalously wet. The rainfall data for the meteorological stations was subjected to a 3 month- SPI computation using a program provided by the World Meteorological Organisation that is recommended for calculation of SPI (Svoboda *et al.*, 2012). The results from analysis were compared to the SPI table value to determine the number of values that corresponded to extremely wet and extremely dry categories (Svoboda *et al.*, 2012).

Table 1: Standard Precipitation Index values

2.0 +	Extremely wet
1.5 to 1.99	Very wet
1.0 to 1.49	Moderately wet
-0.99 to 0.99	Near normal
-1.0 to -1.49	Moderately dry
-1.5 to -1.99	Severely dry
-2 and less	Extremely dry

2.3.2 Determination of Vulnerability Indices

Data for variables which were clustered under respective components of vulnerability were normalized using methodology by UNDP (2012) to eliminate differences in scales and ensure comparability(Vincent, 2004). When vulnerability increased with increasing indicator, normalization was done using equation 5.

$$X_{normalized} = \frac{X_{ij} - MinX_{ij}}{MaxX_{ij} - MinX_{ij}} \qquad \{5\}$$

Conversely, if vulnerability decreased with increasing specified indicator, then normalization was done using equation 6.

$$X_{normalized} = \frac{MaxX_{ij} - X_{ij}}{MaxX_{ij} - MinX_{ij}} \qquad \{6\}$$

Where X_{ij} is the i^{th} indicator for the j^{th} county

Normalization of the data was followed by ranking of the indicators where unequal weights were assigned to each of them because the indicators do not contribute equally to vulnerability(Hebb & Mortsch, 2007). The weights for the indicators were generated using Principal Component Analysis(PCA) that assisted in extracting few orthogonal linear combinations of variables that most successfully captured the common information from the study variables(Gbetibouo *et al.*, 2010).

For a set of N variables (a*1j to a*zj), the PCA was used to normalize each variable using its average and standard deviation(Deressa, 2010)

$$a1j = \frac{a*1j - a*1}{s*1} \qquad \{7\}$$

where a*1 is the mean of a*1j across region and its standard deviation is s*1

A linear combination of a set of core components for each county, j, was used to express the selected variables(Deressa *et al.*, 2008; Deressa, 2010) as given in equation 8 and 9.

$$a_{1j} = V_1 A_{1J} + V_{12} A_{2J} + \ldots\ldots\ldots\ldots V_{1N} A_{NJ}, \quad j=1\ldots\ldots.j \qquad \{8\}$$

$$a_{N1j} = V_{N1} A_{1J} + V_{N2} A_{2J} + \ldots\ldots\ldots\ldots V_{NN} A_{NJ} \qquad \{9\}$$

Where, A's are the components and V's are the coefficients of each component for each variable.

Since only the left hand side of equation 8 and 9 is known, the solution to this equation is undefined. To surmount this shortcoming, the PCA was used to determine the linear combination of the variables with maximum variance that gave the first principal component, A1j. Subsequently, the second linear combination of variables orthogonal to the first were determined, with the maximum remaining variance giving rise to the second principal component, A2j and so on. This procedure theoretically solved for *vn* and λn in equation10.

$$(R - \lambda I)vn = 0 \qquad \{10\}$$

R is the matrix of correlations between the n^{th} components for each variable and solving equation 10 gives a solution for λn (the Eigen values), the characteristic root of R, and associated eigenvectors, vn. Scaling the vns so that the total of their square adds up to the total variance, produces the final set of estimates. This is another restriction that was imposed to achieve determinacy of the problem(Deressa, 2010).

Equation 8 and 9 implies inverting of the system which allows for the recovery of the scoring factors from the model. Consequently, a set of estimates for each K principal components was obtained as follows:

$$A_{1J} = f_{11} a_{1j} + f_{12} a_{2j} + \ldots\ldots. + f_{1N} a_{Nj} \qquad \{11\}$$

$$A_{k1J} = f_{N1} a_{1j} + f_{N2} a_{2j} + \ldots\ldots. + f_{NN} a_{Nj} \qquad \{12\}$$

Based on the expression below, the first principal component, expressed in terms of the original (un-normalized) variables, that gives an index for each household was obtained based on equation 13.

$$A_{1j} = \frac{f_{11}(a_{1j}^{*} - a_{1-}^{*})}{s_1^{*}} + \ldots\ldots \frac{f_{12}(a_{Nj}^{*} - a_{N-}^{*})}{s_N^{*}} \qquad \{13\}$$

The weights obtained from first principal component were multiplied by their respective normalized values of each variable under the three components of vulnerability. Thereafter, the products were summed up and divided by the total weight of variables under each vulnerability component as illustrated in equations 14 to 16(Emebet, 2013).

$$E_c = \frac{\sum_i^j p_i Y_E}{\sum_i^j p_i} \qquad \{14\}$$

$$S_c = \frac{\sum_i^j p_i Y_S}{\sum_i^j p_i} \qquad \{15\}$$

$$AC_c = \frac{\sum_i^j p_i Y_{AC}}{\sum_i^j p_i} \qquad \{16\}$$

Where:

- AC_c is the adaptive capacity of the County
- S_c is the sensitivity of the County
- E_c is the exposure of the county
- Y_E,Y_S and Y_{AC} are standardized values of variables under exposure, sensitivity and adaptive capacity respectively.
- P_i is the weight of the indicators.

The vulnerability index of the counties(VI_c) was computed by getting the sum of S_c and E_c and then subtracting AC_c. using the method adopted from(Ahumada-Cervantes *et al.*, 2015) given in equation 17.

$$VI_c = \frac{E_c + S_c - (1 - AC_c)}{3} \qquad \{17\}$$

Where:

- VI_c is the vulnerability of the county
- AC_c is the adaptive capacity of thecounty
- S_c is the sensitivity of the county
- E_c is the exposure of the county

PCA was run in SPSS software so as to generate the weights of variables clustered under each vulnerability component.

In order to represent the vulnerability of each county on a map, vulnerability indices were normalized further so as to get the final value on a scale of 0-5(Ravindranath *et al.*, 2011) using equation 18.

$$VI_{normalized} = 5\left(\frac{VI - V_{min}}{VI_{max} - VI_{min}}\right) \qquad \{18\}$$

Five categories were created to classify the normalized VIs which included very high ($4 \leq VI_{normalized} < 5$), high ($3 \leq VI_{normalized} < 5$), moderate ($2 \leq VI_{normalized} < 3$), low ($1 \leq VI_{normalized} < 2$) and very low ($0 \leq VI_{normalized} < 1$). The $VI_{normalized}$ values were plotted using GIS (Ahumada-Cervantes *et al.*, 2015)in order to generate the spatial patterns of vulnerability for each study county

3. RESULTS AND DISCUSSION

3.1 Exposure, Sensitivity, Adaptive Capacity and Vulnerability Indices

The PCA analysis resulted into three major principal components whose Eigen values were greater than one. These components explained 100% of the variation in the data set with 51.2%, 25.3% and 23.5% of the variation being accounted for by the first, second and third component respectively. The first principal component obtained from PCA for a given set of vulnerability indicators is considered to be the linear index of all indicators that successfully denotes the maximum information that is in all variables(Gbetibouo *et al.*, 2010). The weights of the vulnerability indicators from the first principal were multiplied by their respective normalized values and later aggregated to obtain the indices. The exposure, sensitivity, adaptive capacity and vulnerability indices for each of the study counties are given in Table 1.

Table 2: Exposure, Sensitivity, Adaptive capacity and Vulnerability indices

County	Exposure Index	Sensitivity Index	Adaptive Capacity Index	Vulnerability Index
Nakuru	0.48	0.71	1.13	0.35
Narok	1.03	0.21	-2.28	1.51
Trans Nzoia	0.19	0.75	2.58	-0.21
Uasin Gishu	0.61	0.64	2.60	-0.12

3.1.1 Exposure Indices

The exposure indices for the counties ranged from 0.19 to 1.03 (Table 16, Figure 29). Narok had the highest exposure index of 1.03 while Trans Nzoia emerged as the least exposed county with an index of 0.19. (Figure 2).

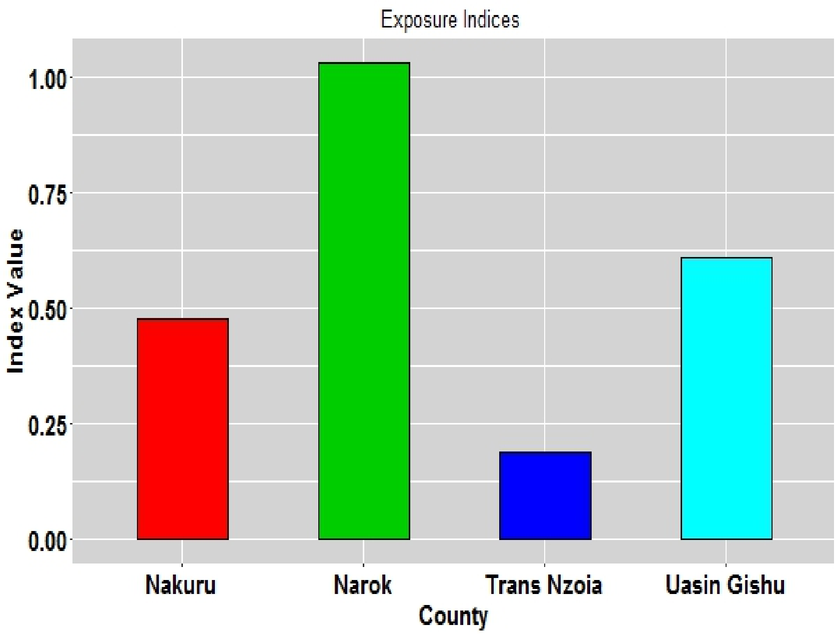

Figure 1: Bar plots of Exposure indices.

The second and third highest exposure indices were recorded in Uasin Gishu (0.61) and Nakuru (0.48) respectively. The growth and development of crops is highly dependent on prevailing climate conditions(temperature and rainfall patterns) and extreme weather events (Li *et al.*, 2015). Climate change exacerbates the exposure of farmers by triggering new and unknown alterations in temperature and rainfall patterns including increased recurrence rate of droughts and floods (Gbetibouo *et al.*, 2010). In comparison, temperature affects maize production to a greater extent than precipitation (Kabubo-Mariara & Karanja, 2007). Evidently, Narok recorded the highest change rate of maximum temperature (0.056^{0}C/year) and minimum temperature (0.055^{0}C/year). Also, it recorded a total of five floods and six droughts during the baseline period. Trans Nzoia registered the second highest change rates of maximum temperature and minimum temperature of 0.054^{0}C/year and 0.049^{0}C/year respectively. A total of three droughts and five floods were observed in the county between 1981 and 2010.

Evidently, the peak exposure index realized in Narok was as a result of its high temperature variation which was highest among the four counties. Additionally, the considerably high frequency of extreme weather events contributed significantly to the peak exposure index in the county. Although Trans Nzoia had the second highest change rates in maximum and minimum temperature, it emerged as the least exposed county due to least frequency of droughts and floods during the baseline period. The least change rates of maximum temperature (0.051^{0}C/year) and minimum temperature (0.045^{0}C/year) were observed in Nakuru County. Uasin Gishu had the same rate of change of minimum temperature with Trans Nzoia (0.54^{0}C/year) and the third highest minimum temperature change rate (0.046^{0}C/year). Notably, Nakuru and Uasin Gishu recorded the highest number of droughts (6) and floods (7). Uasin Gishu and Nakuru recorded higher exposure indices than Trans Nzoia due to their peak frequency of extreme weather events. The results obtained in this study for exposure indices agree with the observation made by (Gbetibouo *et al.*, 2010) that farming areas with high variability in climate patterns and peak occurrence rate of extreme weather events are likely to be highly exposed to climate change.

3.1.2 Sensitivity Indices

Sensitivity indices for the study counties ranged from 0.21 to 0.75 (Figure 3).Trans Nzoia emerged as the most sensitive county with an index of 0.75. The minimal sensitivity was recorded in Narok County with a value of 0.21. The second highest and the second least sensitivity indices were recorded in Nakuru (0.71) and Uasin Gishu(0.64) respectively. Trans Nzoia recorded the highest percentage of farmers who practiced maize production (98%), density of rural population (328people/km^2), percentage of people living under poverty line (50.1%) and absolute reliance of maize production on rainfall (100%).

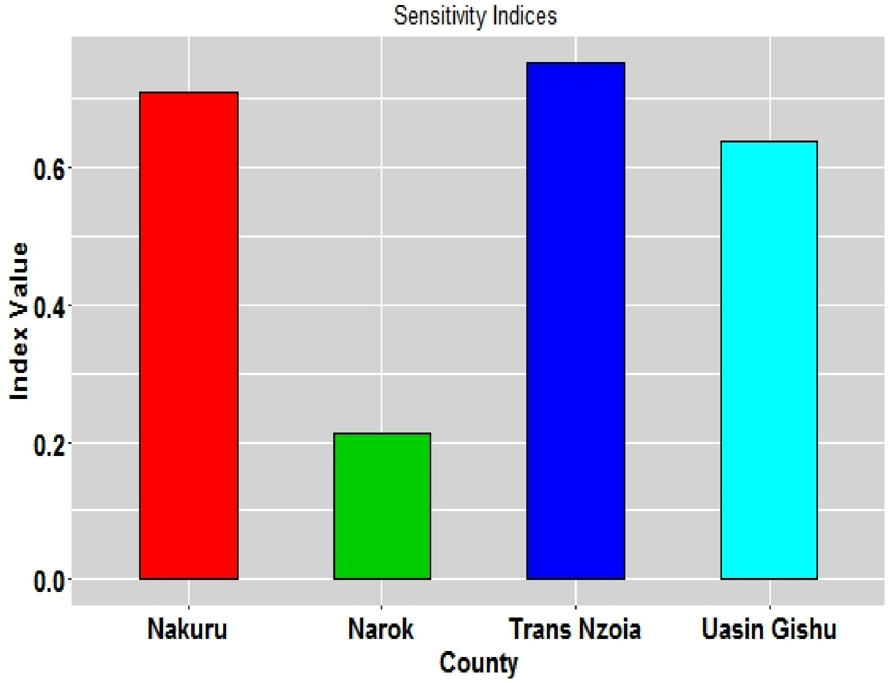

Figure 3: Bar plots of Sensitivity indices

As a result, more people were at the risk of being adversely affected by change in climate and hence exhibited higher sensitivity levels. Narok recorded the least density of rural population (48people/km^2), percentage of farmers who practiced maize production (85.7%) and percentage of people living under poverty line (33.7%). Thus fewer people were exposed to impacts of climate change hence the minimal sensitivity recorded in the county.

The results in this study were consistent with research findings by (Yusuf & Francisco, 2009) and (Hegglin & Huggel, 2008) on sensitivity. These studies found out that the degree of sensitivity was dependent on the number of people that were at risk of being affected by climate change. Nakuru had a lower percentage of rural population density, people living under poverty line and maize farmers compared to Uasin Gishu. However, the percentage dependency of maize production on rainfall was 100% in Nakuru and 99% in Uasin Gishu. Therefore, farmers in Uasin Gishu were not entirely dependent on rainfall for maize production and could lessen the impacts of climate change induced water stress by using irrigation which reduced their sensitivity. This is in line with findings by (Emebet, 2013) who stated that sensitivity to temporary rainfall variability would be reduced by irrigation in a given area.

3.1.3Adaptive Capacity Indices

The adaptive capacity indices for the study counties are presented in Figure 4.

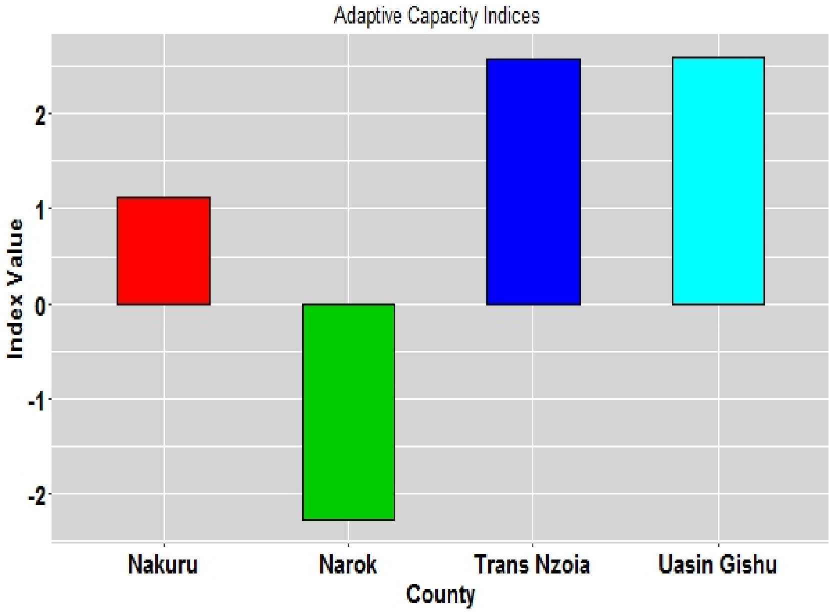

Figure 4: Bar plots of Adaptive Capacity indices

Narok had the minimal adaptive capacity index of -2.28. Not only did Narok record the least percentage of farmers in agricultural organisations (33.3%) but it also had the lowest literacy rate among maize farmers (53.7%). Membership of farmers in agricultural organisations creates a societal network that acts as a platform that facilitates cash flow and transfers which eliminates financial barriers for farmers (Deressa *et al.*, 2008). Also, literacy rates determine the ability of farmers to access knowledge and information and hence improve their coping capability to unfavourable consequences of climate change (Brooks *et al.*, 2005). As a result, in Narok, fewer farmers accessed climate change information and were not able to fully understand, interpret and implement it to improve maize production, hence the low adaptive capacity realized in the county.

The wealth status of farmers can be ascertained by considering the value of farm assets, farm, off farm and net income. Such wealth enables farmers to access resources like markets and technology which are vital in improving their adaptive capacity (Brenkert & Malone, 2005). The net income that accrued from farm and off farm activities was least in Narok County. Therefore, the maize farmers lacked financial capacity to adapt to impacts of climate change. For farmers to access markets to sell their produce, there must be quality and dense infrastructure network in form of roads and other transport routes (Adger *et al.*,2004). Narok had the furthest distance to farm produce outlets, NCPB depots, motorable and tarmac roads. As a result, farmers incurred higher costs in transporting their maize to nearest markets which reduced their revenue considerably and made them more vulnerable to climate change. Although 100% of farmers in the county used improved seeds, lack of irrigation and low usage of chemical fertilizers limited the total annual maize yields which translated to lesser farm income for the maize farmers in Narok.

The peak adaptive capacity during the baseline period was recorded in Uasin Gishu (2.60).It had the highest farm asset value, farm, off farm and net incomes among the four counties. Therefore, in the face of climate change impacts, maize farmers in this county were able to promptly address financial constrains posed by erratic climate patterns. Out of all maize farmers in the county, 91% were literate, 53.1% were members of agricultural organisations and 59.4% saved their income. This meant that a greater portion of maize farmers had access to climate information and could understand, interpret and implement the information for improvement of maize production against a wave of changing climate patterns. Besides, the farm produce markets were closer to farmers in Uasin Gishu and therefore more farmers were able to sell their produce without incurring a lot on transport expenses. The second and third highest adaptive capacity were recorded in Trans Nzoia (2.58) and Nakuru (1.13) respectively.

3.1.3 Vulnerability Indices

The vulnerability indices for the study counties ranged from -0.12 to 1.51 (Table 16). Trans Nzoia had the lowest vulnerability index value of -0.21. Although the county was the most sensitive, its least exposure contributed negligibly to the potential impact of climate change. The county had the second highest adaptive capacity index (2.58) which reduced its vulnerability considerably. Uasin Gishu County recorded a vulnerability index of -0.12 making it the second least vulnerable county. Much as the highest adaptive capacity was realised in this county, the combined effect of its sensitivity and exposure created a greater climate change potential impact and hence increased its vulnerability. Narok registered the highest vulnerability index of 1.51. This is because the significant values of exposure index recorded in the county, contributed greatly to potential impacts of climate stressors and hence increased its vulnerability to a great extent. Moreover, its negative adaptive capacity index meant that the county lacked capability to adjust in order to minimize probable harm, take advantage or cope with consequences of climate change and extremes events. The second most vulnerable county was Nakuru with a vulnerability index of 0.35.

The overall vulnerability is a function of magnitude of exposure, sensitivity and adaptive capacity for the system or area under study (Ezra, 2016; Yusuf & Francisco, 2009). Areas that are highly exposed to climate change and have low adaptive capacity depict peak vulnerability levels (Li *et al.*, 2015). Narok recorded the least vulnerability index because it had the least adaptive capacity and highest exposure. Highly exposed areas or communities do not necessarily have low adaptive capacity or high sensitivity to climate change (Gbetibouo *et al.*, 2010; Islam *et al.*, 2014). As much as Narok was the most exposed county, it registered the least sensitivity and adaptive capacity index. Also, Trans Nzoia was the most sensitive county, but had the second highest adaptive capacity. Vulnerability increases when sensitivity and exposure increases, but reduces as adaptive capacity increases and vice versa (Ahumada-Cervantes *et al.*, 2015). The vulnerability in Trans Nzoia and Uasin Gishu was considerably reduced by significant adaptive capacity realized in the counties. The sensitivity and exposure of Uasin Gishu (potential impact) was higher than in Trans Nzoia. This had an increasing effect on the vulnerability in Uasin Gishu although it had the highest adaptive capacity. The high exposure index in Narok increased its vulnerability considerably while the negative adaptive capacity was inconsequential in reducing peak vulnerability in the county.

3.1.4 Vulnerability Maps

Three categories of vulnerability for each study county were identified and mapped (Figure 5). Trans Nzoia County was classified under the very low category ($0 \leq VI_{normalized} < 1$) since its normalized vulnerability index was 0. Uasin Gishu scored a normalized vulnerability index that lay between 1 and zero (0.3) and therefore was clustered under the same vulnerability class as Trans Nzoia. The vulnerability in Nakuru was classified as low ($1 \leq VI_{normalized} < 2$) due to its normalized vulnerability index of 1.6, while Narok had a normalized vulnerability index of 5 and therefore was classified under very high category of vulnerability ($4 \leq VI_{normalized} < 5$).

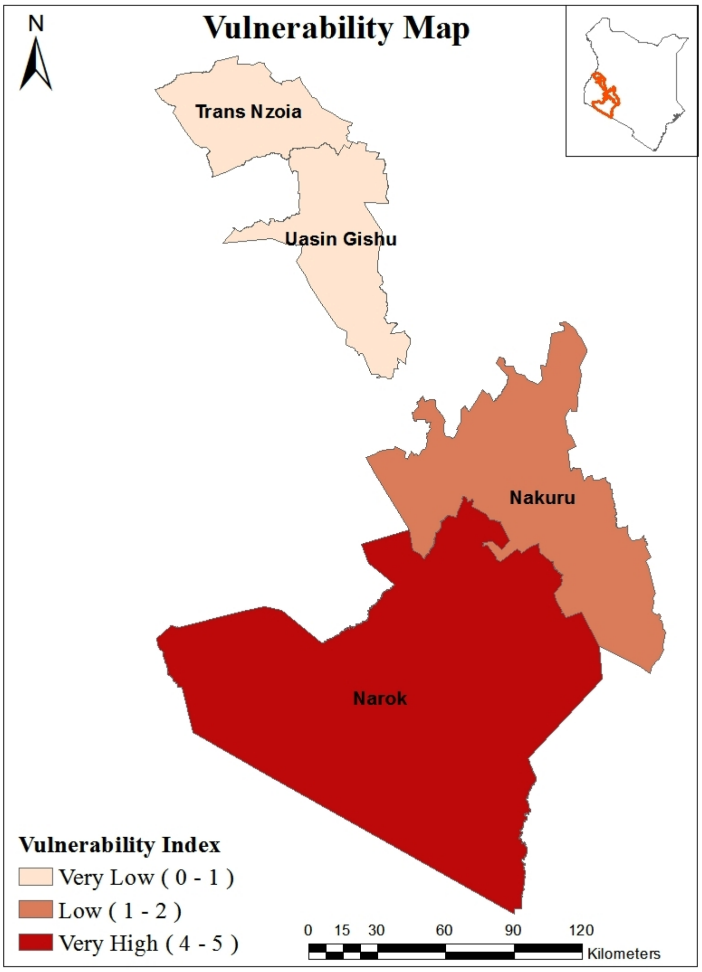

Figure 5: Vulnerability map

4. CONCLUSIONS

Although Trans Nzoia had the highest sensitivity, it emerged as the least vulnerable county as it recorded the least exposure and the second highest adaptive capacity. Due it negative adaptive capacity index, Narok lacked any ability to withstand or cope with negative impact of climate stressors. As a result, it recorded the highest vulnerability index despite having the least sensitivity. The second and third highest vulnerability indices were realized in Eldoret and Nakuru respectively. Trans Nzoia and Uasin Gishu exhibited propensity levels that were classified as very low and therefore had the lowest degree to which climate change would negatively impact maize production in the counties. The vulnerability in Nakuru was higher as compared to Uasin Gishu and Trans Nzoia and therefore maize production was at a higher risk of being adversely impacted by climate change. Narok was the most vulnerable county and hence maize production in the county was highly predisposed to adverse impacts of climate change as compared to the other counties.

There is need to delink maize production from rainfall dependency. Therefore, irrigation using harvested rainfall, surface and ground water should be implemented in all counties in order to suppress the negative impacts on maize production during drought and rainfall depressed seasons.

It was noted that socioeconomic development played a pivotal role in enhancing the adaptive capacity which in turn reduced the vulnerability of the counties considerably. Therefore, in order to curb the high vulnerability in highly vulnerable counties, climate change policies should prioritize socioeconomic development initiatives like rural infrastructural development and educational programs to improve literacy levels.

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