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Vulnerability of Smallholder Maize Production to Climate Variability in Selected Counties in Kenya

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Abstract

The climate affects maize production. Unpredictable rainfall timing, frequency, duration, character, and distribution, particularly during the growing season; rising temperatures exceeding the levels appropriate for maize production; and high incidences of pests and diseases all contribute to declining yields and increased food insecurity. The goal of the study was to find out how much smallholder maize production in Kitui and Laikipia counties was affected by changes in the weather. A questionnaire was used to collect demographic and socioeconomic information from 397 smallholder maize producers. The National Oceanic and Atmospheric Administration provided monthly temperature data in degrees Celsius derived from a combination of Global Historical Climatology Network gridded version 4 and Climate Anomaly Monitoring System datasets. The Centennial Trends version 1.0 precipitation dataset provided monthly rainfall data in millimeters. The vulnerability index was created by combining the exposure, sensitivity, and adaptive capacity indices derived through factor analysis. Drought, famine, climatic changes, crop failure, and purchasing maize increased the vulnerability of smallholder maize production, whereas less frequent water fetching, increased maize yield, access to extension, input subsidies, fertilizer expenditure, and the number of social groups decreased vulnerability. According to the study, smallholder maize production in semi-arid lowland areas was more vulnerable to climate variability than in highland areas. The findings suggest that the national and county governments should monitor vulnerability indicators at the national, county, sub-county, and ward levels in order to inform the design and implementation of appropriate vulnerability-reduction programs.

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1. Introduction

Agriculture is one of the industries that has suffered as a result of climate change. Goal 2 of the Sustainable Development Goals (SDGs) emphasizes the importance of promoting sustainable agriculture in order to achieve food security (United Nations, 2015). In the context of agriculture, vulnerability can be defined as the degree to which the agricultural system is exposed to, sensitive to, and adaptive to climate variability (Tao et al., 2011). Regardless, it is the primary source of food security. For example, maize is a staple food for a large proportion of the population, which could explain the 60% increase in maize cultivation area in Sub Saharan Africa (SSA) between 2007 and 2017(Santpoort, 2020). Climate change affects maize production. Depending on the temperature levels that affect evapotranspiration during the growing season, medium-maturity maize requires 500 millimeters to 800 millimeters of water (Food and Agriculture Organization, 2016). Most maize varieties require more than 1000 millimeters of rain per year (One Acre Fund, 2015). The ideal temperature for maize production is between 18 and 20 degrees Celsius (Food and Agriculture Organization, 2015). Maize production in Kenya is primarily carried out during the two rainy seasons: long rain (March to May) and short rain (October to December) (Republic of Kenya (ROK), 2022). Floods, landslides, and mudslides could occur as a result of heavy rainfall. Floods contribute to water logging, soil erosion, and nutrient leaching, all of which affect soil stability, water holding capacity, hydrogen potential (pH), organic matter content, total nitrogen, and phosphorus (Brevik, 2013). This has an impact on the quality of soil ideal for maize production, resulting in increased fertilizer use to improve soil fertility. Crop failure, on the other hand, is caused by very low rainfall. Drought occurs when there is a prolonged lack of rainfall, which has a negative impact on food security.

Temperature is also important in maize growth and development. High temperatures lower soil moisture content, causing crop loss (Rurinda et al., 2014; Classen et al., 2015). High radiation, in particular, increases water losses, lowering soil moisture and stagnating maize development in the lowlands, particularly during the early stages, whereas in the highlands, when soil moisture is sufficient, low light intensity reduces the rate of photosynthesis, restricting growth (International Institute of Tropical Agriculture, 1982). Climate change is also linked to an increase in agricultural pests and illnesses because it hastens the growth of disease-causing pathogens, pests, and insects (Pareek et al., 2017). As a result, crop yields may be reduced by 80 percent to 100 percent (Republic of Kenya, 2012; Makone et al., 2014). Furthermore, a growth in invasive weeds is related to an increase in atmospheric carbon dioxide levels, which causes climate shifts. Carbon dioxide concentrations rise, stimulating growth and development and, as a result, the geographical extension of invasive plants (Ramesh et al., 2017). Striga has been linked to agricultural losses of up to 90% in Busia, Bungoma, Siaya, Migori, and Kakamega (African Agricultural Technology Foundation, 2017). Temperatures in Kenya are expected to climb by 1.7 degrees Celsius by the 2050s and by 3.5 degrees Celsius by the end of the century, according to global climate models (World Bank Group, 2021). Precipitation, on the other hand, is expected to be unpredictable and very erratic. Rainfall has recently been found to be less when it rains for a long time and more when it rains for a short time (Dutch sustainability unit, 2015). It is also predicted that brief showers will become more common between October and December, as will the frequency, length, and severity of intense rainfall events (World Bank Group, 2021). For example, frequent countrywide droughts have been forecast, affecting farmers and pastoralists in Kenya's east and north (Republic of the Netherlands, 2018). This would be devastating to maize production in Kenya, especially because 80 percent of the land area is already Arid and Semi-Arid Lands (ASALs), receiving just 200 to 700 millimeters of rain each year (Republic of Netherlands, 2018).

Smallholders have low levels of human and physical capital, as well as significant levels of poverty, which limit their capacity to deal with the repercussions of climatic variability considerably more severely than other farmers (Kabubo-Mariara and Kabara, 2015). Furthermore, a reduction in agricultural output as a result of unfavorable climatic change exacerbates poverty among smallholders (IPCC, 2014). Climate variability affects numerous industries directly or indirectly, exacerbating the negative effects on agriculture. For example, the transportation sector contributes to greenhouse gas emissions but is also negatively impacted by climate change due to the destruction of infrastructure such as bridges, ports, roads, rails, and air networks, particularly during extreme weather events, disrupting supply chains for raw materials or food, among other things (Kenya Private Sector Alliance, 2014).

Furthermore, smallholders were more likely to be impacted by illnesses caused by climatic variability, such as water-borne, vector-borne, and cardiovascular disorders, rendering them unable to carry out farming operations and requiring them to shift resources for treatment (IPCC, 2022). Smallholders' conditions may be made worse depending on where they live. Those who live in semi-arid and arid locations are more vulnerable than those who live in high-potential areas since they are exposed to high temperatures for much of the year (Kalele et al., 2021). Agriculture has a vital role, accounting for 75% of total employment and contributing the most to Kenya's GDP when compared to other sectors of the economy. 2022 (United States Agency for International Development; Republic of Kenya) However, climate variability, characterized by unpredictable timing, frequency, duration, character, and distribution of rainfall, particularly during the growing season, along with rising temperatures, weed infestations, and pest and disease incidents, among other issues, has an impact on yields and, as a result, food security in Kenya. Most empirical research on how vulnerable agriculture is to changes in climate has led to vulnerability indices at the regional, national, and household levels. This research has shown that different areas and families are affected in different ways based on their physical and economic characteristics.

Most empirical research has utilized data on agriculture and farmers in general, which does not indicate the vulnerability of smallholder maize output. To address the research gaps highlighted and contribute to current information, new empirical studies evaluating the vulnerability of smallholder maize production in Kenya, disaggregating analyses on total exposure, sensitivity, and adaptive capacity, were required. The study's goal was to examine the amount of susceptibility of smallholder maize production to climatic variability in Kenya's Kitui and Laikipia counties using data from 397 smallholders. The study is crucial for policymakers at the national and county levels to understand the nature of vulnerability influencing smallholder maize production in order to drive policy and development aid priorities.

2. **Literature Review**

2.1. **Studies on vulnerability**

Gbetibouo et al. (2010) investigated the sensitivity of agriculture to climate change in nine South African provinces using a vulnerability index comprised of 19 variables based on Principal Component Analysis. The study discovered that locations with a large concentration of small-scale subsistence farmers who produced with minimal technology and relied on rainfall were especially vulnerable to climate change. The study showed that in the most sensitive regions, minor climatic changes would impair subsistence farmers' livelihoods, but in the least vulnerable places, where exposure was substantial, their great adaptation ability would mitigate the unfavorable effects. The investigation was conducted at the subnational level, which may have missed variation in household agricultural operations, resource endowments, and ecological considerations, among other variables. Furthermore, data at the subnational level include both big and small-scale farmers, yet vulnerability between the two kinds of farmers might vary greatly.

Tajikistan's sensitivity to climate change and variability was examined by Heltberg and Bonch-Osmolovkiy (2010) in both rural and urban regions. For the analysis, ten (10) agro-ecological zones and one (1) urban region were identified. Using equal weighted factors, the researchers created a vulnerability score based on exposure, sensitivity, and adaptive capability. The study's findings revealed that exposure, sensitivity, and adaptive capability differed significantly more independently than the composite vulnerability. The highlands had the most exposure, but also the most adaptive potential and medium sensitivity. Lowland regions were particularly vulnerable. The fundamental flaw of the study was the equal weighting of the exposure, sensitivity, and adaptive capacity components, despite the fact that the variables within each component had a different number of variables. This may skew the relative relevance of the components in the overall vulnerability index (Baptista, 2014). Antwi-Agyei et al. (2012) examined agricultural production susceptibility to drought at the national and regional levels in Ghana. The study's goal was to assess the risk of ten (10) Ghanaian areas. The study defined vulnerability as the sum of exposure and sensitivity less adaptive capability. According to the findings, vulnerability was mostly related with high exposure and sensitivity to drought. According to the study, insufficient adaptive capability owing to high poverty levels and limited capital assets increased susceptibility.

Epule et al. (2017) took a similar method in developing a vulnerability index for Uganda that combined agroecological, meteorological, and socioeconomic factors in analyzing the national and geographical pattern of susceptibility of maize yields to drought. Each component of vulnerability was given its own sub-index, which was then combined to form the vulnerability index. The adaptation capacity was relatively good at the national level, and so the vulnerability score was low. The northern study sites had greater vulnerability indices than the southern study sites. The national exposure index was greater than the exposure indexes at the research locations. The study also discovered that the amount of sensitivity of maize explained 91 percent of the changes in vulnerability, whereas exposure explained 92 percent. The more the exposure, the greater the susceptibility. The study also found that locations in the south had stronger adaptation capacity than those in the north, and that changes in adaptive capacity explained 88 percent of the changes in vulnerability. The study indicated that drought sensitivity and exposure increased with latitude, whereas adaptation capacity decreased at lower latitudes, and that both biophysical and social variables were important in influencing drought vulnerability of maize yields. Although the empirical methods employed by Antwi-Agyei et al. (2012) and Epule et al. (2017) might be used to assess susceptibility for specific locations or systems, the data utilized included both big and small-scale food production. Furthermore, despite the fact that adaptive capacity had two variables and exposure and sensitivity each had one variable, they were all given similar weights, which may interfere with the overall value of the components in the total vulnerability (Fekete, 2011). Sisay (2016) used chosen environmental and socioeconomic factors to examine the susceptibility of agricultural families to climate change in the Dabat and West Belesa Districts of North Gondar, Ethiopia. The study examined the Livelihood Vulnerability Index for each District using the Livelihood Vulnerability IndexI-Intergovernmental Panel on Climate Change framework. The Index is derived by categorizing vulnerability Contributing Factors into exposure, sensitivity, and adaptive capability. The findings suggested that West Belesa was more exposed to the effects of climate change than Dabat District. As a result, the study indicated that social, economic, and natural variables had a significant impact on the vulnerability of farming households in rural regions, which varied by location. Households exposed to the same degrees of unfavorable climate change impacts were vulnerable at varying levels depending on their adaptive potential. Although the data utilized in the study came from households, it was gathered from farmers in general.

Masambaya et al. (2018) evaluated the susceptibility of maize production to climate change in key maize producing counties of Kenya's Rift Valley area (Trans Nzoia, Nakuru, Narok, and Uasin Gishu). Principal Component Analysis was used in the investigation. Vulnerability was defined as the result of exposure, sensitivity, and adaptive capability. According to the study's findings, Trans Nzoia was the least susceptible county because it was the least exposed, most sensitive, and had the best adaptation capacity, while Narok was the most vulnerable because it was the most exposed, least sensitive, and had the lowest adaptive ability. The study indicated that maize production in Narok County was more vulnerable to the negative effects of climate change than in Trans Nzoia County. Unlike Heltberg and Bonch-Osmolovkiy (2010) and Antwi-Agyei et al. (2010), the use of Principal Component Analysis permitted weighting of indicators, avoiding bias in the prominence of vulnerability components (2012). However, like in previous research, small and large-scale maize growers were merged. Epule et al. (2021) investigated the sensitivity of maize, millet, and rice yields to growing season precipitation and socioeconomic factors in Cameroon. The research concentrated on the national and sub-national levels of analysis. Secondary data was used in the study. According to the study, rice had the highest exposure and sensitivity indices, as well as the lowest adaptive capacity index, resulting in the highest vulnerability, whereas millet had the highest adaptive capacity index, lowest sensitivity, and medium exposure index, resulting in the lowest vulnerability. In compared to the other two crops, maize exhibited medium exposure, sensitivity, and adaptation capability, resulting in medium vulnerability. At the sub-regional level, maize production in Northern Cameroon had the highest exposure index, sensitivity index, and lowest adaptive capacity index, resulting in the highest vulnerability index, whereas maize production in Southern Cameroon had the least exposure index, medium sensitivity index, and highest adaptive capacity, resulting in the lowest vulnerability index. According to the study, rice was the most vulnerable crop on a national basis, while maize in the southern region was the most vulnerable on a subnational scale. Furthermore, the study found an inverse link between adaptive capability and vulnerability at both the national and sub-national levels. The research revealed disparities in sensitivity across areas and crops. However, the study used equal weighting, despite the fact that the components of vulnerability had varying numbers of variables.

2.2. **Overview of literature**

The majority of the research used the indicator technique to assess vulnerability. Some studies, including Heltberg and Bonch-Osmolovkiy (2010), Epule et al. (2017), and Epule et al. (2021), used equal weights for the indicators used in the generation of exposure, sensitivity, and adaptive capacity sub-indices, resulting in unequal weighting of the dimensions of the sub-indices in the overall vulnerability index because not all sub-indices had equal indicators. Masambaya et al. (2018) used sub-national data on maize producers in general in their study on the susceptibility of maize production to climate change in five maize-growing counties in Kenya's Rift Valley.

3.Research method

3.1 Area of study

The research was carried out in Kitui and Laikipia counties, which are located in lowland and highland zones, respectively. Farmers cultivating maize on 5 acres or less were deemed smallholders and were thus chosen for the research.

3.1.1. Kitui County

Kitui County is divided into eight sub-counties: Kitui Central, Kitui Rural, Kitui South, Kitui West, Kitui East, Mwingi Central, Mwingi North, and Mwingi West, as well as 40 Wards and 247 settlements (Republic of Kenya, 2018a). The population was estimated at 1,136,187 people (Republic of Kenya, 2019). The absolute poverty rate was projected to be 47.5 percent, higher than the national average of 36.1 percent, while the food poverty rate was estimated to be 39.4 percent, higher than the national average of 32 percent (Republic of Kenya, 2018a). Agriculture contributes to food production, employment, and a source of income. The annual rainfall ranges between 500 and 1050 millimeters with a 40 percent predictability, while the lowest and highest temperatures vary from 22 to 28 degrees Celsius and 28 to 32 degrees Celsius, respectively (Oremo, 2013). Upper Midland comprises nine (9) agro-ecological zones upper midland 3, 3-4 suitable for coffee, upper midland 4 suitable for sunflower, maize, and pigeon peas; lower midland 3 and 4 suitable for cotton, lower midland 5 suitable for livestock, sorghum, fodder, and millet; lower midland 6 and inner lowland 6 suitable for ranching, and inner lowland 5 suitable for livestock and millet production (Republic of Kenya, 2018b). Despite the fact that a significant area (77,551 ha) was set aside for maize growing, the yearly output was 10,858 metric tons (Republic of Kenya, 2018a).

3.1.2. Laikipia County

Laikipia County is split into five administrative sub-counties: Laikipia Central, Laikipia East, Laikipia North, Laikipia West, and Nyahururu, as well as 15 Wards (Republic of Kenya, 2018b). The population of Laikipia County was 518,560 people (Republic of Kenya, 2019). The absolute poverty rate was projected to be 46%, compared to the national average of 36%, while the food poverty rate was estimated to be 24.2 percent, compared to the national average of 32 percent (Council of Governors and Kenya Institute of Policy, Research, and Analysis, 2020). Agriculture employs more than 60% of the global population. The yearly rainfall ranges from 400 to 750 millimeters, while the average annual temperature ranges from 16 to 26 degrees Celsius (Republic of Kenya, 2018b). Upper highland 2 is suitable for wheat and pyrethrum, upper highland 3 is suitable for wheat and barley, lower highland 2 is suitable for wheat, maize, and pyrethrum, lower highland 3 is suitable for wheat, maize, and barley, lower highland 4 is suitable for cattle, sheep, and barley, lower highland 5 and 6 are suitable for ranching, upper midland 5 is suitable for livestock and sorghum, and upper (Jaedzold et al., 2010). The most widely grown crop is maize, which accounts for 51% of total crop area (Republic of Kenya, 2018b).

3.2. Data types and sources

A cross-sectional study approach was utilized, using data from smallholders obtained throughout the 2017 long rain growing season (March to August) to aid in the assessment of the vulnerability of smallholder maize output. Monthly temperature and rainfall data from 1960 to 2017 were collected online. Temperature data in degrees Celsius were taken from NOAA, while monthly rainfall data in millimeters were obtained from Dryad's Centennial Trends Greater Horn of Africa precipitation dataset version 1.0. (2018). The questionnaire was primarily used to gather data on socioeconomic aspects in order to determine smallholders' attitudes, knowledge, perception, traits, views, conduct, and facts. A multistage sampling procedure was used. Respondents from each sub-county were grouped based on Wards before being chosen using simple random sampling. Athi, Mutomo, Ikutha, Ikanga, and Kanziko from Kitui South Sub-County; Yatta Kwa Vonza, Kanyangi, Kisasi, and Mbitini from Kitui Rural; Kyagwitha West, Kyagwitha East, Miambani, and Mulango from Kitui Central; Mwingi Central, Mui, Waita, Kivou, Nguni, and Nuu

Derivation of exposure, sensitivity, adaptive capacity and vulnerability indices

The amount of susceptibility of smallholder maize production to climatic fluctuation was examined using factor analysis. The variables utilized to calculate the vulnerability index (V i) in this study (exposure, sensitivity, and adaptive capacity) were derived from a combination of factors for each component. Because variables were measured in various units, the following method was used to standardize them for comparability:

$$Z_i = \sum_{i=1}^{m} \quad (z_i - \underline{z})/z_{max} - z_{min} \text{ ....1}$$

Where $\underline{z}$ is the mean of z_i across smallholders and z_{max} is maximum value of z while z_{min} is the minimum value of z.

The common factors were written as a linear combination of the following variables, which reflect the key components of vulnerability:

$$F_j = \beta_1 z_1 + \beta_2 z_2 + \beta_3 z_3 + \cdots + \beta_m z_m + \mu_j \text{ ....2}$$

Where F_j represents the first common factor based on the variables representing exposure, sensitivity or adaptive capacity, z represents the respective independent variables associated with the factor, β represents the factor loading while μ represents the proportion of variance not shared between the factor and the respective variable. The square of the coefficient (β) produced the proportion of variance accounted for by the common factor known as the EigenValues (Field, 2009). The solution for equation 2 was rotated to ensure that higher loadings were on the first common factor. Higher loadings on the first common factor ensures that it provides the greatest amount of information from all the variables (Taherdoost *et al.,* 2014). Orthogonal rotation was preferred since it ensures factors are uncorrelated (Goldberg and Velicer, 2006). Orthogonal rotations are replicable in future samples as they reduce sampling error variance while oblique rotations are less parsimonious and tend to increase sampling error variance (Kimani, 2019).

Factor loadings were used to calculate the exposure, sensitivity, and adaptive capacity indices (Nelson, 2007). The factor loadings were used to produce the regression coefficient, which was then multiplied by the actual variable values to obtain the indices for each smallholder (Nelson,2007). The following are the formulae for each smallholder's exposure, sensitivity, and adaptive capacity indices:

$$VC_i = \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \cdots \dots \dots \dots + \beta_n x_n \text{ ....3}$$

Where VC_i represents respective vulnerability component indices while β represents the standard regression coefficients (Nelson, 2007). A positive factor loading for variables measuring exposure, sensitivity and adaptive capacity imply that the respective variables increase exposure, sensitivity or adaptive capacity. On the other hand, a negative factor loading for variables measuring exposure, sensitivity or adaptive capacity imply that the respective variable decreases exposure, sensitivity or adaptive capacity.

The vulnerability index was computed by combining exposure, sensitivity and adaptive capacity indices. A similar empirical model was used by Epule *et al*., 2017; Gbetibouo *et al*., 2010; Antwi-Agyei *et al.,* 2012; Epule et al., 2021 and Mckonen and Berlie, 2021. Vulnerability index based on exposure, sensitivity or adaptive capacity indices was derived for each smallholder as follows:

$$V_i = \sum_{i=1}^{n} \{(E_i + S_i) - AC_i\} \quad \ldots\ldots 4$$

Where V_i is the vulnerability index for smallholder i, E_i is the exposure index for smallholder i, S_i is the sensitivity index for smallholder i, AC_i is the adaptive capacity index for smallholder i. The exposure index was generated from the following variables: rainfall anomaly, temperature anomaly, drought occurrences, famine occurrences, occurrences of crop pests and diseases, irrigation, climate changes and knowledge of soil type. The sensitivity index was generated from the following variables: frequency of fetching water, maize yield, crop failure, age, maize shortage and buy. Adaptive capacity index was generated from the following variables: expenditure on fertilizers, expenditure on certified seeds, education, access to extension services, input subsidies, involvement in social institutions and adaptation. The vulnerability index was classified into lowest, middle and highest tercile. The tercile with most smallholders was used in determining the extent of vulnerability. Extent of vulnerability between the two counties was based on comparison of the distribution of smallholders across the terciles and comparison of the vulnerability index of the median smallholder. Stata software was used in data analysis.

4. Results and Discussions

The results of the study were based on vulnerability analysis based on equation 1-4 in section 3. Prior to data analysis, diagnostic tests was undertaken as explained below:

4.1 Diagnostic tests

The sphericity test of Bartlett was carried out. The test determines Kaiser-Meyer-Olkin (KMO) sampling adequacy, or if the distribution of values in the sample is acceptable for factor analysis (Taherdoost et al., 2014). A KMO greater than 0.5 and close to 1 suggests a good match (Taherdoost et al., 2014).Table 1 summarizes the findings.

Table 1: Results of the Bartlett's test of sphericity

	Exposure	Sensitivity	Adaptive capacity
KMO	0.53	0.61	0.63
Chi-square	189.956	84.86	97.569
p-value	0.000	0.000	0.000
Determinant of correlation matrix	0.616	0.806	0.780

Source: survey data

Table 1 shows that the KMO conditions for conducting factor analysis were met (Taherdoost et al., 2014). In addition, the test compares the correlation matrix against a matrix of zero correlations to determine if the correlation matrix used in component analysis is an identity matrix (Taherdoost et al., 2014). A rejection of the null hypothesis implies that the correlation matrix was not produced from a population with zero correlations, implying that the link between variables is appropriate (Taherdoost et al., 2014). In all cases, the null hypothesis was rejected at the 1% level of significance, meaning that the observed correlation matrix did not come from a population with zero correlation (Taherdoost et al., 2014). Furthermore, the determinant of the correlation matrix was determined to be larger than 0.00001, meeting the condition for factor analysis (Field, 2009).

4.2. Results of factor analysis

Factor analysis was used to determine the extent to which smallholder maize output is vulnerable to climatic fluctuation. Section 3's Equations 2 and 3 were solved to get the factor loadings and standard regression coefficients, respectively (Field, 2009; Nelson, 2007). The findings are shown in Table 2:

Table 2
Results of factor analysis

Variables	Factor loading	Standard regression coefficient	Significance
Exposure			
rainNorm	0.0284	0.0397	Insignificant
tempNorm	-0.0774	-0.00536	Insignificant
cropests_diseases1	0.1628	0.02319	Insignificant
famine	0.6825	0.39075	Significant
drought	0.6216	0.29721	Significant
know_soiltype	0.0193	0.00525	Insignificant
irrigation	0.0425	0.02249	Insignificant
clim_changes	0.6134	0.34403	Significant
Sensitivity			
yieldNorm	-0.321	-0.14658	Significant
crop_failure1	0.441	0.21954	Significant
ageNorm	-0.228	-0.10755	Insignificant
maize_period	0.1243	0.06402	Insignificant
water_freq1	-0.5187	-0.28046	Significant
buy	0.6145	0.37539	Significant
Adaptive capacity			
exten_access	0.5843	0.3255	Significant
edu1	-0.0237	-0.01228	Insignificant
inputSubsidies	0.5456	0.3024	Significant
expCertSeNorm	0.2267	0.06652	Insignificant
expfertNorm	0.3955	0.17145	Significant
NsocigrpNorm	0.4903	0.24475	Significant

Eigenvalue exposure =1.31276
Eigenvalue sensitivity= 1.01163
Eigenvalue adaptive capacity=1.08789
Total observations=397

(Factor loading greater than 0.30 is statistically significant)
Source: Survey data

Table 2 shows that the first factor was utilized to calculate the exposure, sensitivity, and adaptive capacity index (Taherdoost et al., 2014). Variables with factor loadings larger than 0.3 for a sample size of at least 350 are deemed statistically significant to aid analysis (Hair et al., 2006). The following are the findings of factor analysis for variables with substantial factor loading in relation to vulnerability components:

Exposure

Drought, hunger, and climate changes were statistically significant and correlated positively with the component explaining exposure. Famine dramatically boosted the exposure index, as predicted by the Organization for Economic Cooperation and Development, which predicts that lower-income nations will have food deficiencies of more than half the quantities necessary by 2025. (Balasubramanian, 2018). Poor storage may cause maize losses, as shown by Midega et al. (2016), who discovered that farmers lost roughly 40% of stored grain owing to insect and pest infestations. According to FAO et al. (2018), poor yields, agricultural revenue losses, and food price surges increase susceptibility to food availability, access, and stability. This finding shows that activities such as properly preserving corn during surplus for consumption during famine might help to mitigate the negative effects of famine. Famine struck a high proportion of the sample's smallholders.

It was also shown that dryness considerably raised the exposure index. Adepetu and Berthe (2007) discovered that additional drought events enhanced exposure to climate change and related to asset loss, hence increasing vulnerability. Drought damages maize reproductive stages, resulting in yield loss (Aslam et al., 2015). Drought is expected to become more widespread and severe in regions where it already exists, thereby increasing the number of people exposed by 9 percent to 17 percent by 2030. (Hallegatte et al., 2015). The findings show that developing coping strategies such as early warning information and improving access to water might help to mitigate the negative effects of drought. The United Nations Convention to Combat Desertification (2022) recommends enhancing communities' capacity to foresee, respond to, and recover from drought in an effective and timely manner. Mukherjee and Mishra (2018), on the other hand, warn that man-made infrastructure, such as dams and reservoirs built to increase water availability, may create hydrological drought. Climate change has also greatly boosted the exposure index. Late or early beginning of rainfall is one of the recognized climatic shifts that has enhanced the vulnerability of maize output to climate variability (Bedeke et al., 2018). It is important to note that the beginning and conclusion of the growing season vary by area, making focused understanding of the best timing for smallholder maize production critical (Reidsma and Ewert, 2008). Pickson and He (2021) discovered that unpredictability of rainfall patterns increased susceptibility to climatic variability. In Laikipia County, the unpredictability of the beginning of rainfall and the length of the growing season, as well as moisture stress, were assessed to increase sensitivity to climatic variability (Ministry of Agriculture, Livestock, Fisheries and Cooperatives, 2017). These findings show that providing climatic information at the start of each cropping season and during the season might help reduce the negative impact of exposure on smallholder maize output.

Sensitivity

Crop failure, maize yield, water frequency, and purchase were all statistically significant sensitivity factors. The data reveal that purchasing maize considerably boosted sensitivity. Smallholders, particularly the impoverished, are far more exposed to price shifts than non-poor people (Hallegatte et al., 2015). Zelingher et al., (2021) discovered that a slight decrease in Northern American maize output enhanced the chance of a rise in worldwide maize prices. Crop failure also considerably enhanced sensitivity. Crop failure was significant because a high proportion of the sample's smallholders had experienced it. Crop failure is caused by low soil moisture due to delayed rains, highlighting the importance of adjusting cropping dates (Bedeke et al., 2018). Growing drought-tolerant maize cultivars might minimize sensitivity, according to Simtowe et al. (2019), who discovered that crop failure was reduced by 30% in Uganda. The findings point to the need for coping techniques that lower the susceptibility of smallholder maize output to climatic variability. Increases in maize production, on the other hand, considerably lowered sensitivity. The outcome is plausible given that smallholders in both areas were heavily reliant on maize. In the Czech Republic, Maitah et al. (2021) discovered a negative association between maize yield and water shortage, reflecting higher sensitivity. Furthermore, Mulungu and Ng'ombe (2019) discovered that temperatures of 35°C and a modest drop in rainfall can lower maize output by 9%, even for varieties that perform well in other biophysical environments. Furthermore, the CERES-maize model predicts that the change in maize yield owing to climate change in Sub-Saharan Africa by 2050 might be as low as 5% and as high as 25% (Mulungu and Ng'ombe, 2019). Srivastava et al. (2021) predicted an increase in maize yield for Eastern India under rainfed circumstances for the periods (2021-2050) and (2051-2080), with the increase for the period 2051-2080 being less than the increase for the period 2051-2050. Maize output losses were anticipated to be greater under irrigation circumstances from 2051 to 2080. (Srivastava et al., 2021). The discovery implies that irrigation with rainwater captured water might produce higher yields than water from other sources. The weekly frequency of collecting water, on the other hand, considerably lowered sensitivity. This means that smallholders with little water storage capacity must collect water often and are more prone to face water shortages, particularly during dry seasons, owing to their high sensitivity. This is backed by research that discovered that a lack of water related to heightened sensitivity (Sisay, 2016). The most vulnerable areas were those that were primarily reliant on rainfed agriculture (Gbetibouo et al., 2010). This emphasizes the necessity for other water sources to sustain maize cultivation.

Adaptive capacity

Access to extension, input subsidies, fertilizer expenditure, and the number of social groups were all statistically significant factors in the component explaining adaptive capability. Access to extension substantially boosted adaptive ability. Because smallholders are instructed on better agronomic methods, which promote greater maize output, the result was as predicted. According to the Ministry of Agriculture, Livestock, and Fisheries (2017), farmers who live distant from extension staff are more likely to lose out on relevant and up-to-date farming knowledge. Other research has also shown the significance of extension services (Opiyo et al., 2014; Chepkoech et al., 2020). Input subsidies also considerably improved adaptive capacity.
This was predicted since input subsidies reduce the cost of maize production, increasing capacity to produce more maize. Subsidies for inputs like as pesticides, fertilizers, and seeds might be supplied (Searchinger et al., 2020). Previous research (Epule et al. (2017); Antwi-Agyei et al. (2012) discovered that impoverished families could not afford sufficient amounts of input to support maize growing, limiting their ability to cope with the effects of climatic variability. As a result, providing input subsidies might be crucial in improving adaptive capability. According to Searchinger et al. (2020), the influence of input subsidies to higher maize output was small. This was due to larger-scale farmers receiving greater assistance than small-scale farmers. The findings indicate the need of making agriculture inputs more accessible.

The findings also show that increasing the number of social groups considerably boosted adaptive ability. This was supported by Pickson and He (2021), who discovered that farmers who belonged to organizations were better able to adapt to climate change. Social groupings are essential for learning, resource pooling, and information exchange. Furthermore, previous research (Antwi-Agyei et al. (2012); Opiyo et al. (2014); Chepkoech et al. (2020)) suggested that non-governmental and government institutions and policies promoted adaptive capacity, supporting the positive relationship between adaptive capacity and input subsidies, extension access, and the number of social groups. Enhanced fertilizer spending increased adaptive capacity considerably. This indicates that fertilizer was an important input in maize production. This finding suggests that increasing the usage of fertilizer, whether organic or inorganic, might improve smallholders' adaptive ability. According to Sigaye et al. (2020), combining organic and inorganic fertilizer enhances soil characteristics, resulting in greater maize yields and higher economic returns.

Mean exposure, sensitivity, adaptive capacity and vulnerability indices

The average exposure, sensitivity, and adaptive capacity indices obtained from equation 3 were estimated for Laikipia and Kitui County. The vulnerability index was then created by integrating the exposure, sensitivity, and adaptive capacity indices using equation 4. The exposure, sensitivity, and adaptive capacity indices were derived using differential weighting of variables, but the aggregation of these components to the overall vulnerability index used equal weighting (Baptista, 2014). Table 3 displays the average exposure, sensitivity, adaptive capacity, and vulnerability indices for each of the two counties, as well as for both counties combined:

Table 3

Exposure, sensitivity, adaptive capacity and vulnerability indices

Description		Kitui	Laikipia	Combined
Mean exposure index		1.299827	1.236506	1.28021
Mean sensitivity index		0.576215	0.469995	0.54331
Adaptive capacity index		0.377363	0.499167	0.4151
Vulnerability Index		1.498678	1.207334	1.40841
Lowest tercile	Frequency	85	48	133
	Percentage	31	39	33.50
	Minimum vulnerability index	(0.77587)	(0.56949)	(0.7758737)
	Maximum vulnerability index	0.987944	1.003853	1.003853
Middle tercile	Frequency	82	50	132
	Percentage	30	41	33.25
	Minimum vulnerability index	1.016638	1.008913	1.008913
	Maximum vulnerability index	1.742728	1.741506	1.742728
Highest tercile	Frequency	107	25	132
	Percentage	39	20	33.25
	Minimum vulnerability index	1.773481	1.749989	1.749989
	Maximum vulnerability index	3.928847	2.898821	3.928847
50^{th} percentile	Median smallholder	1.513331	1.192464	1.38807

Source: urvey data

Table 3 shows that exposure contributed the most to vulnerability as compared to sensitivity in Laikipia, Kitui, and the combined results for the two counties. Furthermore, the average adaptive capacity index for Kitui County and the two counties combined was the lowest of the three vulnerability components. However, the sensitivity index for Laikipia County was the lowest of the three indices. Furthermore, Kitui County's mean vulnerability index was greater than the combined sample and much higher than Laikipia County's mean vulnerability index. Laikipia County's mean vulnerability index was lower than the combined sample. The vulnerability indices were divided into three terciles: lowest, middle, and highest. The results demonstrate that the majority of smallholders in Kitui County were in the highest tercile, whereas the lowest proportion of smallholders were in the highest tercile in Laikipia County. Laikipia County has the greatest number of smallholders in the middle tercile. Furthermore, the vulnerability index for the median smallholder in Kitui County was greater than the vulnerability index for the median smallholder in the whole sample, as was the vulnerability index for the median smallholder in Laikipia County. According to the findings, a substantial number of smallholders in Kitui County, which is located in the lowlands, were more susceptible than smallholders in Laikipia County, which is located in the highlands. According to the data in Table 3, vulnerability was impacted by exposure far more than sensitivity and adaptive capability. Although adaptive capacity might reduce susceptibility, it was extremely low in Kitui County, exacerbating vulnerability. Overall, the bad effects of exposure were less in Laikipia County because it had a higher score for its ability to adapt and a lower score for its sensitivity index.

The conclusion that smallholders in Kitui County were more sensitive than smallholders in Laikipia County was consistent with Tessema and Simane's (2019) findings that lowland regions had higher exposure and sensitivity but limited adaptation ability. Heltberg and Bonch-Osmolovkiy (2010) came to the same conclusion that lowland regions were more susceptible than highland ones. Although the findings of Heltberg and Bonch-Osmolovkiy (2010) that highland regions had the best adaptation ability and medium sensitivity were similar to the current study, the findings suggesting highland regions were more exposed contradicted the current study. Masambaya et al. (2018) validated the findings that lowland areas were more vulnerable than highland areas and that highland areas were the least exposed and had the greatest adaptation potential. The increased sensitivity of smallholders in Kitui County compared to Laikipia County may be explained by the higher probability of crop failure, which may increase their vulnerability to high prices when purchasing maize to alleviate maize shortages (Hallegatte et al., 2015). Furthermore, Epule et al. (2017) discovered that locations with families unable to invest in agriculture inputs had limited adaptation capacity, which supports the findings for Kitui County, where input investment was substantially lower than in Laikipia County. Gbetibouo et al. (2010) observed that places with higher adaptation abilities were better-resourced and hence less vulnerable, whereas areas with high exposure were mostly situated in extremely degraded land areas. The Ministry of Agriculture, Livestock, Fisheries, and Cooperatives (2021) found that farmers in lowland regions were more sensitive to climatic variability due to increased exposure to drought, heat stress, and moisture stress. Reidsma and Ewert (2008) discovered that places with little water supply, such as Kitui County, will be unable to deal with increased exposure. Furthermore, Kitui County has a lower Human Development Index (0.481) than Laikipia County (0.574). (Republic of Kenya, 2018a and 2018b). Furthermore, Kitui County has a greater level of poverty than the national average (Republic of Kenya, 2018a). The findings show that improving the adaptive capability of smallholder maize growers might help reduce levels of vulnerability.

Conclusion and Policy Implications

This study looked at how vulnerable smallholder maize production is to climate change in Kitui and Laikipia counties. Primary data on demographic and socioeconomic factors were gathered directly from smallholder maize growers throughout the 2017 long rainy growing season (March to August). Temperature data in degrees Celsius were taken from NOAA, while monthly rainfall data in millimeters were obtained from Dryad's Centennial Trends Greater Horn of Africa Precipitation dataset version 1.0. (2018).

In Kitui and Laikipia counties, factor analysis was used to assess the sensitivity of smallholder maize production to climatic variability. The vulnerability indices for Laikipia and Kitui counties, as well as the combined index for the two counties, were calculated using exposure, sensitivity, and adaptive capacity indices. The findings revealed that exposure contributed the most to susceptibility in each county and in both counties together. The study also showed that smallholder maize growers in semi-arid lowland areas were more susceptible than smallholders in highland areas. This conclusion is supported by the fact that Kitui County has a greater proportion of smallholders in the top tercile than Laikipia County, and the median smallholder in Kitui County has a substantially higher vulnerability index than the median smallholder in Laikipia County and the whole sample.

This study shows that smallholder maize output is sensitive to climate change. This vulnerability is expected to worsen food insecurity in Kenya, necessitating concerted initiatives aimed at minimizing it. Smallholders require assistance from the government at both the national and county levels, including input subsidies and improved water supplies. This is because drought, hunger, crop failure, and buying maize were key factors affecting exposure and sensitivity, whereas maize yield and a lower frequency of fetching water lowered sensitivity. Fertilizer investment, on the other hand, boosted adaptive capability. Furthermore, social groups should be developed to improve learning as well as a platform via which the government or donor agencies may channel support to smallholders to boost adaptive ability.

The current study adds to our understanding of smallholder maize production's vulnerability to climate variability and confirms the theoretical underpinnings that, while different groups or individuals may be exposed to similar levels of climate variability, the consequences may differ due to differences in sensitivity and adaptive capacity. The current study's findings focused on analysis at a local scale, with smallholders with 5 acres of land or fewer chosen to determine sensitivity to climatic variability, which may differ from vulnerability in large-scale maize production. Furthermore, the current study chose two semi-arid counties, one in the highlands and the other in the lowlands, and found disparities in susceptibility despite both being in semi-arid environments. Furthermore, factor analysis was used to ensure distinct weighting of indicators within each component in order to avoid bias in the relevance of each component to the overall vulnerability score. The study also delved into further detail to examine the variables that had a significant impact on the exposure, sensitivity, and adaptive capacity indices, as well as the vulnerability index.

The goal of this study was to find out how sensitive smallholder maize production is to changes in climate and how well it can adapt in certain Kenyan counties. The study focused on smallholder maize cultivation, and the findings may not be applicable to large-scale maize production. Furthermore, the research sites were mostly semi-arid, so the results may not be generalizable to high-potential areas. More studies should be done to compare the sensitivity of large-scale maize production to the vulnerability of smallholder maize production. Further study might be conducted to examine the susceptibility of maize production in high- and low-potential locations.

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