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RESEARCH

Mapping climate vulnerability to support climate adaptation in maize farming systems in Kenya

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Abstract

A systematic knowledge of climate vulnerability distribution within a country is important to design informed climate change adaptation planning which will contribute to food security. We used a vulnerability index for maize farming-related hazards, which combines both biophysical and socio-economic factors for Kenya at a disaggregated level. These factors include: exposure, sensitivity, and adaptive capacity (capacity of a system to adapt to shocks) related to maize farming. We show that high-yield maize zones have high climate sensitivity, which is inversely related to exposure. In contrast, adaptive capacity on maize farms is highly variable across counties of Kenya. We found that most counties in Kenya have a low potential impact of climate change on maize farming suggesting resilience to hazards that affect maize farms. Sensitivity analysis of the vulnerability index, which we propose in this work, suggests that adaptive capacity has the highest influence on vulnerability. This study emphasises the need to disaggregate climate vulnerability assessments in order to address key food crops, on which in turn, hazard-adaptation instruments can be targeted. The vulnerability index proposed in this work therefore provides a basis for climate adaptation recommendations at a localised scale, which can be used by policymakers and practitioners.

Keywords Climate vulnerability · Smallholder · Maize systems · Spatial distribution · Kenya

1 Introduction

Maize production is influenced by a wide number of factors ranging from climate change, soil fertility, pests and diseases, inputs, and farm management, but also, indirectly, by farmers' access to markets, road infrastructure, land tenure security, and a range of other socio-economic factors (Ali et al., 2023; Biswal et al., 2022). Climate change is projected to reduce maize yield under rain-fed conditions (Degife et al., 2021; Sloat et al., 2020; Lobell et al., 2011; Jones & Thornton, 2003). This impact on yield is compounded by declining soil fertility across sub-Saharan Africa (Zachary et al., 2020). Maize is the main food crop for about 96% of Kenyans and over 75% of total maize harvest is produced by smallholder farmers with less than 2 ha (Grace et al., 2014). Demand for maize in Kenya has more than doubled between 2005 and 2016 (FAO, 2016), as a result of rapid population growth (about 2.6% per annum) and increased maize demand from the livestock sector, particularly for poultry and dairy farming (Marechera et al., 2019; GAIN Report, 2019; IPCC, 2014). This results in an increasing gap between production and consumption, leading to maize supply shortages in Kenya (Olwande & Mathenge, 2012). Some of these shortages have been attributed to climate impacts, with a 13% national production decline between 2020 and 2021 attributed to unreliable precipitation patterns, increased temperature, and drought (KIPPRA, 2022). Climate change and variability render producers vulnerable and ultimately result in food insecurity. There is a need to take targeted and reliable measures to improve maize production, while making maize production less vulnerable to climate shocks.

Vulnerability to climate change and its extremes refers to how strongly a system is affected by and unable to cope with negative impacts (Adger, 2006; Füssel, 2007). The interaction between biophysical, socio-economic, and institutional

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factors determine how vulnerable maize farms may be to climate shocks. Vulnerability is also context-specific, since its determinants may change across agroecological zones, scales, and crop types (O'Brien et al., 2004; Eriksen & Kelly, 2007; Shukla et al., 2021). The Intergovernmental Panel on Climate Change (IPCC) conceptualises vulnerability as a composite function of three interrelated components, exposure, sensitivity, and adaptive capacity (Krishnamurthy et al., 2014). Exposure refers to the magnitude and degree to which a system is subjected to climatic variation and associated biophysical stressors such as soil fertility constraints. Sensitivity refers to the inherent susceptibility of a system once exposed and is determined by factors such as ecological, social and economic characteristics. Adaptive capacity refers to the ability of a system to adjust, cope or recover from climatic shocks and stressors (Adger, 2006). Vulnerability assessments are mainly indicator-based, because vulnerability is not directly measurable. Thus, indicators are used to quantify the underlying processes (Tate, 2012; Williams et al., 2018).

To the best of our knowledge, no study in Kenya has specifically addressed the vulnerability to climate change of maize-cultivating small farms over the whole country. Research on declining maize production in Kenya has focused on exposure, sensitivity, or adaptive capacity of agricultural systems in specific areas of the country, but that research has had limited attention paid to the ways these components interact. For example, existing studies include the exposure component of climate hazard based on soil types and crop management and their effects on maize production in western Kenya, (Ngome et al., 2013), impacts of seasonal climate variability on maize production (Mumo et al., 2018), and economic studies on decision-making in the face of climate shocks (Bozzola et al., 2016). Quantification of the interaction between climate variables with factors that make farms vulnerable to climate impacts and their adaptive capacity is important to consider, since the capacity to adapt varies spatially and temporally. This missing quantification is necessary for identifying vulnerability hotspots to formulate sustainable adaptation practices that may increase maize production. Several studies have been conducted to examine causes of changes in maize yield. For example, at regional levels, Tesfaye et al. (2015) project a decrease in maize yields by 2050 over southern and eastern Africa. Mumo et al. (2018) observed that maize yield in Kenya was slightly decreasing by 0.07 tons/ha/decade, along with high inter-annual yield variability, while the world average maize yield was increasing by 0.6 tons/ha/decade. In addition, Davenport (2018) projects future maize yields declining by 11% in eastern Kenya and 7% in western Kenya until the 2030s. Similar declines of maize yield, suitability, and production have been reported by other studies (Ochieng et al., 2016; Omoyo et al., 2015; Kogo et al., 2021), showing that climate change is and will continue to penalise maize production in the region. These studies however do not provide information on factors that contribute to vulnerability of maize farms. Such a vulnerability framework combines socio-economic and biophysical characteristics. This article aims to examine vulnerability of maize systems to climate change at county level throughout Kenya. Three specific objectives are used to fill in the identified literature gaps on vulnerability in maize systems in Kenya. (1) To analyse the spatial dynamics of components of vulnerability (exposure, sensitivity, and adaptive capacity) for maize farming. (2) To identify the potential impact of climate change on maize farms in Kenya, and (3) to identify the highest contributing factors to vulnerability in maize farming areas. This study is relevant for decision-making on adaptation planning by identifying highly vulnerable counties and contributors to vulnerability in these areas.

2 Materials and methods

2.1 Study area

The study area is the country of Kenya, which is located on the eastern side of Africa, and lies astride the equator between longitude 34°E–42°E and latitude 5°S–5°N (Fig. 1, left). The country's precipitation and temperature regime follow a bimodal pattern. The precipitation regime is classified into a long rainy season occurring from March to May and a short rainy season, occurring from October to November. The Inter-tropical Convergence Zone is responsible for the precipitation regimes (Ongoma and Chen, 2017; Yang et al., 2015). Precipitation ranges from less than 250 mm in northern, arid and semi-arid lands to 2000 mm in western parts of Kenya. The lowest temperatures are experienced in highland areas and highest temperatures are experienced in lowland areas. The annual mean temperature ranges from 15 °C to 35 °C (Mutimba et al., 2010).

There are seven agroecological zones (AEZ) in Kenya (Fig 1, right), which are classified according to precipitation, temperature, and moisture availability for crop production (Jaetzold, 2007; Somborek et al., 1982). The agro-climatic zones range from humid, sub-humid, semi-humid, semi-arid, arid, and very arid. Maize farming is practiced in all seven agroecological zones, however there are local differences in maize yield across agroecological zones: the highest yields being achieved in the humid, semi-humid, and semi-arid zones (Table 1).

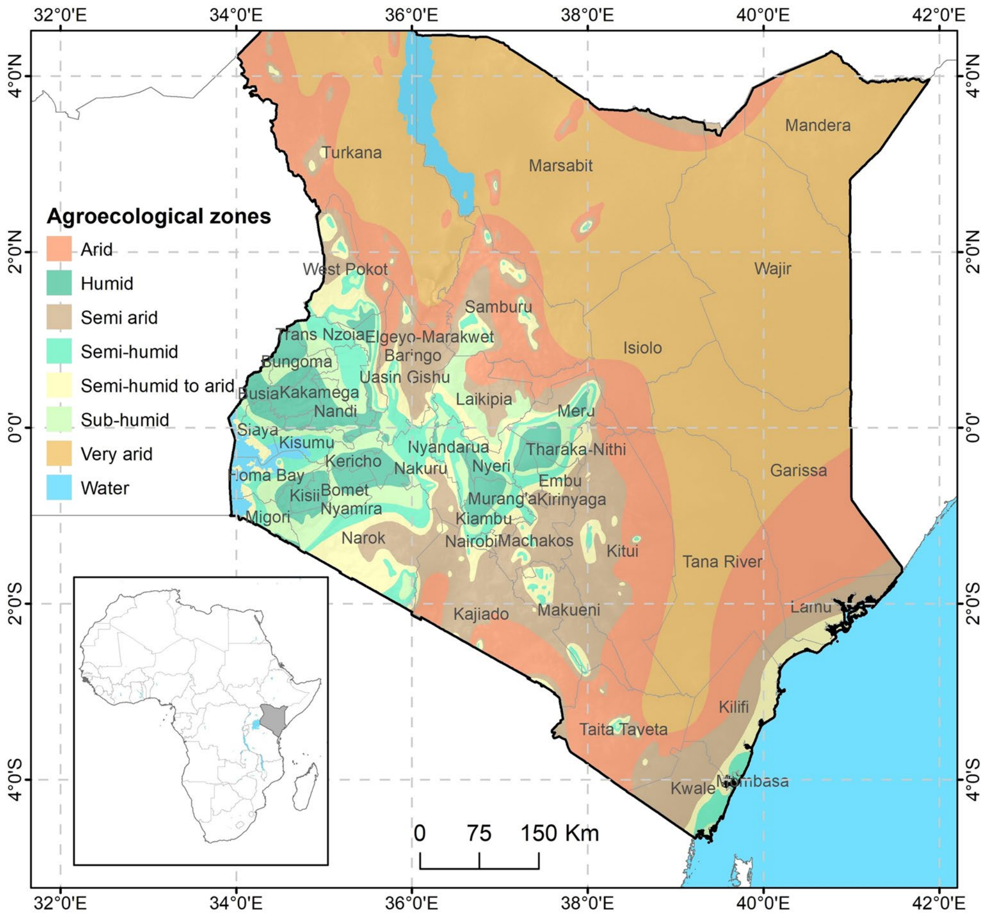


Fig. 1 Location of Kenya in East Africa (left) and distribution of the counties across the agroecological zones in Kenya

Table 1 Counties in Kenya grouped according to maize average maize yield from highest (1) to lowest (8)

Yield classification	Counties
1.	Baringo, Nandi, Uasin Gishu, Trans Nzoia, and Elgeyo Marakwet
2.	Bomet, Kericho, Nakuru, and Narok
3.	Kisii and Nyamira
4.	Migori, Homa Bay, Kisumu, Siaya, Kakamega, Bungoma, Busia, and Vihiga
5.	Nyandarua, Nyeri, Kiambu, Murang'a, and Kirinyaga
6.	Taita Taveta, Kwale, Kilifi, Tana River, and Lamu
7.	Marsabit, Tharaka Nithi, Isiolo, Meru, and Embu
8.	Makueni, Kitui, and Machakos

(Sourced from Kilimo Data by MOALF, 2020)

2.2 Developing vulnerability indicators

We develop a quantitative composite vulnerability index for maize production in Kenya. We express vulnerability (V) as a function of exposure (E), sensitivity (S), and adaptive capacity (AC). Table 2, shows the variables selected for each component of vulnerability.

The exposure component consists of temperature, precipitation, and soil variables which may influence maize farming. Temperature variables include mean annual temperature and variation of temperature during the year, which are positively related to vulnerability. Precipitation variables include accumulated yearly precipitation and its variation within the year, which are respectively negatively and positively related to vulnerability. Precipitation and temperature values were averaged for the period 2008 and 2018. Five components of soil that are indicators of soil health and fertility are used as variables in this study: soil bulk density, soil organic carbon, soil cation exchange capacity, soil pH, and soil available nitrogen.

The sensitivity component refers to the characteristics that make a maize farming system vulnerable to changes in the exposure variables. Reliance on agriculture pre-disposes farms to increased vulnerability to impacts from changes in climate and environment (Kotir, 2011). In order to show the extent of the sensitivity of farms to these changes, we selected variables that describe agricultural system characteristics, such as irrigation use, land under agriculture, area under subsistence agriculture, and farms growing maize. The data was obtained from the Kenya national census in 2019.

Table 2 Indicators used for assessing each of the three vulnerability components (exposure, sensitivity and adaptive capacity), their functional relationship to maize production in the composite index calculation and data sources

Parameter	Contributing indicators	Functional relationship with index	Data Source
Exposure			
Temperature	Mean annual temperature	Positive	W5E5
	Variation of temperature during the year	Positive	W5E5
Precipitation	Sum of rainfall received	Negative	W5E5
	Variation of rainfall received during the year	Positive	W5E5
Altitude	Height above sea level	Negative	USGS
Soil	Soil bulk density	Negative	ISRIC
	Soil cation exchange capacity	Negative	ISRIC
	Soil organic carbon	Negative	ISRIC
	Soil pH	Positive	ISRIC
	Soil nitrogen	Negative	ISRIC
Sensitivity			
Reliance on rainfed agriculture	% Number of households reliant on rainfall	Positive	KNBS, 2019
Agricultural land	% of land under agricultural production	Positive	KNBS, 2019
Area under subsistence agriculture	% area under subsistence agriculture	Positive	KNBS, 2019
Maize cultivating households	% of land under maize production	Positive	KNBS, 2019
Adaptive capacity			
Reliance on firewood	% number of households relying on firewood use per county	Positive	KNBS, 2019
Land tenure	% of households with secure tenure per county	Negative	CIDP (2015; 2017)
Average household size	Average household size per county	Positive	KNBS, 2019
Road density	Average road coverage per county	Negative	Survey general, Kenya, 2006

Note: W5E5 data comes from Lange 2019; Lange et al., 2021; Cucchi et al., 2020

Adaptive capacity refers to characteristics that support the ability of farms to adjust to adverse impacts and is based on three conditions that we selected from the sustainable livelihood framework: satisfaction of basic needs, resources for innovation, and resources for transforming innovation into actions. Specific variables under these three functions are: average household size, reliance on firewood, land tenure, and road density.

The selection of indicators for components of vulnerability was based on literature (Adhikari et al., 2015; Murthy et al., 2015; Bouroncle et al., 2017). Selection of adaptive capacity indicators was limited by availability of spatial information covering all counties in Kenya.

2.2.1 Parameter normalisation, impact and vulnerability calculation

The input indicators for components of vulnerability exposure, sensitivity, and adaptive capacity were normalised according to their functional relationship with their respective component of vulnerability. This normalisation follows the "min-max" approach (OECD, 2005; OECD, 2008) and adjusts for differences in units of measurements across indicators. Indicators with positive relationships were normalised using Eq. 1, whereas indicators with a negative relationship to their component were normalised using Eq. 2. Normalisation ensures that indicators range from 1 to 0 and that their direction of change is the same (Murthy et al., 2015).

$$Xi - normalised\ value = \frac{Xi - Xmin}{Xmax - Xmin} \tag{1}$$

$$Xi - normalised\ value = \frac{Xmax - Xi}{Xmax - Xmin} \tag{2}$$

Normalised values for exposure and sensitivity range from 0 (low exposure; low sensitivity) to 1 (high exposure; high sensitivity), while values for adaptive capacity were inverse to this: 0 (low adaptive capacity) to 1(high adaptive capacity).

The potential impact of climate change on maize farms was analysed as a factor of exposure and sensitivity without considering adaptive capacity. We therefore multiplied normalised values of exposure with normalised values of sensitivity (Bouroncle et al., 2017; Locatelli et al., 2008). Understanding the potential impact of climate change on maize farms allows for disaggregation of adaptive capacity impacts on vulnerability, as areas with high adaptive capacity are expected to have a reduced vulnerability index.

We assume equal weights for each of the variables, because there is no a priori knowledge about the selected indicators' contributions to vulnerability in maize production systems. This approach was necessary as this study does not incorporate participatory expert weighting of different components of vulnerability, and to our knowledge, there is no existing study in Kenya ranking vulnerability components. This is in line with studies that used equal weighting because of lack of theoretical literature to guide setting of weights based on relative importance of components (Etsy et al., 2005). To offset a lack of weighting of components, we conduct a robustness test as recommended by Cahill (2005), Cherchye et al. (2008), Permanyer (2011), and Zheng and Zheng (2015).

We obtain a final vulnerability index using the following expression:

$$V = E * S/AC \tag{3}$$

The resulting variables are then normalised to range from 0 (low vulnerability) to 1(high vulnerability). The general approach is summarised in the flow chart (Fig. 2).

In a final step, we assess the importance of all indicators used in creating the composite index by consecutively excluding each indicator within each component to ascertain their impact on the vulnerability ranking. The subsequent change in vulnerability ranks across counties was plotted to identify those indicators which have the strongest influence on vulnerability. Lastly, we evaluated individual components of vulnerability and the final vulnerability index using three variables, using an outcome-based approach to evaluation (Shukla et al., 2021): (i) maize production (country scale), (ii) maize harvested area, and (iii) maize crop yield (county scale; kg/ha). In a second validation step, we conducted a Spearman's rank correlation test between vulnerability ranks and ranks of the three aforementioned variables to assess the validity of the index (Merino et al., 2019; Shukla et al., 2021).

3 Results

3.1 Distribution of vulnerability components

The spatial distribution of composite indicators of vulnerability in terms of exposure, sensitivity, and adaptive capacity are shown in Fig. 3. Counties in eastern and south-eastern Kenya have higher exposure index values than counties in western Kenya (Fig. 3a). Counties in semi-arid AEZ (e.g., Kitui) have high exposure (>0.6) and are in low yielding zones, whereas counties in humid AEZ (e.g., Trans Nzoia) have low exposure index values (<0.4) and are in high yielding maize AEZ. The spatial distribution of the sensitivity index (Fig. 3b) shows that a majority of counties have a high sensitivity index (>0.6). Sensitivity of counties to maize production factors increases from east to west. High yielding maize zones west of the country have a high sensitivity index, while low yielding zones east of Kenya, have low sensitivity index. The spatial distribution of adaptive capacity indicates that a majority of counties, in both low and high maize yielding zones, have relatively high adaptive capacity (>0.6). This is with the exception of Uasin Gishu, a high yield maize zone that has low adaptive capacity. The lowest adaptive capacity is in central and southwest Kenya (Fig. 3c).

Figure 4 shows the distribution of exposure, sensitivity, and adaptive capacity across counties. The distribution of exposure is bimodal and almost equally separated

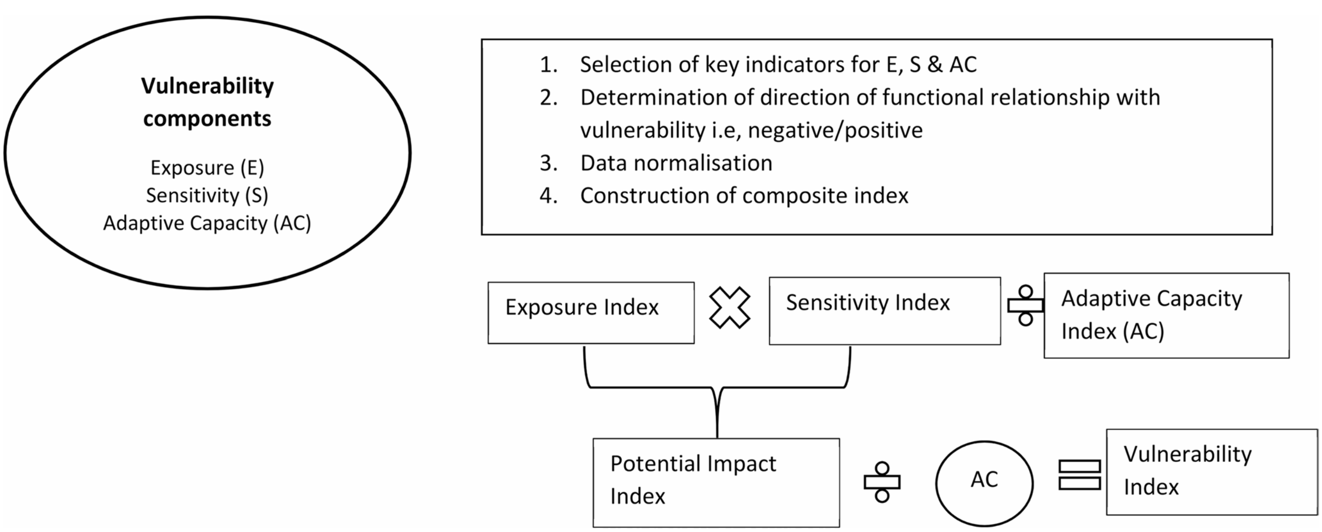


Fig. 2 Flow chart showing the combination exposure, sensitivity and adaptive capacity indicators used in developing the composite vulnerability index for maize systems in Kenya

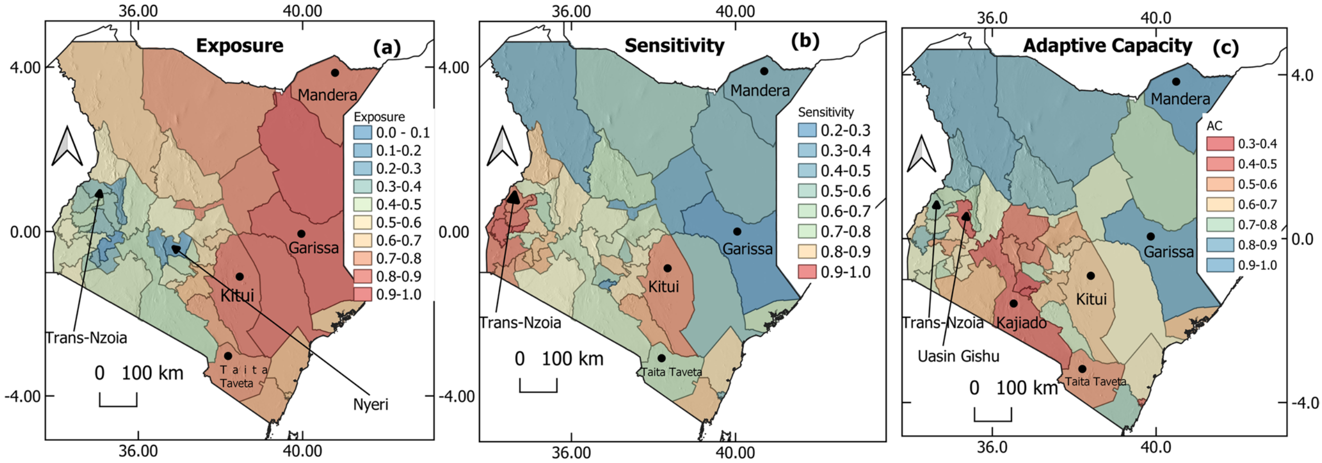


Fig. 3 Spatial distribution of exposure to vulnerability indicators (**a**) and their sensitivity (**b**), and adaptive capacity (**c**) across various counties in Kenya

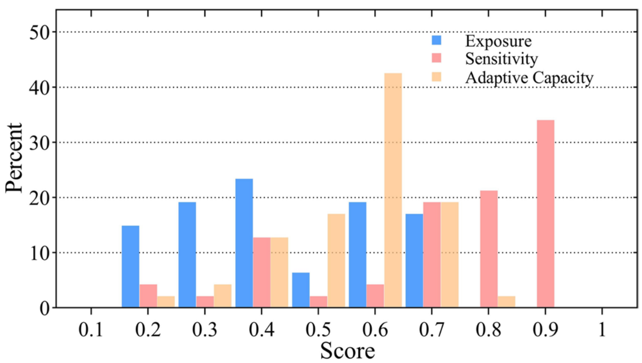


Fig. 4 Distribution of counties across normalised exposure, sensitivity and adaptive capacity values across Kenya

at the centre, indicating strong variability in exposure among counties. Only 43% of Kenyan counties have a normalised exposure value above 0.5, indicating that a majority of counties have a relatively low exposure to maize farming hazards. The distribution of sensitivity and adaptive capacity are skewed to the right, indicating high sensitivity and adaptive capacity for many counties in Kenya. Over three quarters (77%) of counties in Kenya have a sensitivity from 0.7. Among these, nearly half (45%) have a score above 0.8, which indicates high sensitivity of counties to factors that affect maize farming.

3.2 Relationships between parameters

The interaction among sensitivity, exposure and adaptive capacity across counties in Kenya is shown in Fig. 5. Many counties with high exposure have low sensitivity (e.g., Garissa, Tana River, and Wajir) while those with low exposure have high sensitivity (e.g., Kericho, Nyamira, and Bomet; Fig. 5a). Unlike exposure and sensitivity, exposure and adaptive capacity are positively correlated, since counties with high exposure also have high adaptive capacity and vice versa (Fig. 5b). We found no association between normalised sensitivity and adaptive capacity ($p > 0.05$, Fig. 5c).

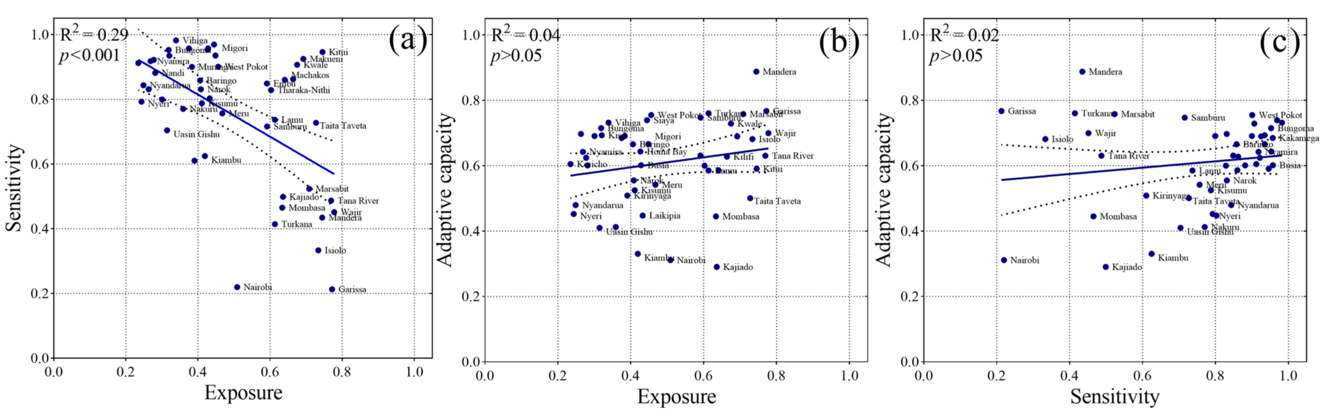


Fig. 5 Scatter plot showing the relationship between normalised (**a**) exposure and sensitivity, (**b**) exposure and adaptive capacity and (**c**) sensitivity and adaptive capacity

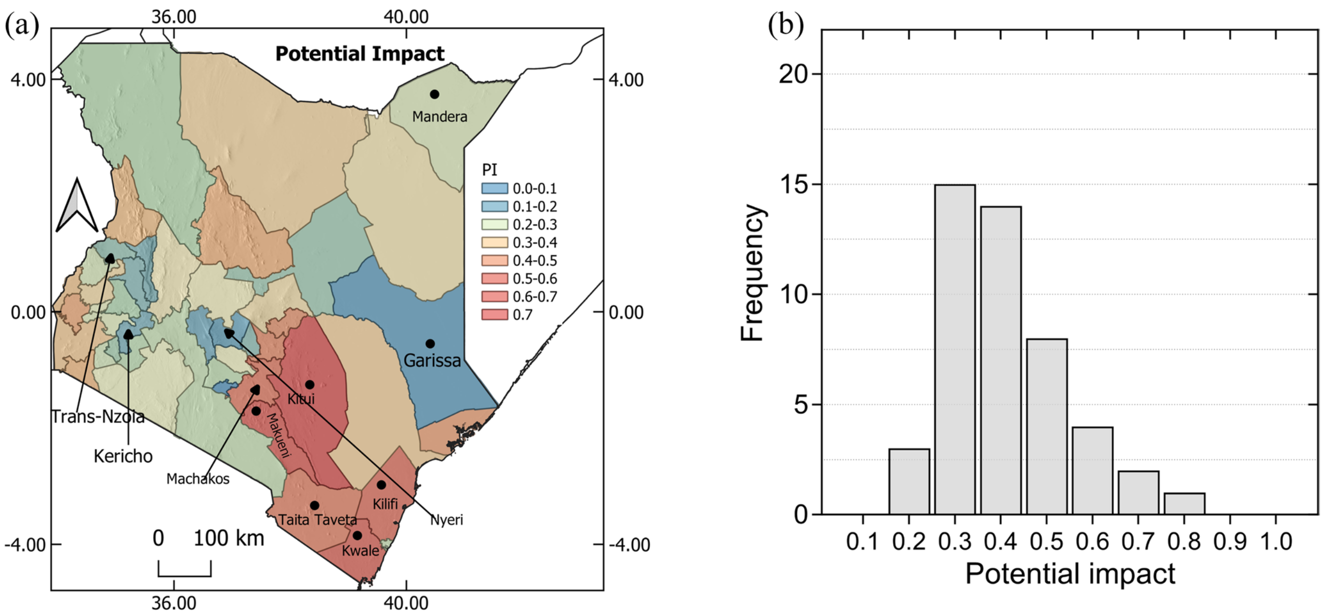


Fig. 6 (**a**) Spatial distribution of potential impact and (**b**) their normalised distribution across various counties in Kenya

3.3 Distribution of potential impact of climate change on maize farms

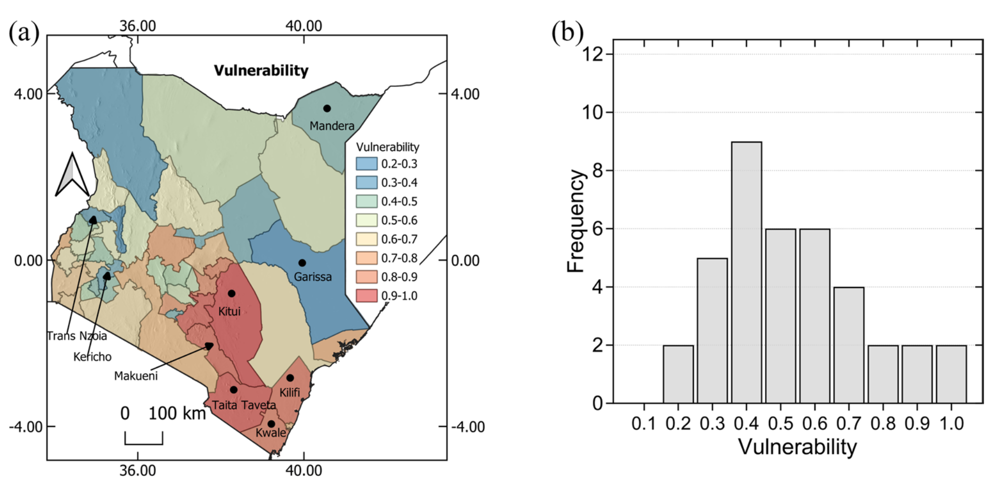
The spatial distribution of potential impacts of climate change on maize farming shows interaction of exposure and sensitivity without including adaptive capacity. We find a generally low potential impact for most counties in Kenya (Fig. 6a). The distribution of potential impact of climate is skewed to the left, with a majority of counties (77%) falling below 0.5 and only 26% (11 counties) having a potential impact index above 0.6 (Fig. 6b). Higher potential impact on maize production is found for the low-yield maize zones (e.g., Kwale and Kilifi in the south; Kitui and Makueni in the south-eastern part of the country). Lower potential impact is found in central parts of Kenya (e.g., Nyeri and Nairobi) and east of Kenya (e.g., Garissa).

3.4 Climate vulnerability clusters for Kenyan counties

The spatial distribution of vulnerability clusters within Kenya is heterogenous. High vulnerability is concentrated in southern Kenya in areas classified as low yielding maize zones (e.g. Kitui). High yielding maize zones in western Kenya have a relatively low vulnerability index. Turkana county in the north and Garissa county in the east have the lowest vulnerability, whereas Kitui and Taita Taveta counties in the eastern and southwest respectively have the highest vulnerability (Fig. 7a). Overall 60% of counties have a high vulnerability index with values equal to or greater than 0.6, while 40% have an index of 0.5 and below (Fig. 7b).

We assess the link between climate vulnerability and potential impact of climate change on maize farming and

Fig. 7 (**a**) Spatial distribution of vulnerability clusters and (**b**) their normalised distribution across various counties in Kenya



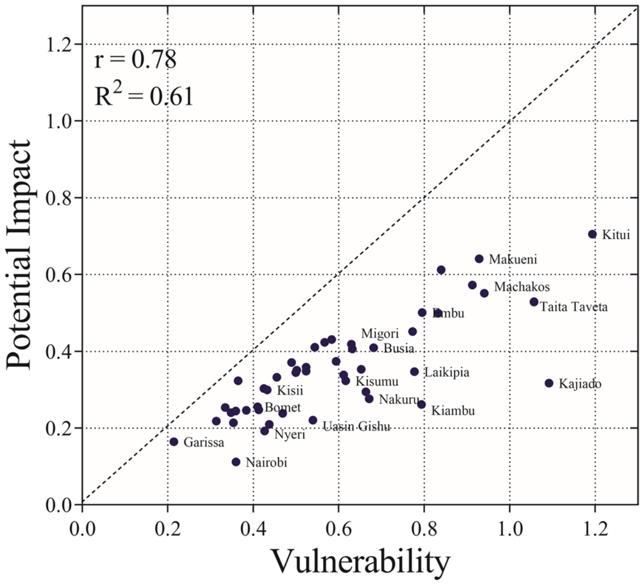


Fig. 8 Scatter plot showing the relationship between normalised potential impact and vulnerability

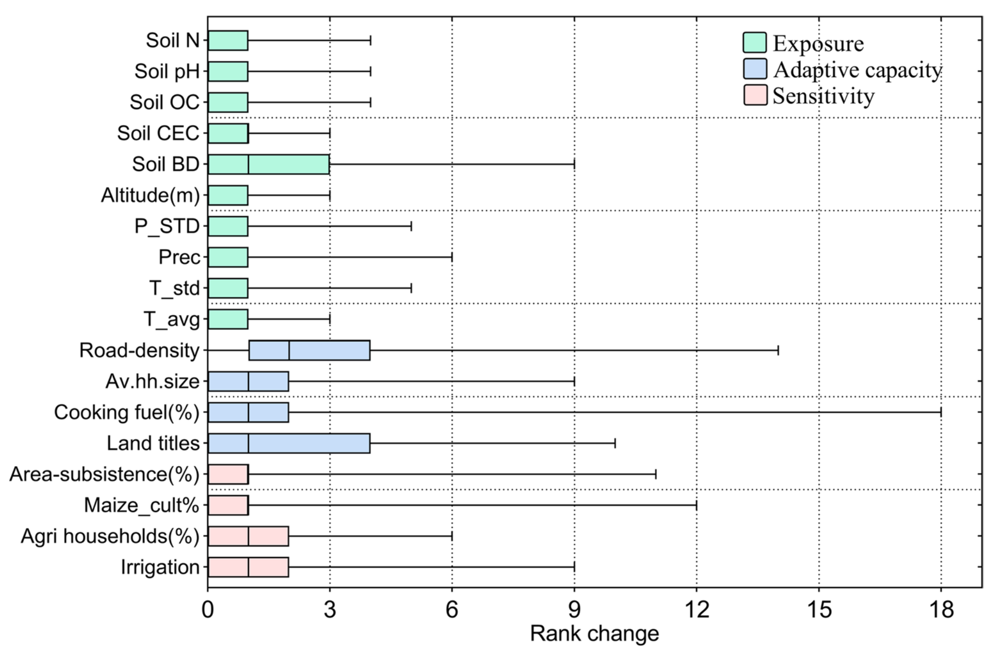
found them to be positively correlated, with vulnerability increasing as potential impact on maize farms increases (Fig. 8).

3.5 Indicator importance and evaluation of the vulnerability index

We used local sensitivity analysis as described by Tate (2012) and Shukla et al. (2021) to show changes in the vulnerability ranking of counties with exclusion of a single indicator that contributes to the vulnerability index. Our results show that exclusion of single indicators of adaptive capacity and sensitivity have the highest impact on the vulnerability index in general (Fig. 9). Exclusion of road density and land titles from the adaptive capacity component, resulted in average changes of 2.9% and 2.4% respectively, whereas exclusion of farms mainly cultivating maize and farms with irrigation from the sensitivity component, resulted in average changes of 1.5% and 1.4% respectively. Exclusion of soil bulk density and soil cation exchange capacity from the exposure component resulted in average changes in vulnerability ranking by 1.8% and 1.0%, respectively.

To evaluate the final vulnerability index, we spatially correlated each constructed index of exposure, sensitivity, potential impact, adaptive capacity, and the vulnerability index with maize yield, harvested area, and maize production. Our results show that sensitivity is significantly positively correlated to maize production (r=0.55), maize harvested area (r=0.55), and maize yield (r=0.53) (Fig. 10), meaning that as sensitivity increases, so do maize production, harvested area, and yield. Exposure is not significantly correlated with maize production, harvested area and maize yield (p>0.05). Vulnerability however, is significantly positively correlated with maize production and harvested area. The potential impact index correlates moderately with maize production (r=0.32), maize harvested area (r=0.31) and weakly with maize yield (r=0.25). There is no significant relationship between both adaptive capacity and selected validating indicators. Our final vulnerability index is moderately correlated with maize production (r=0.34) and maize harvested area (r=0.32) and very weakly with maize yield (r=0.14) (Fig. 10). The choice to consider the individual indices alongside the final vulnerability indices was made to identify the spatial importance of singular components within the vulnerability index.

Fig. 9 Rank-based estimate of indicator importance of variables. The boxplots show changes in the vulnerability rank across all counties when the respective indicator is excluded. Higher values indicate greater importance of an indicator in determining the vulnerability rank



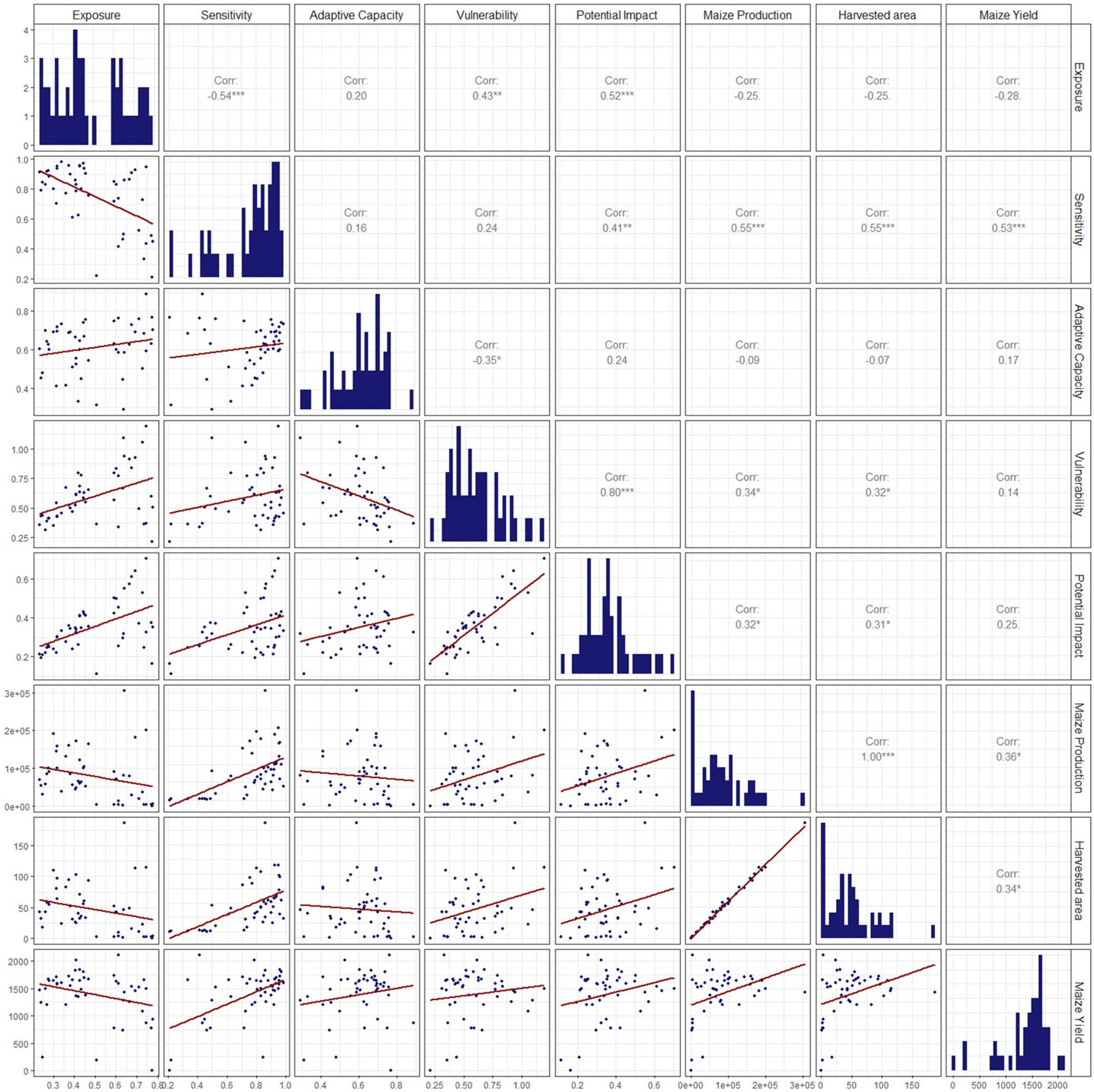


Fig. 10 Cross correlation between exposure, sensitivity, adaptive capacity, risk, potential impact, maize production, harvested area and maize yield. The asterisks indicate significant correlation ($p<0.05$)

As a final step, we correlated ranks of vulnerability with ranks of actual maize production, harvested area, and yield with a Spearman's correlation according to (Shukla et al., 2021). We found a negative correlation (not shown in Fig. 10) between ranks of vulnerability and actual maize production ($r=-0.45$), maize harvested area ($r=-0.45$), and maize yield ($r=-0.32$).

4 Discussion

Our study contributes to scientific literature in producing a of vulnerability map of maize farming households across all counties in Kenya. To the best of our knowledge, no such study exists, that brings together information on socio-economic and biophysical factors to vulnerability of maize farming in Kenya.

We selected exposure variables that cover key requirements of maize cultivation (e.g., temperature and precipitation) during the growing season. Low precipitation and high temperatures may cause water and heat stresses, which negatively impact maize production (Waqas et al., 2021; Sah et al., 2020). As a result, the exposure index maps depict areas suitable for maize cultivation and, inversely, areas with poor conditions for maize cultivation. The western part of Kenya has a lower exposure index and falls mainly in semi-humid and humid agroecological zones that are also classified as high yield maize zones by the ministry of agriculture (MOALF, 2020). This indicates that variables selected for the exposure index accurately portray the spatial distribution of areas that are suitable for maize production within Kenya. The sensitivity index, which includes the share of agricultural land, irrigation, reliance on subsistence agriculture and maize cultivation, was high in most counties. It emerged that sensitivity was inversely related to exposure, with counties in western Kenya having low exposure and high sensitivity, while counties in northern and eastern parts of Kenya have high exposure and low sensitivity. This may result from the fact that counties with high exposure and low sensitivity are found in areas classified as arid zones and contribute a small percentage to the total maize production in the country – this is in line with the results from Wanyama et al. (2019).

Our results suggest that there is resilience to yield reductions related to hazards affecting maize farming as the potential impact index is generally low across the counties. This finding, however, does not negate the need for adaptation planning, because specific low-yield maize zones (e.g., Kwale, Kilifi, Kitui, and Makueni) exhibit higher potential impact of climate change on maize farms. This indicates that these areas have both higher exposure and sensitivity index, and underlines the relevance of understanding drivers of vulnerability at the local level (Thornton & Herrero, 2014; Weis et al., 2016). Studies on vulnerability have noted that climate change alters the biophysical properties of agricultural land, in turn increasing climate vulnerability (Thornton et al., (Thornton, et al., 2014); O'Brien et al., 2007). It is therefore important to study how individual variables drive vulnerability and potential implications on adaptation decisions (Leichenko et al., 2014).

Vulnerability across Kenyan counties is generally high and was found to be weakly correlated with exposure, implying that vulnerability is not dependent only on biophysical factors, but on social and economic ones, too. Vulnerability is higher in counties of southern Kenya, with more agriculture-reliant households and lower adaptive capacity. Counties in northern Kenya, which are reliant on pastoralism and have fewer maize-reliant households (FEWSNET, 2013) and lower vulnerability to shocks affecting maize farming. Counties in very arid, arid and semi-arid AEZ of the northern, eastern, and southern parts of Kenya experience frequent droughts and high precipitation variability ranging between 250 and 400 mm annually (Schilling & Werland, 2023). This highlights the importance of site-specific adaptation planning. Although counties in northern and eastern Kenya are considered to be vulnerable to climate change, our vulnerability index suggests that these counties have a lower vulnerability compared to counties in humid and sub-humid zones. This could be explained by Kenya's livelihood classification that portrays counties in northern and eastern Kenya as having low dependence on crop production but a higher reliance on pastoralism, and a semi-nomadic lifestyle (FEWSNET, 2013; KFSSG, 2008).

Our sensitivity analysis may provide a basis for decision-making support for Kenyan counties. We found that adaptive capacity indicators have the greatest impact on the vulnerability index. Specifically, land tenure and road density (i.e., availability of resources), has the highest impact on the vulnerability index. As depicted in Supplementary Information (SI) 1(a), spatial distribution of land tenure security is higher in counties with low vulnerability. There is variation in adaptive capacity in terms of distribution and between different contexts (Adger et al., 2007). For high vulnerability counties with insecure land tenure, strengthening tenure rights and security can provide means of lowering vulnerability, because secure tenure has been found to shape adaptation decisions which could in turn reduce vulnerability (Akugre et al., 2022; Murken & Gornott, 2022; Antwi-Agyei et al., 2015). In addition, improving access to resources such as extension services through road access, could facilitate the transmission of knowledge of adaptation options that would serve to increase adaptation uptake and reduce vulnerability to maize related hazards.

The sensitivity analysis also shows that soil bulk density and soil nitrogen have a greater impact on the vulnerability index amongst the exposure variables. SI 2 shows that low-yielding counties have high index values for soil bulk density and low for soil nitrogen. Soil bulk density connotes soil compaction, which reduces the uptake of nutrients, hinders root growth, and limits water infiltration (Keller et al., 2013; Keller et al., 2021). Soil compaction also reduces air permeability and reduces water infiltration resulting in restricted root growth and nutrient uptake. These effects limit key soil functions such as infiltration, water storage, organic matter decomposition, and nutrient transformation (Schjønning et al., 2015). Agroecological practices have been forwarded as one way of dealing with soil health. For example, cover crops and mulch support provision of soil nutrients, preserve soil structure, and conserve humidity in dry seasons or in arid regions (Temegne et al., 2021).

Our study highlights that vulnerability is a multi-faceted and dynamic construct. Decisions related to reducing vulnerability thus should be site-specific, so as to help in developing contextually relevant and inclusive adaptation strategies that take into consideration the ability of stakeholders to implement recommended actions.

Limitations in our research may influence the interpretation of our findings. First, our study relies on secondary data for building of our index; the accuracy and reliability of our results therefore are dependent on the quality and completeness of this data. To overcome this limitation, extensive searches for additional data sources were made and variables used for sensitivity and adaptive capacity were cross-checked for accuracy by comparing them with official government reports. We also recognise that variability may exist within the counties due to differences in topography, climate and socio-economic factors. Our study is, however, limited to county level data and the availability of spatial data that covers all 47 counties in Kenya. Future studies could therefore delve into within-county vulnerability assessments to address vulnerability within and across counties. Third, the vulnerability index focuses on maize farming and may not be directly applicable to other crops. However, the approach in selecting crop specific exposure variables could support the creation of other vulnerability indices for other crops grown across the counties.

Despite these limitations, we believe that our study contributes to the ongoing research on vulnerability assessments and provides a basis for further research of vulnerability of different crops in Kenya and beyond. This study advances current climate vulnerability assessment methods in three principal ways: (1) in integrating often neglected factors in vulnerability assessments such as reliance on rainfed agriculture, land tenure, cooking fuel (as an indicator of poverty) and prevalence of subsistence agriculture which show underlying conditions, (2) in providing a picture of vulnerability for a staple crop across a country and (3) in integrating social factors with biophysical factors to capture maize farming vulnerability.

5 Conclusion

Our study contributes to scientific literature by combining both socio-economic and biophysical indicators in mapping vulnerability among maize farms across all counties in Kenya. This can support evidence based adaptation planning at county level. Our study focuses on vulnerability of maize farms showing the association between exposure, sensitivity, adaptive capacity, and their contributions to vulnerability across the counties in Kenya. We also show the interaction of exposure and sensitivity linked with a potential impact of climate change on maize farms and the link between adaptive capacity and vulnerability. The main conclusion is that vulnerability is dynamic and context-specific.

We conclude that knowledge about components of vulnerability provides a baseline for the selection and recommendation of adaptation strategies by focusing on relevant contributors to vulnerability. This can be important for decisions on prioritisation of adaptation strategies. Our results can inform existing policies such as the Strategy for Revitalizing Agriculture from 2004 and the Kenyan Climate Smart Agriculture Strategy for 2017–2026, which aim at adapting to climate change and increasing resilience of agricultural systems, and on setting priorities in terms of building resilience in maize based agricultural systems in Kenya.

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Data availability All data used in this manuscript is publicly available from the cited sources. Processed data are available from the corresponding author upon reasonable request.

Declarations

Conflict of interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this article.

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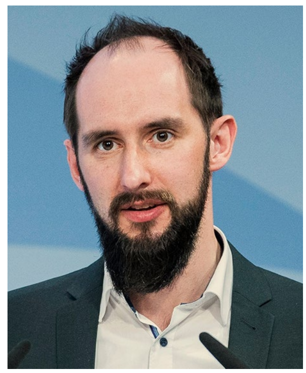

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