

## Research

# Vulnerability and adaptation of maize smallholder farmers to climate change: a Sub-Saharan African context

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## Abstract

This study analyzed smallholder maize farmers' perceptions of climate change vulnerability and adaptation strategies in the eastern Democratic Republic of the Congo. The study used a cross-sectional quantitative approach, with smallholder farmers selected based on farm size (less than 10 hectares). Using simple random sampling techniques, 210 smallholder farmers in South Kivu Province was selected from October and November 2021. The data were analyzed using frequency analysis, non-parametric Mann–Whitney U-tests, Tobit regression model and structural equations modeling, which demonstrated that demographic and socioeconomic factors influenced smallholder farmers' perceptions and adaptation strategies to climate change. The findings revealed that the level of education, size of the field, and activities of smallholder farmers had significant effects on climate change perception and adaptation strategies. Smallholder farmers' perceptions had a negative ( $p < 1\%$ ) influence on maize smallholder farmers' adaptation to climate change. Common efforts should be made to encourage smallholder farmers to feel committed enough to implement climate change adaptation measures that are effective in mitigating or preventing climate change risk. The results of this study would have implications for policies to support maize smallholder farmers in their efforts to mitigate and resilient to climate change in sub-Saharan Africa. Firstly, the promotion of climate literacy must be sufficient to provide farmers with information on climate and forecasting. Secondly, to empower smallholder farmers with means and resources to prevent and reduce the effects of climate change. Lastly, enhancing the current environment for the agriculture sector will advance community inclusivity and food security.

**Keywords** Vulnerability · Adaptation · Climate Change · Perception · Modeling · South Kivu · Sub-Saharan Africa

## 1 Introduction

In the Democratic Republic of the Congo (DRC), maize (*Zea mays*) is the main cereal crop and one of the three major staple foods. Farmers rely on maize for food security and income generation; however, their production is limited by climate change [1, 2]. Many climate-vulnerable regions have significant information and knowledge gaps, which impede decision-making and the assessment of perceived climate change risks, as well as people's adaptation strategies [3]. Furthermore, the chronological gap between information on climate trend analysis, climate scientists' future projections, and farmers' perceptions and adaptation information created and will continue to fuel the scientific climate debate [4]. Understanding the effects of climate change on maize production and farmers' adaptation strategies can help in properly addressing farmer empowerment decisions and promoting climate-sensitive agriculture interventions and policies [5].

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Climate change perception in agriculture studies [6–8] revealed evidence for perceived changes in climatic attributes such as decreased rainfall, increased temperatures, earlier cessation of rainfall, shorter rainy seasons, and new crop diseases. Because of the incremental nature and length of time required for human response to climate change, it is more difficult for individuals to perceive this phenomenon sensory and experientially [9–11]. The difficulty in addressing the climate change crisis is exacerbated by its complexity and systemic dimension, which leads to significant confusion about the causes of the disaster and adaptation strategies [12, 13].

The purpose of this study was to analyze maize farmers' perceptions of climate change vulnerability and adaptation strategies in eastern DRC. We investigated the social-psychological determinants of vulnerability perception and adaptation strategies related to climate change among small-scale maize farmers in a Sub-Saharan African context, the South Kivu province of the Democratic Republic of Congo. This study sought to determine maize smallholder farmers' perceptions of climate change, define the nature and extent of vulnerability to climate change, and present their behavior in response to various climatic hazards. The findings of this study will be used to understand maize farmers' exposure and sensitivity to climate change, as well as to provide policy guidance on the most appropriate adaptation strategies for promoting maize farming and the sustainability of the eastern DRC.

## 2 Literature review

### 2.1 Understanding maize smallholder farmers' vulnerability to climate change

Climate change vulnerability may differ among small farming communities and be determined by a combination of multiple social and biophysical processes [14]. Several definitions have been developed to better understand vulnerability. All definitions are context-based, incorporating cultural, political, and socioeconomic factors that interact with climate and agricultural activity [15, 16]. For Bedeke et al. [14], vulnerability refers to both the degree to which a system is sensitive to and incapable of dealing with the negative consequences of climate change and other socioeconomic stressors. The definition of vulnerability used in this study was inspired by Epule and New [17], who defined vulnerability as “the extent to which a system is susceptible or exposed to and unable to cope with the negative effects of climate change, climate variability and extreme weather events”. Approaches to assessing social vulnerability to climate change are primarily focused on understanding the complex relationships between climate, land use, livelihood, public health, and food systems, which influence household climate change vulnerability and adaptive capacity [14]. Multiple indices have been used in the literature for assessing climate change vulnerability. Epule et al. [16] developed and assessed an agricultural yield vulnerability index for yields affected by climate change in Uganda [16, 17], Cameroon [18], and other sub-Saharan African countries [19, 20]. The vulnerability index is examined using three key assessment concepts: exposure, sensitivity, and adaptive capacity. The vulnerability to climate change is assessed by examining its associated effects [14]. In addition to vulnerability index, this study investigated farmers' perceptions of climate change and its effects [21]. Climate literacy assessments were critical for conducting a vulnerability analysis of maize farmers in Sub-Saharan Africa [22]. This study assumed that smallholder farmers who are well-informed about climate change and its consequences are more likely to develop effective adaptation strategies.

Climate change is expected to aggravate food insecurity in Sub-Saharan Africa (SSA) by 2050 because it has a negative impact on maize consumption and daily calorie consumption [23]. Teshome et al. [22] discovered that climate change and variability are affecting maize production in eastern Ethiopia, with 78% of smallholder maize farmers reporting increasing temperatures and 83% reporting decreasing rainfall. Drought, diseases and pests, dwindling soil fertility, and declining crop yields were perceived as the major impacts of climate change on maize production by farmers. Farming households in Ghana are particularly vulnerable to climate change and weather variability in terms of food, water, and health [24]. Malagasy smallholder farmers, according to Harvey et al. [25], live in precarious conditions and are inherently vulnerable to any shocks that affect their agricultural systems. Smallholder farmers are particularly vulnerable to crop productivity declines because they cultivate in very small plots of land (< 1 ha), devote the majority of their land to crop production for household consumption, and obtain low crop yields. Climate change and variability have a negative impact not only on crop field stages and yields but also on cereal postharvest management. Insect pests caused at least 30% weight losses in grain storage in SSA. Fungal growth has caused food spoilage, reduced germination, discoloration, and caking, and may produce toxins (mycotoxins) that can cause health problems and even death [26, 27].

Climate change is a major threat to the DRC's efforts to reduce poverty and ensure food security. Climate change is expected to have a significant impact on the livelihoods of smallholder farmers in eastern DRC who rely on rain-fed maize. Although climate-based suitability analysis indicates that the country's southern, eastern, and northeastern regions are suitable for maize production, climate change projections based on climate extremes show that the DRC is expected to lose maize production potential, and its suitable areas will become moderately suitable in most cases [28]. The decreased amount of rainfall in Eastern DRC between 2013 and 2019 warned farmers about the common effects of climate change, such as pest proliferation, decreased soil fertility, floods, and crop failure. The observed farm impacts endanger agricultural sustainability by reducing yields and farmer incomes, resulting in food insecurity and rural exodus [5]. This situation exacerbates farmers' vulnerability due to the direct negative effects of climate change on crop suitability and productivity, on which farmers depend for both their livelihoods and income.

## 2.2 Maize smallholder farmers' need for climate change adaptation strategies

Smallholder farmers use adaptation strategies in various ways to mitigate climate change and maintain regional food production stability [29–33]. The Fourth IPCC Assessment emphasized that adaptation strategies, to improve local adaptation capacity, are essential for mitigating the potential negative effects of climate change [29, 34]. To increase farmer resilience and agricultural productivity, maize farmers and SSA policy are taking practical steps to mitigate the economic losses associated with climate change [33, 35]. Epule et al. [16] applied the systematic adaptation tracking approach in the Sahel to categorize climate change mitigation actions. In terms of prevalence, 4 climate change adaptation options were found in Sahel: technically related adaptation actions (49%), indigenous problem-solving adaptations (41.7%), socially associated adaptation actions (5%) and economics-related adaptation actions.

Empirical studies have provided tools for assessing farmer adaptation strategies as well as national, regional, and international policies. Understanding climate change conditions tools are intended to provide farmers with effective climate change mitigation strategies. For a regional impact assessment, the Tradeoff Analysis model for Multi-Dimensional Impact Assessment (TOA-MD) is used to simulate technology adoption and associated economic, social, and environmental outcomes in a heterogeneous farm population [34]. The development of Representative Agricultural Pathways (RAPs) and Representative Concentration Pathways (RCPs) scenarios helps to characterize the range of uncertainty impact and provides detailed insight into adapting to and mitigating the effects of climate change [32]. Researchers used the Cropping System Model (CSM)-CERES-Maize model to predict the effect of climate change on growth and yield under various RCP scenarios. Crop models such as the Decision Support System for Agrotechnology Transfer (DSSAT) estimate the impact of climate change and the development of adaptation strategies on crop growth [29, 32]. Rainwater harvesting (RWH) strategies are used to mitigate the effects of climate change on crop production [37]. When dealing with climate change and high temperatures, the crop model Agricultural Production Systems sIMulator (APSIM) is used to investigate the interaction of sowing date and cultivar [38]. Rahimi-Moghaddam et al. [39] implemented the Regional Integrated Assessment (RIA) to assess climate change and adaptation in South Africa, which links climate, crops, economic data, and tools developed by the Agricultural Model Intercomparison and Improvement Project (AgMIP).

Most climate change adaptation strategies implemented by maize smallholders in SSA countries are complementary and influenced by household socio-demographic characteristics, access to input and output markets, credit service, weather information, and other forms of institutional factors [14, 32, 33]. Farmers in SSA implemented climate change adaptation (CCA) in maize postharvest management to mitigate the effects of climate change after harvesting [26, 40]. Farmers in Tanzania used herbs, wood ash, commercial chemicals, proper drying, hygienic conditions, pre-processing, proper handling and packaging of, or use of metal silos and other hermetic storage devices as post-harvest loss control measures [40].

Smallholder maize farmers in the DRC combine indigenous and local knowledge and practices to respond to the effects of climate change [5, 41, 42]. According to Karume et al. [28], Climate Smart Agriculture (CSA) practices in agricultural production are gradually being adopted by smallholder maize farmers in DRC. Crop rotation, fallow practices, bio-fertilizers, bio-pesticides, mulching, cropping diversity, planting date adjustment, and strengthening off-farm activities were among the CSA practices. Farmers in South Kivu's agroecological zones developed climate change adaptation strategies based on personal and societal experiences. Soil conservation and water management, water harvesting and storage techniques, early planting, crop and livestock diversification, selection of heat or drought-tolerant varieties, and planting of weed-tolerant crop varieties are all examples of such strategies [5, 8, 41, 43, 44]. According to previous studies [31, 45, 46], adopting climate change adaptation strategies is influenced by socio-demographic factors (age, gender, level of education, length of time in farming, etc.) as well as farming activity factors (attitude towards climate change,

perceived risk and self-efficacy, area of farmland, value-added performance of its strategies including farm yield, net farm income). This study sought to identify the factors that influence the adoption of climate change adaptation practices.

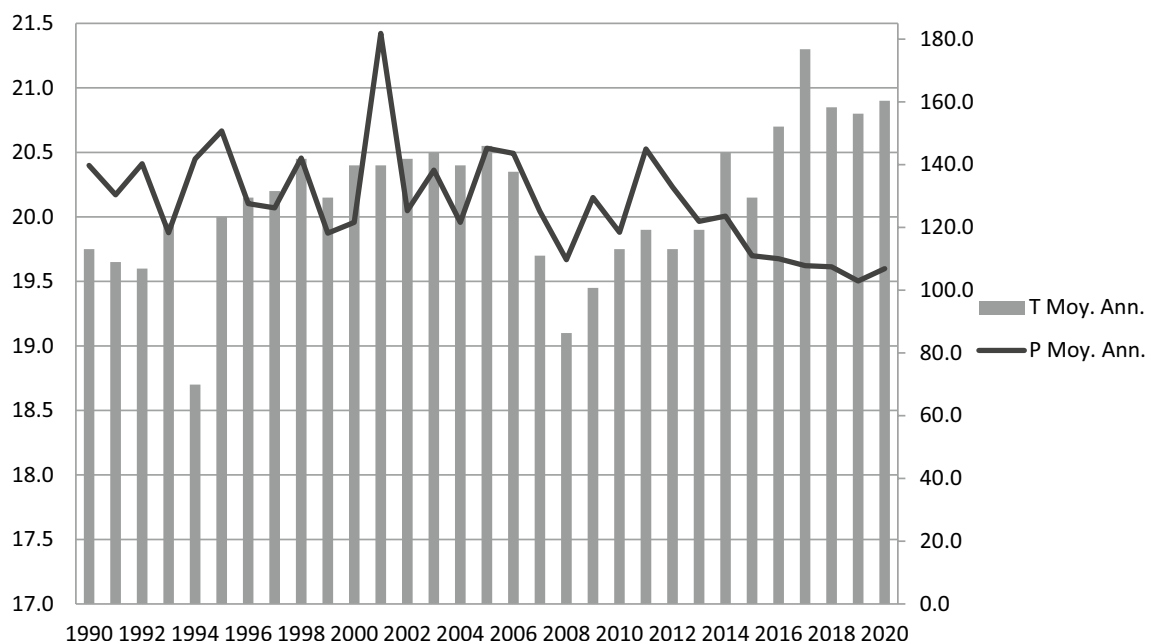
### 3 Methods and materials

#### 3.1 Study area

The research was conducted in the territories of Kabare and Walungu in the province of South Kivu in eastern DRC. Kabare territory is 1960 km<sup>2</sup> and is located between 2°30' south latitude and 28°30' east longitude. Its altitude varied between 1460 and 3000 m. Kabare has a humid tropical climate with a 9-month rainy season (from September to May) and a 3-month dry season (from June to August). The yearly average temperature is 22.6 °C, the relative humidity ranges from 68 to 75% (CRSN-Lwiro climatological service, 1973–2018), and the annual rainfall total is 1500 mm. The vegetation is made up of a farmed savannah that has taken the place of the natural *Albizia grandibacteata* forest [47]. The climate factors listed above imply that agricultural activities are advantageous. Farming provides 92.6% of household income, but the soil is depleting. Because of the high population density, the landscape has become a checkerboard of very small plots planted without regard for the soil's resting period (fallow land). Walungu is located between 2°38' south latitude and 28°40' east longitude, with altitudes ranging from 1000 m (in the east at Kamanyola) to 2000 m in Mulumemunene [48]. Walungu has a total area of 1800 km<sup>2</sup>. Kabare has 868,616 people and Walungu has 368,857.

The Walungu territory has a cold tropical climate at low altitude, with a dry season (May—September) and a rainy season (September—May), with temperatures ranging from 17 °C (in July) to 20 °C (in October), and annual rainfall ranging from 900 to 1500 mm, with an annual average of 1300 mm. The region's soils are diverse, but in general, sandy-clay soils of the red laterite type, loose black soils, rocky soils, and alluvial soils near the marshes predominate [47]. The vegetation comprises grassland savannahs, the Mugaba and Mushwere forest reserves, and scattered forests.

Temperatures were mostly steady between 1990 and 2020, except in 1994 and 2007 when they hit a low average and peaked in 2017. The annual average rainfall (Fig. 1) in South Kivu fluctuated with explosive oscillations during the period, particularly from 2000 to 2001, when there was a high rate of precipitation. Figure 1 depicts the average annual temperature and rainfall in Sud-Kivu province from 1990 to 2020.



**Fig. 1** Temperature and rainfall evolution in South Kivu from 1990 to 2020 (Source: Data collected at the Lwiro Research Centre, 2016): T Moy. Ann.= Annual average temperature; P Moy. Ann.= Annual average rainfall

## 3.2 Data collection

The study used a cross-sectional quantitative approach, with smallholder farmers selected based on farm size (less than 10 hectares). Data were collected using a 3-stage random sampling approach. The first stage involved randomly selecting 4 districts (Bugorhe, Miti, Irambi-Katana, and Mudaka) in Kabare and 2 districts (Kamanyola and Nyangezi) in Walungu. The second stage involved selecting the villages in each district. These villages were chosen because of their importance in maize production. Thus 11 villages were selected in Kabare and 6 in Walungu. In the final stage, smallholder maize farmers were randomly selected from the list of farmers provided by the agronomist in each village. The sample size was calculated using the Yamane formula (1973), with a 7% margin of error [22]. According to the 2020 provincial agricultural inspectorate's report, Kabare and Walungu had approximately 32,953 maize farming households. We, therefore, found a sample size of 210 farming households. By then, approximately 10 to 15 smallholder maize farmers had been surveyed. Smallholder Farmers in Kabare with at least two fields were discovered to be farming in fields that were located in two or more villages. Smallholder farmers were identified using only the cultivated area, among other indicators proposed by Nyambo et al. [49]. Farmers with fewer than 10 hectares were chosen for this study.

Data were collected from smallholder farmers between October and November 2021. Informed oral consent was obtained from all participants. The questionnaire was administered using KoboCollect and included various indication scale items. Smallholder farmers' perspectives and adaptation strategies in response to climate change were assessed using a five-point Likert scale (5 = strongly agree to 1 = strongly disagree). Smallholder farmers' perception items focused on conceptualization, operationalization, and measurement [6, 9, 46, 50, 51]. Thirteen items were identified because of these studies. The items were closely and/or distantly related to theoretical dimensions of perception. After removing certain items, the results of the item generation and the interviews were combined to produce ten items divided into four dimensions (simultaneous variation in temperature and precipitation, temperature disturbance, irregularity of rainfall and strong winds, and precipitation disturbance). The deletion was based on four criteria: (a) removing duplicates and keeping an item in a dimension only once, (b) merging items that described the same phenomenon and adjusting their frequency of appearance, (c) deleting ambiguous and irrelevant items, and (d) reformulating items into clear and easily understandable sentences [52]. A similar method was used to select adaptation items. Adaptation conceptualization, operationalization, and/or measurement studies were chosen [10, 45, 53, 54]. 30 items were identified and referred to one or other theoretical dimensions of adaptation. In the end, 12 items subdivided into five dimensions (Technical capacity, Infrastructure facilities, Human capacity, Institutional capacity, and Economic capacity) were selected [4]. Exposure was a multidimensional concept composed of 4 items subdivided into two main dimensions (Less exposure to high-temperature precipitation and more exposure to high-temperature precipitation). Sensitivity was also composed of 8 items subdivided into three main dimensions (Social group, Social and political situation, and Agricultural activity).

## 3.3 Data analysis

MS Excel 16, SPSS 23, and LISREL 9.1 were used to process and analyze the collected data. In this study, descriptive analysis (frequency analysis and non-parametric Mann–Whitney U-tests), the Tobit regression model, and structural equation modeling were both used. The Tobit regression model was used to identify the socioeconomic variables impacting maize producers' perception and adaption [55]. The Tobit regression model was used because the dependent variables (adaptation and perception) were censored variables with values ranging from 0.99 to 5 [56].

### 3.3.1 Structural equation modeling

Two structural models were estimated to test the nature of the relationship between smallholder maize farmers' perception and adaptation to climate change. The first analyzed the impact of climate change on perception, as well as perception on sensitivity, exposure, and adaptation. The second investigated the effects of climate change on adaptation. The dimensions associated with each construct were converted into mean scores and so served as observable indicators for the construct in its relationship to the other latent variables in the two estimated models [57]. Structural equation modeling was conducted in three stages [58]. Firstly, the structural model parameters were tested using general equations of the following  $X = \Lambda X\xi + \varepsilon$  (Eq. 1) composed respectively of standardized structural coefficients and measurement errors [59, 60]. The estimation allowed arbitrary values to be assigned to the parameters  $\lambda$  and  $\varepsilon$  using variance–covariance

matrices. We then confirmed the absence of multi-collinearity through satisfactory discriminant validity for all the constructs used in both models. The absence of a strong correlation between the constructs significantly reduced the inference errors [61]. Finally, the multi-normality of the data was confirmed by the low values of Skewness and Kurtosis in the two structural models.

### 3.3.2 Measurement of variables

These values were lower than 2 and 7, respectively, which are the thresholds for serious concerns with data normality [60]. Secondly, the estimation provided an opportunity to assess the goodness of fit of the models thus estimated. Four indicators were used for this purpose: chi-square, chi-square/df, RMSEA, and CFI [62]. Reliability was tested using both Cronbach's  $\alpha$  and Jöreskog's rho coefficients [63]. Cronbach's  $\alpha$  was obtained from the results of the exploratory factor analysis. In this case, an  $\alpha \geq 0.70$  indicated that the concept measurement was reliable. Jöreskog's  $\rho$  (rho) (Composite Reliability) was calculated using the results of the confirmatory factor analysis, taking into account both the relationships between the latent variables and their measures and the measurement error [58]. As for alpha, rho values  $\geq 0.70$  confirmed the reliability of the constructs under analysis. The validity of the latent variables was established by testing both convergent and discriminant validity. Convergent validity was tested using the mean variance extracted for each construct and dimension. Convergent validity was confirmed when the dimensions of each construct exhibited an average extracted variance  $\geq 0.50$  [64]. This result indicated that items attached to each dimension explained the latter better than they would for other dimensions. Discriminant validity was tested by comparing the mean variance extracted for each dimension with the square of the simple correlation between paired dimensions [58]. Thirdly, the direction and strength of the relationship between the different latent variables were tested using a t-value  $\geq 1.96$  with a significance level  $\leq 0.05$  [57]. The Kaiser Meyer Olhkin (KMO) index and Bartlett's sphericity test were used to test the suitability of the data for analysis by factor.

## 4 Results and discussion

### 4.1 Descriptive analysis results

Results presented in Table 1 show more female maize farmers (56%) than male maize farmers (44%). The results of this study were not consistent with those of Bedeke et al. [65] and Teshome et al. [22], who found more male than female maize smallholder farmers. This is explained because both authors interviewed the household heads. In SSA Africa, although women are numerous in the field [33], they are limited in the management of agricultural income because they are not household heads. In this study, investigations were carried out immediately in the fields, and women outnumbered men. Around 70% were aged between 35 and 55. The smallholder farmers' education indicated that only 11% had not studied. 51% had attended high school, and 20% had attended university. Married represented 84% and others (single, widowed, and divorced) represented 16%. Apart from farming, 46% were self-employed, and 24% worked for a private or public institution. The families included about 8 persons, 3 of whom were employed in maize farming. Household heads, spouses, and children (especially daughters, were engaged in maize farming. In the province of South Kivu, maize was grown on an average of 1.5 fields and 0.609 hectares. These findings are consistent with studies of [14, 15, 22, 33, 65] conducted in SSA. Maize farming is done by working persons aged 30 to 60 who are married, have more than five dependents, and are not highly educated. The agricultural income from maize was estimated to be CDF 467,671 (USD 234), with a variation coefficient of 132%. This result, like that of Abokyi et al. [66] in Ghana, indicates the large differences in farm income between maize farmers in SSA.

Table 2 summarizes the distribution of smallholder maize farmers' perceptions on climate change by gender, age and education. The mean scores for all items are above 2.5. The mean perception scores of smallholder farmers are highest for decrease rainfall (4.06), rainfall irregularity (3.89), late rainfall onset (3.82) and early rainfall interruption (3.47). Violent winds (2.71) and Hot dry and rainy seasons (2.84) showed low scores below 3. The estimated results from non-parametric Mann-Whitney U-tests revealed no statistically significant difference in the gender perceptions of climate change. Balasha et al. [5]'s findings, which were conducted in South Kivu, fully corroborated these results. In other words, men and women both perceive the same effects on their farms. Rainfall irregularity showed substantial disparities among smallholder farmers based on their age and education level. Depending on their farming experience (farmers over 45 years old) and their availability in the fields (farmers with only primary school education), farmers have indicated that they

**Table 1** Maize farmer socioeconomic descriptive statistics

Variables	Modalities	Frequency (n = 210)	%
Gender	Female	117	56
	Male	93	44
Age	25–35	27	13
	36–45	70	33
	46–55	75	36
	> 55	38	18
Education	None	24	11
	Primary	39	19
	High school	106	51
	University	41	20
Marital status	Married	177	84
	Other	33	16
Other activities	None	26	12
	Employment	51	24
	Business	36	17
	Self-employment	97	46
		Mean	Standard deviation
HH size	Number	7.62	2.71
HH members in agriculture	Number	2.95	1.44
Number of fields	Number	1.47	0.59
Land size	ha	0.609	0.614
Agricultural income	CDF	467,671	617,513

HH Household, CDF Congo Democratic Francs; 1 USD = 2000 CDF in 2021, ha = hectare

can no longer predict crop seasons due to extremely erratic rains. There was also a considerable age difference on hot days item. Younger farmers (up to 45) were more likely to report very hot days. They reported that hotter days reduce field labor time and had a negative impact on crop growth and yields. These findings were in line with those of Bedeke et al. [65], Teshome et al. [22] and Balasha et al. [5], who discovered that smallholder farmers perceived increasing warm days and nights and decreasing amounts of rainfall as indications of climate change. Additionally, Teshome et al. [22] and Balasha et al. [5] discovered that the perceptions of smallholders regarding climate change were influenced by socioeconomic factors including education and age. The mean scores reported in Table 2 on climate change exposure show that high temperatures in recent years (4.10), followed by being affected by high temperatures more than three times last year (3.93), had the highest mean scores. Farmers experiencing high temperatures more than three times last year and those claiming observed heavy rainfall three times or less last year demonstrated significant differences in age and education. In fact, persons over 45 and those who finished primary school scored higher than others. The elder and primary farmers reported that current temperatures are significantly higher than in previous years. Table 2 shows that the greatest mean scores for climate change sensitivity were for lack of government subsidies (4.08), agricultural dependence (3.69), and insecurity (3.52). There were significant gender and education disparities for agricultural dependence. Women and farmers who finished primary education had higher ranked scores than others. They were more vulnerable to the effects of climate change, which hampered their agricultural production [67]. Older farmers indicated their vulnerability to climate change hazards (flooding, erosion, drought, etc.). Performing his studies in a sub-Saharan context, Epule et al. [16]'s findings supported this study by demonstrating that maize farmers were exposed to climate change threats due to their educational background on the subject, which was influenced by their financial status. Additionally, they showed how low-income farmers typically have less resources to deal with the effects of climate change since they have less access to planting materials, advanced agricultural equipment, and inputs [17, 68]. Similar to this study, Fisher et al. [69] discovered that farmers' sensitivity to floods and droughts was enhanced by their poverty (lack of resources), inadequate information as well as the lack of sub-Saharan African government involvement. As a result, farmers' ability to track the agricultural calendar and forecast agricultural seasons is diminished.

Several strategies enabled smallholder farmers to mitigate the effects of climate change. Table 3 demonstrates that the identified strategies had mean scores greater than 2.5. Higher average scores (over 4) were observed for easy access to

**Table 2** Maize smallholder farmers' perception risks, exposure and sensitivity on climate change

Dimensions	Items	Mean scores		Gender		Age		Education		p-value
		Female	Male	p-value	≤45	>45	≤Primary	>Primaire		
Perception	Decrease rainfall	103.15	108.46	0.48	99.53	110.63	0.14	113.40	102.12	0.17
	Rainfall irregularity	101.00	111.16	0.18	96.86	112.92	0.03**	117.86	100.20	0.03**
	Late rain onset	105.51	105.48	1.00	109.73	101.87	0.30	107.10	104.82	0.78
	Early rainfall interruption	108.43	101.81	0.38	108.78	102.68	0.42	101.24	107.33	0.46
	Aborted rains	105.62	105.35	0.97	104.88	106.03	0.87	98.13	108.66	0.18
	Hot days	104.48	106.78	0.77	113.46	98.66	0.06*	112.71	102.41	0.22
	Hot night	100.58	111.69	0.16	107.27	103.98	0.67	115.24	101.33	0.10
	Violent winds	105.30	105.75	0.96	106.06	105.02	0.90	109.19	103.92	0.54
	Hot nights and days	101.19	110.92	0.20	111.15	100.65	0.16	113.46	102.09	0.17
	High temperatures in the past years	107.12	103.46	0.597	104.92	106.00	0.875	109.05	103.98	0.500
Exposure	Affected by high temperatures last year at most thrice	107.14	103.44	0.525	103.42	107.28	0.507	102.61	106.74	0.514
	Affected by high temperatures more than thrice last year	104.88	106.28	0.836	98.28	111.69	0.048**	115.10	101.39	0.063*
	Affected by heavy rainfall at most 3 times last year	107.58	102.88	0.505	97.62	112.27	0.037**	120.25	99.18	0.006***
Sensitivity	Agricultural dependence	114.23	94.52	0.012**	102.05	108.46	0.412	126.28	96.60	0.000***
	Lack of government subsidies	106.24	104.58	0.830	104.90	106.01	0.885	104.22	106.05	0.828
	Tribal conflicts	109.94	99.91	0.194	105.27	105.70	0.955	103.94	106.17	0.789
	Insecurity (theft and looting)	103.41	108.12	0.545	102.63	107.96	0.492	108.61	104.17	0.598
	Field's low altitude	107.75	102.67	0.519	110.56	101.15	0.230	98.56	108.48	0.244
	Affected by flooding, erosion, etc	103.79	107.65	0.631	97.59	112.29	0.066*	110.43	103.39	0.418
	Drought and water shortages	103.50	108.02	0.569	93.99	115.38	0.007***	114.80	101.51	0.122
	Limited crop diversification	102.90	108.77	0.453	101.80	108.67	0.378	103.44	106.38	0.728

\*\*\* p-value < 1%, \*\* p-value < 5% et \* p-value < 10%



**Table 3** Maize smallholder farmers' adaptation strategies to climate change

Items	Mean scores		Gender		Age		Education		p-value
	Female	Male	Female	Male	≤45	>45	≤ Primaire	> Primaire	
Land ownership	3.44	105.00	105.90	105.00	99.12	110.98	111.01	103.14	0.348
Rural income	4.09	105.62	105.41	105.62	102.41	108.15	100.81	107.51	0.427
Farmers education	3.05	117.49	95.97	117.49	100.39	109.89	94.21	110.34	0.062*
Having studied for many years (> 12 years)	2.62	115.04	97.92	115.04	110.54	101.17	102.11	106.95	0.581
Easy access to rural roads	3.64	110.46	101.56	110.46	107.57	103.72	97.35	108.99	0.159
Easy access to main roads	4.17	110.58	101.46	110.58	99.26	110.85	102.17	106.93	0.565
Access to market	4.12	105.69	105.35	105.69	103.66	107.08	94.36	110.28	0.056*
Easy access to credit	3.29	110.97	101.15	110.97	98.25	111.72	96.80	109.23	0.149
Easy access to information	2.60	105.54	105.47	105.54	97.76	112.15	106.72	104.98	0.837
Adopting new varieties	3.09	118.01	95.56	118.01	101.07	109.30	98.33	108.57	0.243
Changing varieties	3.57	112.39	100.03	112.39	98.37	111.62	114.29	101.73	0.147
Modification of the agricultural calendar	3.24	116.46	96.79	116.46	105.65	105.37	102.54	106.77	0.624

\*\*\* p-value < 1%, \*\* p-value < 5% et \* p-value < 10%

main roads, market access, and other rural income. Smallholder farmers have stated that having access to basic infrastructure and resources allows them to purchase agricultural supplies and market their produce more easily. These findings align with those of Kutyauro et al. [27]. Males in rural Sub-Saharan Africa developed climate change adaptation strategies that were more effective and faster. Men scored higher statistically than women in the following items: farmer education, years of schooling exceeding 12 years, adoption of new varieties, and agricultural calendar alteration. In contrast to the findings of this study on the use of agricultural varieties and techniques, Balasha et al. [5] has discovered that women are more inclined to use pesticides and plant living hedges in an effort to increase crop yields. Farmers over the age of 45 scored higher in terms of finance accessibility, information availability, and crop variety change. These farmers stated that their farming experience had provided them with the resources necessary to cope with climate change. These findings align with those of Yegbemey et al. [45]. Farmers that have completed studies have reported easier market access than other farmers. According to them, their market was not only physically accessible, but they were able to expand into other markets outside of their region by utilizing modern information technology. As found by Epule in the Sahel, farmers were developing adaptation strategies to cope with non-climatic and climatic drivers [36]. This is why, according to Matimolane et al. [70], all of the adaptation strategies assessed had high mean scores and no significant differences for most of the socio-demographic factors.

The Tobit regression results (Table 4) showed that the model was well-defined and significant, with  $\text{Prob} > F = 0.0244 < 0.05$ . Age, gender, and household members involved in agriculture did not affect maize farmers' adaptations. Similar to the findings of Apata et al. [71] in Nigeria, gender, age, and household members working in agriculture did not affect farmers' adaptability to climate change. Furthermore, Acquah and Onumah [72] discovered that age and household members involved in agriculture had no impact on farmers' adaptability to climate change risks. However, these findings contradict those of Asrat and Simane [73] and W. Tesfaye and Seifu [74], who discovered that household size, age, gender of the household head, household members involved in agriculture, farming experience, climate information, and extension advice all influenced farmers' ability to perceive and adapt to climate change.

Table 4 indicates that the level of education, field size, and other activities significantly influenced climate change adaptation. The educational level has positively improved farmers' adaptability to climate change by enhancing their understanding of the possible benefits of adaptation. In Nigeria, Apata et al. [71] discovered similar findings. Farmers' perceptions of and adaptations to climate change were influenced positively by land size. Farmers are more likely to implement adaptation measures when their field size is larger. These findings are consistent with those of Yegbemey et al. [45], who discovered that land size, farming experience, and membership in an organization were positively and significantly correlated with both the farmer's decision to adapt to climate change in North Benin. Income from activities other than agriculture helped farmers' adaptation by providing access to agricultural inputs, training, and new technologies. Farmers with secondary occupations and non-agricultural income were found to be most resilient to climate change [45, 75].

## 4.2 The perception of vulnerability among maize smallholder farmers to climate change

The factorial and confirmatory perception analysis (Table 5 and Fig. 2) revealed that the data are factorable because the KMO index was 0.692 ( $> 0.5$ ) and Bartlett's sphericity test was 502.021 (ddl: 78; sig.: 0.000). The representation qualities (commonalities) of selected items were greater than 0.5, varying between 0.519 and 0.769. Items were strongly correlated on a single factor, with weights greater than 0.5, ranging from 0.624 to 0.867. The extracted dimensions explain 63.489% ( $> 60\%$ ) of the variance in South Kivu maize producers' perceptions of climate change. All four dimensions

**Table 4** Tobit regression analysis

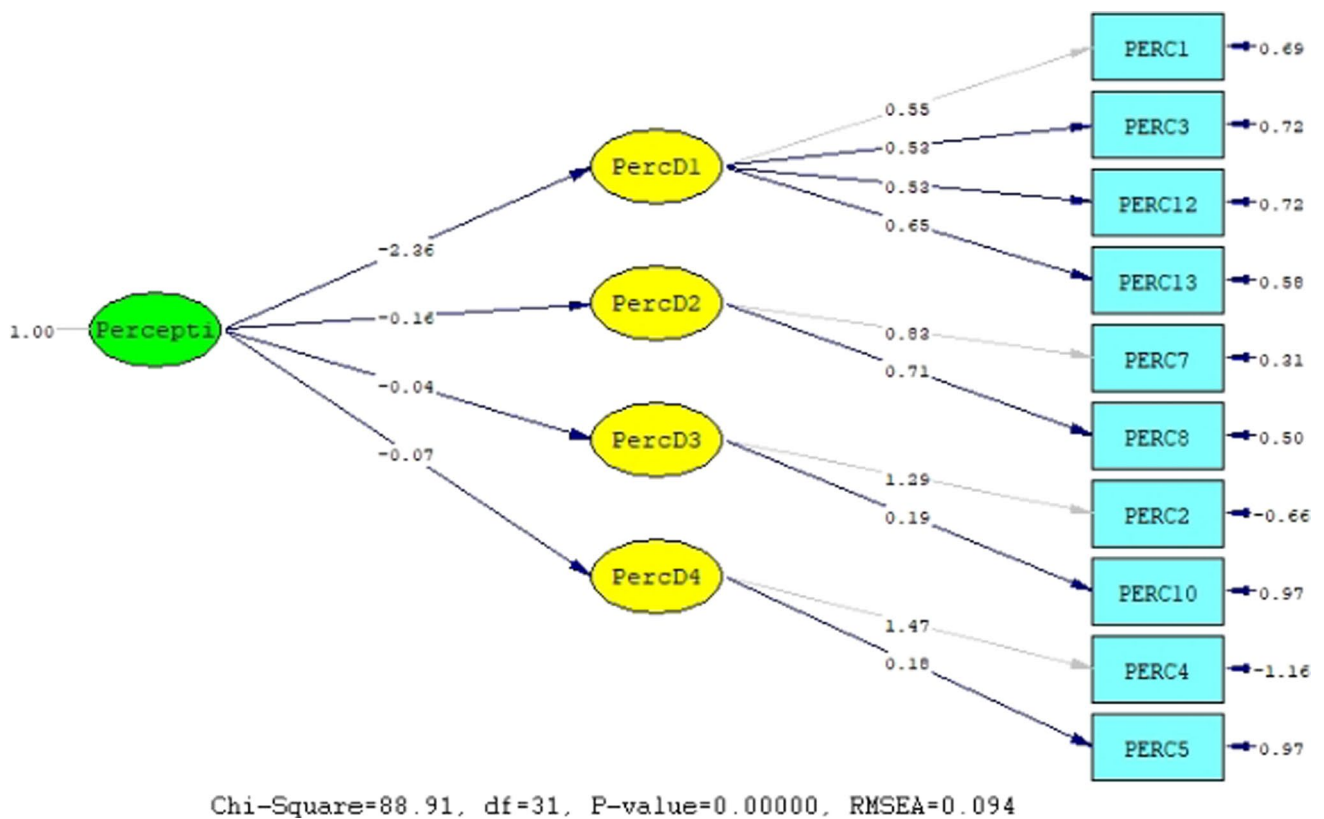
Climate change Adaptations	Coef	P > t
Age	0.0117571	0.556
Gender	0.0596686	0.252
Education	0.0094055	0.030**
Other activities	0.0036012	0.001***
HH members in agriculture	0.0202411	0.124
Land size	0.0479811	0.05*
_cons	3.327507	0.000

$\text{Prob} > F = 0.0244$ ;

\*\*\* p-value < 1%, \*\* p-value < 5% et \* p-value < 10%

**Table 5** EFA and CFA perception

Code	Scale items and dimensions	EFA	CFA	Communalities $\alpha = 0.934$
Simultaneous variation of temperature and rainfall		Eigenvalues = 2.546		
PERC1	Decrease rainfall	0.723	0.57	0.541
PERC3	Late rain onset	0.722	0.52	0.647
PERC13	Hot dry and rainy seasons	0.628	0.469	0.535
PERC12	Hot nights and days	0.624	0.52	0.671
Temperature disruption		Eigenvalues = 1.437		
PERC7	Hot days	0.867	0.83	0.674
PERC8	Hot night	0.836	0.71	0.769
Irregularity of rainfall-violent winds		Eigenvalues = 1.204		
PERC2	Rainfall irregularity	0.797	0.53	0.734
PERC10	Violent winds	0.681	1.19	0.519
Rainfall disruption		Eigenvalues = 1.161		
PERC5	Aborted rains	0.756	1.47	0.609
PERC4	Early rainfall interruption	0.753	0.18	0.534
Model fit quality		$\chi^2/df$ : 2.868; RMSEA: 0.0943; GFI: 0.925, CFI: 0.795, IFI: 0.805		



**Fig. 2** Perception's CFA

have eigenvalues more of than one, ranging from 2.546 for the first component to 1.161 for the last, demonstrating that the extracted factors are worth more than a single item. The scale also demonstrated high reliability. Cronbach's alpha coefficient of 0.730 is higher than the threshold of 0.70 proposed by Hair Jr Joseph et al. [64]. Cronbach's alpha values for dimensions ranged from 0.611 to 0.869. The confirmatory factor analysis confirmed, with good fit indices, that the model correctly matched the data. Except for item 5 and item 4, the results revealed that all of the structural coefficients

related to each item and dimension were high and above the minimum acceptable level of 0.60. These findings were consistent with those of Amani et al. [76] in the Uvira highlands and Balasha et al. [5] in the marshlands of South Kivu, where farmers reported heavy rain, late rainfall shorter and less abundant rainfall during the rainy season, an increase in dry spells and strong winds during the rainy season, an increase in temperature, and more showers during the dry season. Farmers' attitudes differed depending on where they farmed. Farmers in wetlands had a favorable perception of climate change, particularly in light of the availability of water. Farmers have stated that climate change vulnerabilities have impacted not only agriculture but also other sectors (food security, economic growth, and livelihoods) [68].

### 4.3 Climate change adaptation of smallholder maize farmers

According to the climate change adaptation results shown in Table 6 and Fig. 3, the data are factorable. The final results of the exploratory factor analysis are satisfactory: eigenvalues > 1; commonalities > 0.5; structural factor coefficient on one component > 0.50; and explained variance of 65.641%. The reliability data show a Cronbach's alpha of 0.761. The dimensions were also more reliable, with Cronbach's alpha ranging from 0.727 to 0.950. Confirmatory factor analysis results are also conclusive. Farmers used indigenous and easily accessible economic and physical strategies to adapt to climate change [76]. The adaptation strategies presented in Table 4 have confirmed the studies of Balasha and Nkulu [42] on agroecological practices in Kabare, Mutwedu et al. [77] on the integration of agriculture and livestock farming in eastern DRC, and Bele et al. [68] on access to information, education, and support for rural incomes. Farmers stated that access to infrastructure (rural roads, main roads, and markets) is a national challenge [78]. As a result, farmers in rural areas face higher transportation costs and longer time to market, making them more vulnerable [77, 79]. The government's efforts to ensure rural access and promote markets and post-harvest facilities remained minimal. Farmers' organizations, agricultural cooperatives, and non-governmental organizations organized farmers into community works (Salongo in the local language) to maintain roads, markets, and storage facilities. These efforts helped in dealing with climatic hazards, particularly during the dry season, but were insufficient to be effective during the rainy season. Rwanda's government adopted Umuganda (the local language for community work) to promote climate change mitigation in both urban and rural areas [80, 81]. According to Uwimbabazi [80] community work in Rwanda has benefited the public but has not been successful in addressing farmers' climate change challenges.

Maize farmers reported that, due to a lack of formal financial services in their villages [82], they have turned to informal financial services such as solidarity mutual and village credit and savings associations. Farmers are organized by

**Table 6** EFA and CFA adaptation results

Code	Scale items and dimensions	EFA	CFA	Communalities $\alpha = 0.761$
Technical capacity		Eigen values = 2.302		
ADAP27	Changing varieties	0.779	0.74	0.635
ADAP26	Adopting new varieties	0.766	0.62	0.632
ADAP28	Modification of the agricultural calendar	0.759	0.58	0.598
Infrastructure facilities		Eigen values = 1.767		
ADAP14	Easy access to rural roads	0.780	0.61	0.632
ADAP15	Easy access to main roads	0.774	0.72	0.616
ADAP16	Access to market	0.760	0.44	0.539
Human capacity		Eigen values = 1.358		
ADAP10	Farmers education	0.662	0.81	0.739
ADAP11	Having studied for many years (> 12 years)	0.835	0.60	0.724
Institutional capacity		Eigen values = 1.274		
ADA17	Easy access to credit	0.855	0.26	0.743
ADAP18	Easy access to information	0.706	1.31	0.645
Economic capacity		Eigen values = 1.176		
ADAP3	Land ownership	0.709	0.57	0.709
ADAP4	Rural income	0.753	0.45	0.665
Model fit quality		$\chi^2/dl$ : 1.40; GFI: 0.951; CFI: 0.936; IFI: 0.939; RMSEA: 0.0438		

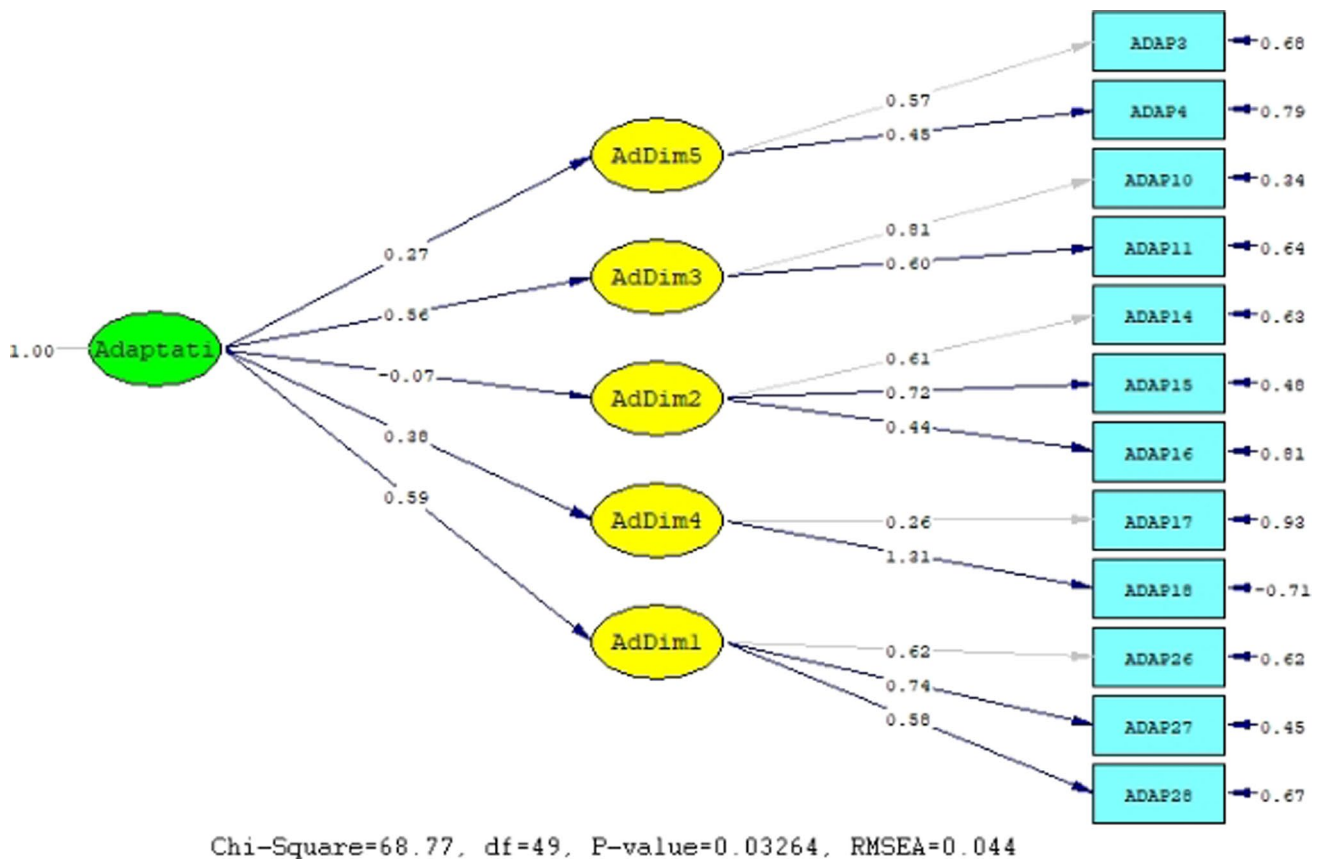


Fig. 3 Adaptation CFA Results

establishing a common fund to which each member contributes a set amount of money regularly. Farmers seeking credit use this fund for agricultural expenses (purchase of inputs, payment of farm labor, and rent payment). Following the harvest, the creditor is required to repay the borrowed funds so that another creditor may receive them in the future. Each member receives the savings at the end of the cycle, which is usually annual, to prepare for the following cropping season. These findings supported Mulume Bonnke et al. [82] research, which discovered that in rural South Kivu, 93% of agricultural finance was provided by the informal financial sector, which, according to Batung et al. [83] and Fisher et al. [69], has enabled farmers to become more resilient to climate change.

The land is acquired by maize farmers through purchase, inheritance, gift, lease, or tenant. Land ownership is socially perceived in DRC rural communities as a source of cultural identity, a family or community asset, a factor of production, and an investment [84]. Consistent with this study, studies of Yegbemey et al. [85], Hansungule and Jegede [86], and Molua et al. [84] found that land ownership provided farmers with the ability to adapt to climate change. Landowners, as opposed to tenants, reported rationally exploiting fields by implementing climate-resilient practices. Land tenure security, according to Yegbemey et al. [85] and others, is an important factor in climate change adaptation. Farmers demonstrated no willingness to invest resources in climate change adaptation in the context of climate and land uncertainty.

#### 4.4 Relationship between perception, exposure, sensitivity, and adaptation

Figure 4 and Table 7 show that all fit indices have satisfied values. The findings demonstrated that maize farmers' perceptions of climate change had a positive ( $p < 0.1\%$ ) influence on their exposure and level of sensitivity. This means for every perception of climate change, the degree of exposure and sensitivity increases by 0.0140 and 1.386, respectively. Farmers' perceptions additionally had a negative ( $p < 0.1\%$ ) influence on maize farmers' adaptation to climate threats. The degree of adaptation decreased by 52.2% for every 100% change in perception of climate change. This means that climate change is increasing the vulnerability of maize farmers in South Kivu, as they are unable to cope with the effects of change.

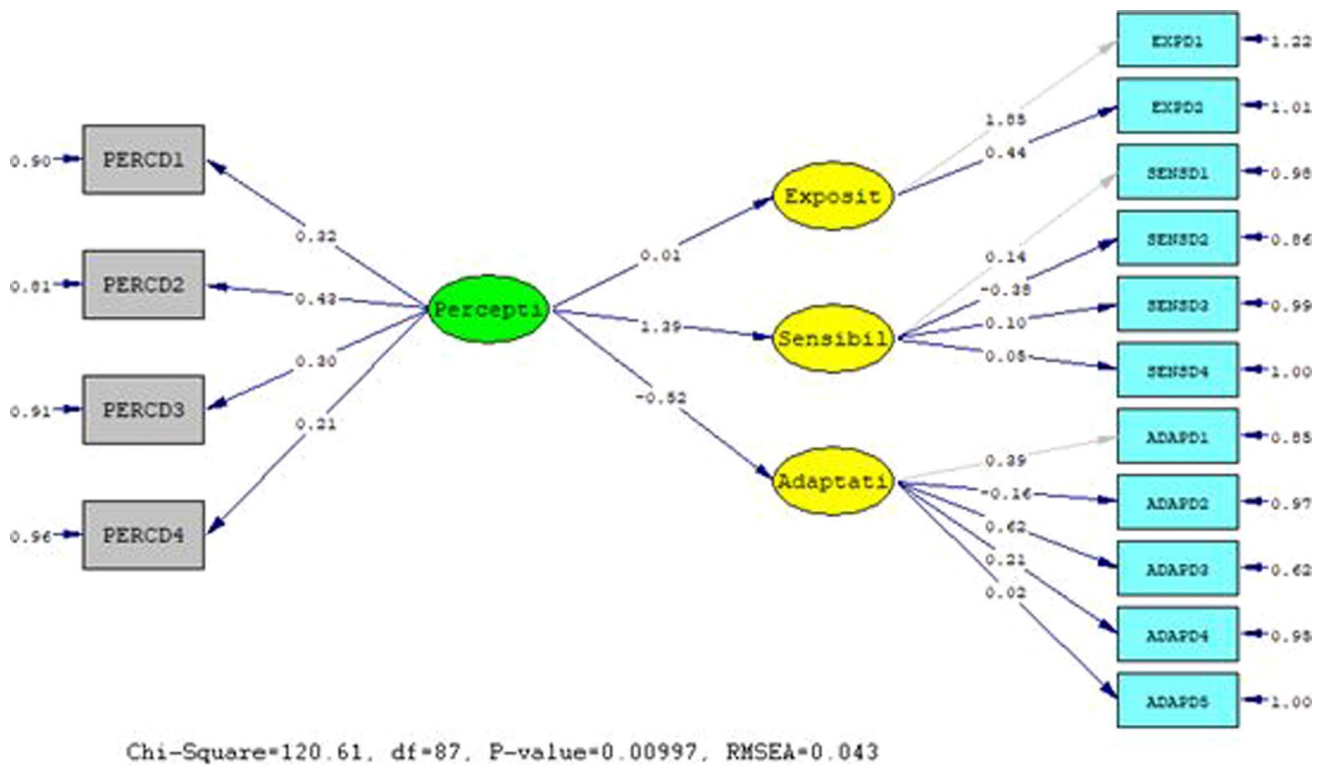


Fig. 4 Model Results

Table 7 Relationship between perception, exposure, sensitivity, and adaptation

Parameters	Estimators	standard Error	T-value	P-Value
Perception → exposure	0.0140	0.0501	0.280	0.00638
Perception → sensitivity	1.386	0.0738	18.769	0.000
Perception → Adaptation	- 0.522	0.0605	-8.624	0.000
Model fit quality	$\chi^2/df$ : 1.386; GFI: 0.928; AGFI: 0.901; CFI: 0.949; IFI: 0.949; RMSEA: 0.0429			

In line with this study, Ishaya et al. [87] found that farmers’ knowledge of advanced adaptation strategies, economic and social capital, and access to information on climate change scenarios explained climate change adaptation in Nigeria. The above considerations justified the negative relationship between farmers’ perceptions of climate change and their adaptability to climate change in South Kivu. Despite being aware of climate change, maize farmers in Kabare territory, for example, continued to cultivate traditional varieties (Bambou and Ecavel) that were not resistant to current climatic hazards, claiming a lack of resources to purchase varieties resistant to climate change.

The findings of this study contradicted those of Sofoluwe et al. [6], who discovered that perception of climate change has a direct positive and favorable influence on adaptation strategies to improve the quantity and quality of agricultural production. Farmers use adaptation strategies as resilience to mitigate the negative impact of climate change [31]. For Wachinger et al. [88] there was no significant relationship between climate change perception and adaptation strategies.

Thus, farmers’ perceptions of climate change were strongly related to expected desired behaviors rather than past experiences [31], and farmers perceived decreased risk after implementing adaptation strategies. This was explained by farmers emotionally reacting to a climate change threat Slovic and Peters [89]. Such emotional and affective responses appeared to have a role in climate change adaptation. Climate change perception was insufficient in South Kivu province to urge farmers to implement adaptation measures. Common efforts should be made to encourage farmers to feel committed enough to implement climate change adaptation measures that are effective in mitigating or preventing climate change risk.

This study's methodological and practical limitations were a lack of time series and global data on maize growing throughout the region in order to assess vulnerability Index indicators. The study excluded large-scale farmers (for example those who cultivate more than 10 hectares). The results from all farmers will be compared over time and by maize farming category. Because a qualitative investigation (interviewing key stakeholders) was not conducted, no preliminary information about public and private initiatives to mitigate climate change effects was gathered. The findings of this study on maize smallholder farmers' vulnerability and adaptation strategies to climate change should be used with caution, and further research should be conducted to understand how maize farmers perceive and respond to climate change by implementing effective management strategies, as well as to identify opportunities for promoting farmer literacy and climate-smart agriculture in SSA.

## 5 Conclusion

Maize smallholder farmers face a threat from climate change, resulting in decreased agricultural productivity, disruption of the agricultural calendar, and crop diseases. The findings of this study revealed that the level of education, size of the field, and activities of the smallholder farmers had significant effects on climate change perception and adaptation strategies. Farmers' perceptions had a negative ( $p < 1\%$ ) influence on maize smallholder farmers' adaptation to climate change. Common efforts should be made to encourage farmers to feel committed enough to implement climate change adaptation measures that are effective in mitigating or preventing climate change risk. The results of this study would have implications for policies to support maize smallholder farmers in their efforts to mitigate and resilient to climate change in SSA. Firstly, the promotion of climate literacy must be sufficient to provide farmers with information on climate and forecasting. Secondly, to empower smallholder farmers with means and resources to prevent and reduce the effects of climate change. Lastly, enhancing the current environment for the agriculture sector will advance community inclusivity and food security.

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**Author contributions** Conceptualization: GMM, LMN, FNL; Methodology: GMM, LMN, FNL Formal analysis and investigation: GMM, LMN; Writing—original draft preparation: GMM and LMN; Writing—review and editing: GMM; Supervision: FNL.

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**Data availability** The data that support the findings of this study are available from the corresponding author upon reasonable request.

## Declarations

**Ethics approval and consent to participate** The maize smallholder farmers who participated in the survey provided oral consent confirming their willingness to participate in the survey.

**Competing interests** The authors have no competing interests to declare relevant to the content of this article.

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## References

1. Kulimushi PZ, Basime GC, Nachigera GM, Thonart P, Ongena M. Efficacy of *Bacillus amyloliquefaciens* as biocontrol agent to fight fungal diseases of maize under tropical climates: from lab to field assays in south Kivu. *Environ Sci Pollut Res.* 2018;25(30):29808–21.
2. Malembaka R. Characterization and screening of Native Arbuscular Mycorrhizal Fungi Isolates from Maize (*Zea Mays* L.) Agro Ecosystems in South Kivu, Democratic Republic of Congo [PhD Thesis]. University of Nairobi; 2020.
3. Mcsweeney C, New M, Lizcano G, Lu X. The UNDP climate change country profiles: improving the accessibility of observed and projected climate information for studies of climate change in developing countries. *Bull Am Meteorol Soc.* 2010;91(2):157–66.

4. Akponikpè PI, Johnston P, Agbossou EK. Farmers' perception of climate change and adaptation strategies in Sub-Saharan West-Africa. In: 2nd International Conference: Climate, Sustainability and Development in Semi-arid Regions August. 2010. p. 134147.
5. Balasha MA, Munyahali W, Kulumbu JT, Okwe AN, Fyama JNM, Lenge EK, et al. Understanding farmers' perception of climate change and adaptation practices in the marshlands of South Kivu, Democratic Republic of Congo. *Clim Risk Manag.* 2023;39:100469.
6. Sofoluwe NA, Tijani AA, Baruwa OI. Farmers' perception and adaptation to climate change in Osun State. Nigeria *Afr J Agric Res.* 2011;6(20):4789–94.
7. Arnold BN, Lambertine MN, Yves KM, Jacques KM, Christelle AM. *Changement climatique et production agricole au Sud-Kivu, République Démocratique du Congo.* 2017
8. Cirimwami JPK, Ramanarivo S, Mutabazi AN, Muhigwa B, Bisimwa EB, Ramanarivo R, et al. *Changement climatique et production agricole dans la région du Sud-Kivu montagneux à l'Est de la RD Congo.* *Int J Innov Appl Stud.* 2019;26(2):526–44.
9. Maddison D. *The perception of and adaptation to climate change in Africa*, vol. 4308. Washington: World Bank Publications; 2007.
10. Deressa T, Hassan R, Tekie A, Mahmud Y, Ringler C. Analyzing the Determinants of Farmers' Choice of Adaptation Methods and Perceptions of Climate Change in the Nile Basin of Ethiopia. *Sustainable Solutions for Ending Hunger and Poverty.* IFPRI Discussion Paper 00798. IFPRI, Washington DC; 2008.
11. van der Linden S. The social-psychological determinants of climate change risk perceptions: Towards a comprehensive model. *J Environ Psychol.* 2015;41:112–24.
12. Wolf J, Moser SC. Individual understandings, perceptions, and engagement with climate change: insights from in-depth studies across the world. *WIREs Clim Change.* 2011;2(4):547–69.
13. Bonnemaïn A. *Perceptions et représentations du changement climatique auprès des populations dans leur cadre de vie [PhD Thesis].* LabEx ITEM; 2016.
14. Bedeke SB, Vanhove W, Wordofa MG, Natarajan K, Van Damme P. Vulnerability to climate change among maize-dependent smallholders in three districts of Ethiopia. *Environ Dev Sustain.* 2020;22(2):693–718.
15. Epule TE, Peng C, Lepage L, Chen Z. Poverty and gender oriented vulnerabilities to food and water scarcity in Touroua. Cameroon *J Hum Ecol.* 2012;38(2):81–90.
16. Epule TE, Ford J, Lwasa S, Lepage L. Vulnerability of maize yields to droughts in Uganda. *Water.* 2017;9(3):181.
17. Epule TE, New MG. Vulnerability of crop yields to variations in growing season precipitation in Uganda. *SN Appl Sci.* 2019;1(8):899.
18. Epule TE, Chehbouni A, Dhiba D, Etongo D, Driouech F, Brouziyne Y, et al. Vulnerability of maize, millet, and rice yields to growing season precipitation and socio-economic proxies in Cameroon. *PLoS ONE.* 2021;16(6):e0252335.
19. Epule TE, Poirier V, Chehbouni A, Salih W, Kechchour A, Kambiet PLK, et al. A new index assessing adaptive capacity across Africa. *Environ Sci Policy.* 2023;149:103561.
20. Epule TE, Chehbouni A, Dhiba D, Molua EL. A regional stocktake of maize yield vulnerability to droughts in the Horn of Africa. *Environ Monit Assess.* 2024;196(1):76.
21. Twecan D, Wang W, Xu J, Mohammed A. Climate change vulnerability, adaptation measures, and risk perceptions at households level in Acholi sub-region. *Northern Uganda Land Use Policy.* 2022;115:106011.
22. Teshome H, Tesfaye K, Dechassa N, Tana T, Huber M. Smallholder farmers' perceptions of climate change and adaptation practices for maize production in eastern Ethiopia. *Sustainability.* 2021;13(17):9622.
23. Tesfaye K, Gbegbelegbe S, Cairns JE, Shiferaw B, Prasanna BM, Sonder K, et al. Maize systems under climate change in sub-Saharan Africa: potential impacts on production and food security. *Int J Clim Change Strateg Manag.* 2015;7(3):247–71.
24. Adu DT, Kuwornu JKM, Anim-Somuah H, Sasaki N. Application of livelihood vulnerability index in assessing smallholder maize farming households' vulnerability to climate change in Brong-Ahafo region of Ghana. *Ksetsart J Soc Sci.* 2018;39(1):22–32.
25. Harvey CA, Rakotobe ZL, Rao NS, Dave R, Razafimahatratra H, Rabarijohn RH, et al. Extreme vulnerability of smallholder farmers to agricultural risks and climate change in Madagascar. *Philos Trans R Soc B Biol Sci.* 2014;369(1639):20130089.
26. Stathers T, Lamboll R, Mvumi BM. Postharvest agriculture in changing climates: its importance to African smallholder farmers. *Food Secur.* 2013;5(3):361–92.
27. Kutyaurolo I, Masamha B, Maringe P. Exploring climate change adaptation strategies in maize (*Zea mays*) postharvest management practices among smallholder farmers. *Outlook Agric.* 2021;50(2):148–57.
28. Karume K, Mondo JM, Chuma GB, Ibanda A, Bagula EM, Aleke AL, et al. Current practices and prospects of climate-smart agriculture in democratic Republic of Congo: a review. *Land.* 2022;11(10):1850.
29. Moradi R, Koocheki A, Nassiri Mahallati M, Mansoori H. Adaptation strategies for maize cultivation under climate change in Iran: irrigation and planting date management. *Mitig Adapt Strateg Glob Change.* 2013;18(2):265–84.
30. Harvey CA, Saborido-Rodríguez M, Martínez-Rodríguez MR, Viguera B, Chain-Guadarrama A, Vignola R, et al. Climate change impacts and adaptation among smallholder farmers in Central America. *Agric Food Secur.* 2018;7(1):57.
31. van Valkengoed AM, Steg L. Meta-analyses of factors motivating climate change adaptation behaviour. *Nat Clim Change.* 2019;9(2):158–63.
32. Ahmad I, Ahmad B, Boote K, Hoogenboom G. Adaptation strategies for maize production under climate change for semi-arid environments. *Eur J Agron.* 2020;115:126040.
33. Adeagbo OA, Ojo TO, Adetoro AA. Understanding the determinants of climate change adaptation strategies among smallholder maize farmers in South-west, Nigeria. *Heliyon.* 2021;7(2):e06231.
34. Claessens L, Antle JM, Stoorvogel JJ, Valdivia RO, Thornton PK, Herrero M. A method for evaluating climate change adaptation strategies for small-scale farmers using survey, experimental and modeled data. *Agric Syst.* 2012;111:85–95.
35. Bedeke SB, Vanhove W, Gezahegn M, Natarajan K, Van Damme P. Adoption of climate change adaptation strategies by maize-dependent smallholders in Ethiopia. *NJAS Wagening J Life Sci.* 2019;88(1):96–104.
36. Epule TE, Ford JD, Lwasa S, Lepage L. Climate change adaptation in the Sahel. *Environ Sci Policy.* 2017;75:121–37.
37. Lebel S, Fleskens L, Forster PM, Jackson LS, Lorenz S. Evaluation of in situ rainwater harvesting as an adaptation strategy to climate change for maize production in Rainfed Africa. *Water Resour Manag.* 2015;29(13):4803–16.
38. Rurinda J, van Wijk MT, Mapfumo P, Descheemaeker K, Supit I, Giller KE. Climate change and maize yield in southern Africa: what can farm management do? *Glob Change Biol.* 2015;21(12):4588–601.



39. Rahimi-Moghaddam S, Kambouzia J, Deihimfard R. Adaptation strategies to lessen negative impact of climate change on grain maize under hot climatic conditions: a model-based assessment. *Agric For Meteorol.* 2018;253–254:1–14.
40. Abass AB, Ndunguru G, Mamiro P, Alenkhe B, Mlingi N, Bekunda M. Post-harvest food losses in a maize-based farming system of semi-arid savannah area of Tanzania. *J Stored Prod Res.* 2014;57:49–57.
41. Iragi MD. Suitability assessment and projected impact of climate change on rice yield in two agro-ecological zones in South Kivu, Democratic Republic of Congo [MSC thesis]. Uganda Makerere Univ. 2015
42. Balasha MA, Nkulu JMF. Potential threats to agricultural food production and farmers' coping strategies in the marshlands of Kabare in the Democratic Republic of Congo. *Cogent Food Agric.* 2021;7(1):1933747.
43. Harera Paul M. Climate variability and household food security in Masisi, North Kivu Province, Dr Congo [Thesis]. Kampala International University: College of Humanities and Social Sciences. 2019. <https://ir.kiu.ac.ug/jspui/handle/20.500.12306/14047>. Accessed 3 Jan 2023.
44. Bagula EM, Majaliwa JGM, Mushagalusa GN, Basamba TA, Tumuhairwe JB, Mondo JGM, et al. Climate change effect on water use efficiency under selected soil and water conservation practices in the ruzizi catchment, Eastern D.R. Congo. *Land.* 2022;11(9):1409.
45. Yegbemey RN, Yabi JA, Aihounton GB, Paraiso A. Modélisation simultanée de la perception et de l'adaptation au changement climatique : cas des producteurs de maïs du Nord Bénin (Afrique de l'Ouest). *Cah Agric.* 2014;23(3):177–87.
46. Acquah H de-Graft, Nunoo J, Darfor KN. Farmers' perceptions and adaptation to climate change: evidence from Ghana. *Environ Agric Cross-Bord Migr. CODESRIA.* 2015;35–52
47. Mondo JM, Chuma GB, Kwalya PB, Balagizi SA, Ndjaji SS, Mugumaarhahama Y, et al. Neglected and underutilized crop species in Kabare and Walungu territories, Eastern D.R. Congo: identification, uses and socio-economic importance. *J Agric Food Res.* 2021;6:100234.
48. Chuma BG, Mondo JM, Sonwa DJ, Karume K, Mushagalusa GN, Schmitz S. Socio-economic determinants of land use and land cover change in South-Kivu wetlands, eastern D.R. Congo: Case study of Hogola and Chisheke wetlands. *Environ Dev.* 2022;43:100711.
49. Nyambo DG, Luhanga ET, Yonah ZQ. A review of characterization approaches for smallholder farmers: towards predictive farm typologies. *Sci World J.* 2019;22(2019):1–9.
50. Mertz O, Mbow C, Reenberg A, Diouf A. Farmers' perceptions of climate change and agricultural adaptation strategies in rural sahel. *Environ Manage.* 2009;43(5):804–16.
51. Joshi B, Ji W, Joshi NB. Farm households' perception on climate change and adaptation practices: a case from mountain district of Nepal. *Int J Clim Change Strateg Manag.* 2017;9(4):433–45.
52. DeVellis RF, Thorpe CT. Scale development: theory and applications. Thousand Oaks: Sage publications; 2021.
53. Adger WN, Huq S, Brown K, Conway D, Hulme M. Adaptation to climate change in the developing world. *Prog Dev Stud.* 2003;3(3):179–95.
54. Agossou SMD. Adaptation aux changements climatiques: perceptions, savoirs locaux et stratégies d'adaptation des producteurs des communes de Glazoué et de Savalou au centre du Bénin [PhD Thesis]. UAC; 2008.
55. Akano O, Modirwa S, Oluwasemire K, Oladele O. Awareness and perception of climate change by smallholder farmers in two agroecological zones of Oyo state Southwest Nigeria. *GeoJournal.* 2023;88(1):39–68.
56. JO A, Tiamiyu AO, Akintaro OS, Gbadamosi SA, Agunloye TO. Adoption of climate change adaptation strategies among maize farmers in Ogbomosho agricultural zone of Oyo state, Nigeria. 2019
57. Vieira AL. Interactive LISREL in practice. 2011;
58. Giannelloni JL, Vernet E. Etudes de marché. Vuibert; 2019.
59. Byrne S, Hart PS. The boomerang effect a synthesis of findings and a preliminary theoretical framework. *Ann Int Commun Assoc.* 2009;33(1):3–37.
60. Ullman JB, Bentler PM. Structural equation modeling. In: Weiner I, editor. *Handbook of psychology*. 2nd ed. Hoboken: John Wiley & Sons, Inc.; 2012. p. hop202023. <https://doi.org/10.1002/9781118133880.hop202023>.
61. Grewal R, Cote JA, Baumgartner H. Multicollinearity and measurement error in structural equation models: implications for theory testing. *Mark Sci.* 2004;23(4):519–29.
62. Bagozzi RP, Yi Y, Singh S. On the use of structural equation models in experimental designs: two extensions. *Int J Res Mark.* 1991;8(2):125–40.
63. Churchill GA Jr. A paradigm for developing better measures of marketing constructs. *J Mark Res.* 1979;16(1):64–73.
64. Hair Jr Joseph F, Black William C, Babin Barry J, Anderson Rolph E. *Multivariate data analysis*. 7th ed. Upper Saddle River: Prentice Hall; 2009.
65. Bedeke SB, Vanhove W, Wordofa M, Natarajan K, Van Damme P. Perception of and response to climate change by maize-dependent smallholders. *Clim Res.* 2018;75(3):261–75.
66. Abokyi E, Strijker D, Asiedu KF, Daams MN. The impact of output price support on smallholder farmers' income: evidence from maize farmers in Ghana. *Heliyon.* 2020;6(9): e05013.
67. Bellon MR, Hodson D, Hellin J. Assessing the vulnerability of traditional maize seed systems in Mexico to climate change. *Proc Natl Acad Sci.* 2011;108(33):13432–7.
68. Bele MY, Sonwa DJ, Tiani AM. Local communities vulnerability to climate change and adaptation strategies in Bukavu in DR Congo. *J Environ Dev.* 2014;23(3):331–57.
69. Fisher M, Abate T, Lunduka RW, Asnake W, Alemayehu Y, Madulu RB. Drought tolerant maize for farmer adaptation to drought in sub-Saharan Africa: determinants of adoption in eastern and southern Africa. *Clim Change.* 2015;133(2):283–99.
70. Matimolane S, Chikoore H, Mathivha FI, Kori E. Maize producers' vulnerability to climate change: evidence from Makhuduthamaga Local Municipality, South Africa. *J Disaster Risk Stud.* 2022;14(1):1165.
71. Apata TG, Samuel KD, Adeola AO. Analysis of Climate Change Perception and Adaptation among Arable Food Crop Farmers in South Western Nigeria. 2009.
72. Acquah H, Onumah EE. Farmers perception and adaptation to climate change: an estimation of willingness to pay. *Agris -Line Pap Econ Inform.* 2011;3:31–9.
73. Asrat P, Simane B. Farmers' perception of climate change and adaptation strategies in the Dabus watershed. *North-West Ethiopia Ecol Process.* 2018;7(1):1–13.
74. Tesfaye W, Seifu L. Climate change perception and choice of adaptation strategies: Empirical evidence from smallholder farmers in east Ethiopia. *Int J Clim Change Strateg Manag.* 2016;8(2):253–70.

75. Yesuf M, Di Falco S, Deressa T, Ringler C, Kohlin G. The impact of climate change and adaptation on food production in low-income countries: evidence from the Nile Basin, Ethiopia. *Intl Food Policy Res Inst*; 2008.
76. Amani RK, Riera B, Imani G, Batumike R, Zafrá-Calvo N, Cuni-Sánchez A. Climate change perceptions and adaptations among smallholder farmers in the mountains of eastern Democratic Republic of Congo. *Land*. 2022;11(5):628.
77. Mutwedu VB, Bacigale SB, Mugumaarhahama Y, Muhimuzi FL, Munganga B, Ayagirwe RBB, et al. Smallholder farmers' perception and challenges toward the use of crop residues and agro-industrial byproducts in livestock feeding systems in Eastern DR Congo. *Sci Afr*. 2022;16: e01239.
78. Ali R, Barra A, Berg C, Damania R, Nash J, Russ J. Infrastructure in conflict-prone and fragile environments: evidence from the Democratic Republic of Congo. *World Bank Policy Research Working Paper*; 2015.
79. Ulimwengu JM, Funes J, Headey DD, You L. Paving the Way for Development: The Impact of Road Infrastructure on Agricultural Production and Household Wealth in the Democratic Republic of Congo. 2009. p. 46
80. Uwimbabazi P. An analysis of Umuganda : the policy and practice of community work in Rwanda. [Thesis]. 2012. <https://researchspace.ukzn.ac.za/handle/10413/8964>. Accessed 12 Aug 2023.
81. Uwimbabazi P. Indigenous Practice for Social Economic Development: An Analysis of Umuganda. *Home Grown Solut*. 2019;
82. Mulume Bonnke S, Dontsop Nguetzet PM, Nyamugira Biringanine A, Jean-Jacques MS, Manyong V, Bamba Z. Farmers' credit access in the Democratic Republic of Congo: empirical evidence from youth tomato farmers in Ruzizi plain in South Kivu. *Cogent Econ Finance*. 2022;10(1):2071386.
83. Batung ES, Mohammed K, Kansanga MM, Nyantakyi-Frimpong H, Luginaah I. Credit access and perceived climate change resilience of smallholder farmers in semi-arid northern Ghana. *Environ Dev Sustain*. 2023;25(1):321–50.
84. Molua EL, Sonwa D, Bele Y, Foahom B, Mate Mweru JP, Wa Bassa SM, et al. Climate-smart conservation agriculture, farm values and tenure security: implications for climate change adaptation and mitigation in the Congo Basin. *Trop Conserv Sci*. 2023;16:194008292311699.
85. Yegbemey RN, Yabi JA, Tovignan SD, Gantoli G, Haroll Kokoye SE. Farmers' decisions to adapt to climate change under various property rights: A case study of maize farming in northern Benin (West Africa). *Land Use Policy*. 2013;34:168–75.
86. Hansungule M, Jegede AO. The impact of climate change on indigenous peoples' land tenure and use: the case for a regional policy in Africa. *Int J Minor Group Rights*. 2014;21(2):256–91.
87. Ishaya, Abaje IB. Indigenous people's perception on climate change and adaptation strategies in Jema'a local government area of Kaduna State. *Nigeria J Geogr Reg Plan*. 2008;1(8):138–43.
88. Wachinger G, Renn O, Begg C, Kuhlicke C. The risk perception paradox—implications for governance and communication of natural hazards. *Risk Anal*. 2013;33(6):1049–65.
89. Slovic P, Peters E. Risk perception and affect. *Curr Dir Psychol Sci*. 2006;15(6):322–5.

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