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Vulnerability of family farming systems to climate change: The case of the forest-savannah transition zone, Centre Region of Cameroon

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ABSTRACT

Family farms are especially vulnerable to the negative effects of climatic variations and changes. In this regard, this paper assessed the factors that influence family farmers' vulnerability to climate variability and change in the transition zone between forest and savannah in the northern part of the Centre Region of Cameroon. The study did this by combining primary data (gathered from a survey of 180 smallholder farmers) with secondary data (information on temperature and rainfall). Field observations were also conducted on these family farms in Mbangassina, Ntui, Batchenga, and Obala from January to March 2020, March to May 2021, and July to September 2021. We used statistical tools for both descriptive, multivariate and inferential analyzes. Small farmers have faced the highest temperatures and heat waves. Everybody living in this community is exposed to the same temperatures and heat waves. Maybe smallholder farmers are susceptible or vulnerable to these heat waves and high temperatures. Extreme droughts, which are becoming more often, and diminishing rainfall totals were assumed to be the key contributors to climate sensitivity. According to the findings, family farms in Obala are just marginally vulnerable to climatic variability and change (1.1 vulnerability score), whereas those in Batchenga, Ntui, and Mbangassina have considerable vulnerability indices (2.16, 2.17, and 2.99 vulnerability scores respectively). A significant noncausal correlation exists between vulnerability and four and five continuous and discontinuous explanatory factors, respectively. The binomial logistic regression model demonstrates statistically significant inverse causal links between five of the six explanatory factors and the sensitivity of family farmers to climate change. According to the model, useful agricultural area ($\beta = -0.348$, $p < 0.0001$), soil fertility ($\beta = -0.568$, $p < 0.05$), *Dioscorea* spp. ($\beta = -0.926$, $p < 0.05$), precipitation during these 10 to 30 years ($\beta = -0.582$, $p < 0.05$), and annual income ($\beta = -0.002$, $p < 0.01$) all contributed to lessening smallholder farmers' vulnerability to unfavorable climate variability and change. The drought variable has a significant positive causal relationship. This leads to the conclusion that these six explanatory variables largely impact smallholder farmers' vulnerability to climate fluctuation and change. According to the study's conclusions, family farmers should be given more financial help and reliable climatic information to reduce their vulnerability to climate fluctuation and change.

Introduction

Climate change threatens livelihoods, food security, and hazards and fragilities by increasing natural disasters and extreme weather events

(Atedhor, 2015; Leal Filho et al., 2018). Regardless of its limitations, climate change targets have an impact on the overall economy (Morton, 2007). Millions of farmers rely on agricultural productivity, which is being harmed by climate change and related extreme events. Food

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insecurity is becoming more prevalent in developing countries as a result of increased exposure to and vulnerability to climate change (FAO, 2021). Global temperatures have been rising since the turn of the twentieth century, and today's natural and societal systems all around the world are suffering from the effects of climate change (IPCC, 2014). Anthropogenic global warming is around 1 °C higher than pre-industrial levels (FAO, 2016). If this trend continues on its current path, it is expected to rise in the coming decades (Huppmann et al., 2018). A universal phenomenon, climate change has an unrestricted impact on all spheres of society and the economy. However, environmental and socioeconomic factors differentiate the degree of susceptibility of a system, household, and location (Adger et al., 2003). It must now be regarded as a normative priority to comprehend how vulnerable impoverished people's livelihood systems are in the context of larger transformational shifts, including social and political as well as biophysical ones (UNDP, 2014).

According to empirical studies, populations across Africa are already feeling the effects of the continent's changing climate (Boko et al., 2007; Chimi et al., 2022; IPCC, 2014; Lobell et al., 2011). Droughts in Sub-Saharan Africa are already making it more difficult for people to cultivate crops and keep cattle. The fundamental reason for this is Africa's weak socioeconomic system, which has an impact on the continent's willingness to achieve the SDGs (McBean and Rodgers, 2010). Subsistence agriculture, in contrast to commercial/large-scale agriculture, which makes greater use of irrigation water and chemical fertilizers, is distinguished by a reliance on traditional farming methods and rainfall for crop moisture requirements, making it vulnerable to erratic rainfall and drought (Tsubo and Walker, 2007). As a result, climate change and variation have increased the vulnerability of agricultural productivity (Mongi et al., 2010). Because they rely on climate-sensitive industries, emerging countries are expected to be more vulnerable to the consequences of climate change. After all, the effects of climate change vary spatially and across geopolitical boundaries (Madu, 2020). While local or community-level exposure, sensitivity, and adaptability are clear, they also represent bigger effects, causes, or determinants that shape or influence vulnerabilities at the local level (Smit and Wandel, 2006). The degree to which regions, groups, or households are exposed to and sensitive to hazards from climate change is determined by a combination of biophysical and socioeconomic factors (Shukla et al., 2021). As a result, the level of vulnerability of a system is determined by its sensitivity and capacity for adaptation, as well as the type, scale, and rate of climatic change to which it is exposed (Marshall et al., 2010). Extreme weather and climatic events caused by rising global warming would have a devastating impact on vulnerable economic sectors such as agriculture (Paterson and Charles, 2019).

Family farmers are particularly vulnerable to climate change since they rely significantly on rain-fed agriculture (Chanana-Nag and Aggarwal, 2020; FAO, 2018). Farmers in poorer nations are especially vulnerable to the negative consequences of climate variability and change due to their low or nonexistent resilience, poor governance, and weak institutions (Marini, 2018; Meybeck et al., 2018; Odame Appiah et al., 2018; Partey et al., 2020). High temperatures, irregular and limited rainfall, a lack of information, prolonged droughts, the absence of weather/climate forecasting systems, limited drought forecasting, and a lack of contingency and preparedness plans, for example, have been shown in studies in Sub-Saharan Africa to contribute to smallholder farmers' vulnerability to the effects of climate variability and change (Awazi et al., 2020; Fongnzossie et al., 2018; Funwi et al., 2020; Rurinda et al., 2014; Serdeczny et al., 2017). However, climate change and variability, in particular, have a significant influence on farmers in Sub-Saharan Africa, making them very vulnerable (Rurinda et al., 2014; Awazi et al., 2020). In the face of climate change challenges, Cameroon's Vision 2035 emergency plan and Growth and Employment Strategy Paper (GESP) prioritize economic and financial growth over environmental deterioration and the sustainability of regional agricultural systems (Beckline et al., 2018). Family farmers are commonly

limited to marginal areas, without equal living, according to Beckline et al. (2018), Chia et al. (2019), Ndi (2019), and O'Brien and Leichenko (2000). They also point out that Cameroon's praiseworthy policies do not always target family farmers or underutilized irrigation facilities to mitigate crop losses caused by rainfall variability. Climate change has a direct influence on family farmers' ability to meet expanding local food demand. Cameroon is a resource-rich country. Smallholders with little resources are left in control of the agricultural sector, which employs a sizable portion of the population and more than 90 percent of some rural areas (Tume and Fogwe, 2018) and generates around 30 percent of the national income. As the source of more than 80% of Cameroon's food consumption, these farmers significantly contribute to the country's socioeconomic stability and food security (Molua, 2006). Even with varied adaptation measures such as local irrigation, postponed planting dates, land conservation, bi-seasonal farming, and intercropping, small-scale agriculture in Cameroon is increasingly challenged by climate unpredictability and change (Awazi et al., 2020). Family farming receives little government assistance, or in some circumstances, that assistance is monopolized by dishonest government employees (Mugiya and Hofisi, 2017).

Family farmers in Cameroon are already experiencing the negative effects of climate change and variety (Chimi et al., 2022; Fongnzossie et al., 2018). The northern part of the Centre Region of Cameroon is susceptible to and vulnerable to climate change due to its predominantly rural and agricultural population (Chimi et al., 2022). Several studies have found that locations with a high concentration of rural population and a significant dependency on energy and water are particularly vulnerable to climate change and variability (Chimi et al., 2022). The timely implementation of adaptation methods can significantly reduce vulnerability to climate change (Atedhor, 2015). The adoption of efficient climate change adaptation strategies has been impeded by a lack of improved seeds, irrigation water availability, knowledge of weather impacts, and financial resources to purchase modern technologies (Chimi et al., 2022; Ishaya and Abaje, 2008). As a result, the poor and those who rely largely on natural resources are the most vulnerable to climate change (Chimi et al., 2022; Ishaya and Abaje, 2008). Climate change vulnerability research was first performed in the 1990 s to establish policies and methods to mitigate this risk (Hinkel, 2011). The purpose of this study was to better comprehend the magnitude and complexities of climate change and its consequences. The susceptibility of a system to climate change is determined by both its sensitivity to environmental changes and its ability to adapt to such changes (IPCC, 2014). The success of adaptations is measured by their ability to reduce or lessen the negative effects of climate change or to provide favorable results that prevent danger (Atedhor, 2015; Smit and Wandel, 2006). This is because the ability to adapt to change invariably entails vulnerability (Adejuwon, 2006; Atedhor, 2015). A community that is harmed by climate change but has access to resources such as pesticides, information, storage facilities, and irrigation facilities will be less vulnerable than a population that is similarly afflicted but has less adaptation capacity. As a result, the processes that define exposure, sensitivity, and adaptive capacity are inextricably linked (Atedhor, 2015). It is impossible to convey and incorporate farmer distress and practical adaption strategies into national climate change policy.

Farmers' challenges can only be expressed and integrated into national climate change strategies after the factors that determine agricultural vulnerability are identified. The research topic used to reach this goal is how to quantify agricultural sensitivity to climate change and variability in the Centre Region. Few studies have thoroughly and comprehensively investigated the factors that influence smallholder farmers' susceptibility to climate change in Africa in general and Cameroon in particular, employing multivariate and inferential statistical techniques and producing results that are both technically sound and scientifically reliable. The majority of studies have relied heavily on descriptive and conceptual approaches. In light of the aforementioned, the purpose of this study is to give a complete assessment of the factors

that influence smallholder farmers' vulnerability to climate variability and change using multivariate and inferential statistical methodologies. The papers sought to assess farmers' perceptions of vulnerability to variation and change in climate, investigate the determinants of farmers' vulnerability to variation and change in climate, and capture the degree of variation in climatic parameters using farmers' perceptions and climatic data from the study area. This study contributes to the expanding body of knowledge on the benefits and limitations of quantitative vulnerability assessments, as well as the rising body of knowledge on agricultural sensitivity to climate change. The findings will be

confirmed through discussion and evaluation of adaptation solutions that take into account the agroecological diversity of forest-savannah transition zones. The outcomes of the study will help decision-makers who wish to reduce poverty in their decision-making processes.

Conceptual framework

Long understood as the degree to which a system is exposed to risks, the degree to which it is sensitive to change, the potential effects of exposure and sensitivity on the system, and the degree to which the

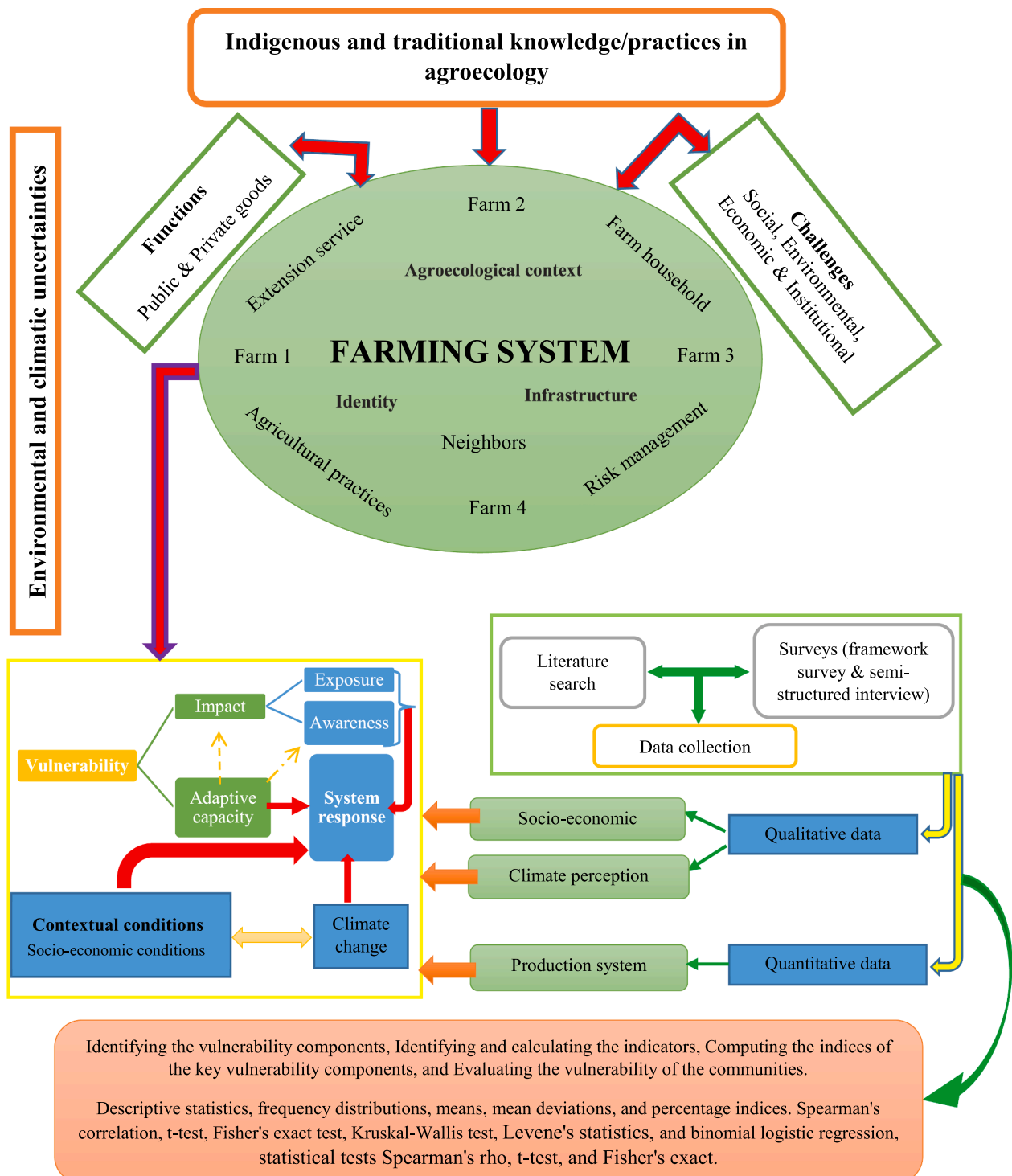


Fig. 1. Conceptual framework of the study.

system can adapt to environmental changes, vulnerability assessment has long been understood (IPCC, 2014). However, because vulnerability is caused by intricate interactions across socioeconomic, institutional, and environmental systems, assessing and quantifying it remains difficult (Krishnamurthy et al., 2014). Furthermore, a system's exposure to and sensitivity to risk may result in potential current and future consequences, demanding a forward-looking perspective when assessing vulnerability. As a result, the vulnerability assessment method used in this study will be a combination of contextual (bottom-up) and outcome (top-down).

The contextual approach focuses on the external factors that impact how vulnerable individuals or human systems are. This technique usually incorporates "participatory" strategies and is especially useful for responding to system realities (Fritzsche et al., 2014). The outcome vulnerability strategy, on the other hand, focuses on building scenarios for how the system will respond in the event of climate change. The contextual vulnerability model for agriculturally dependent individuals in the forest-savannah ecotone will address the social and financial circumstances that contribute to the agricultural sector's susceptibility to climate change. However, it should be noted that, in addition to changing the setting, contextual factors might affect exposure to climate change (O'Brien et al., 2007).

The contextual vulnerability produces responses that, at the end of these complex interactions, either increase exposure and sensitivity due to the influence of socioeconomic and financial conditions on climate change or produce adaptive measures in response to the pressure of climate change on socioeconomic and financial constraints. The present work is to assess the factors that influence the vulnerability of family

farmers to climate variability and change in the forest-savannah transition zone in the northern part of the Centre Region of Cameroon. The conceptual phase goes from defining vulnerability and the concepts surrounding it and the links between them. After that, the implementation of the data collection process is done, this with the aim of determining the factors that circumvent the farmers (Fig. 1). The findings will be used to generate scenarios and forecasts.

A discussion in light of the results obtained and the consideration of the state of vulnerability of agricultural systems will support the results obtained.

Material and methods

Study area

The study was conducted in Cameroon's Centre Region, specifically, its northern portion (Fig. 2). Over 80% of those employed in the agricultural industry are smallholder farmers, making agriculture the community's principal economic activity (Chimi et al., 2022). The principal crops grown in Centre Cameroon's northern Region are food, cash, and vegetable crops (Chimi et al., 2022). This area is characterized by a bimodal rainfall pattern on the one hand and by a transitional rainfall pattern between the bimodal patterns of the far south and the unimodal pattern of northern Cameroon (MINEPDED, 2015). The choice of the study area is based on the climatic regime. The area is subject to a sub-equatorial Guinean forest climate of the "Guinean forest, high Cameroonian" type, defined as follows: Average annual rainfall: 1,400 to 1,600 mm; absolute dry season: December to February; relative dry

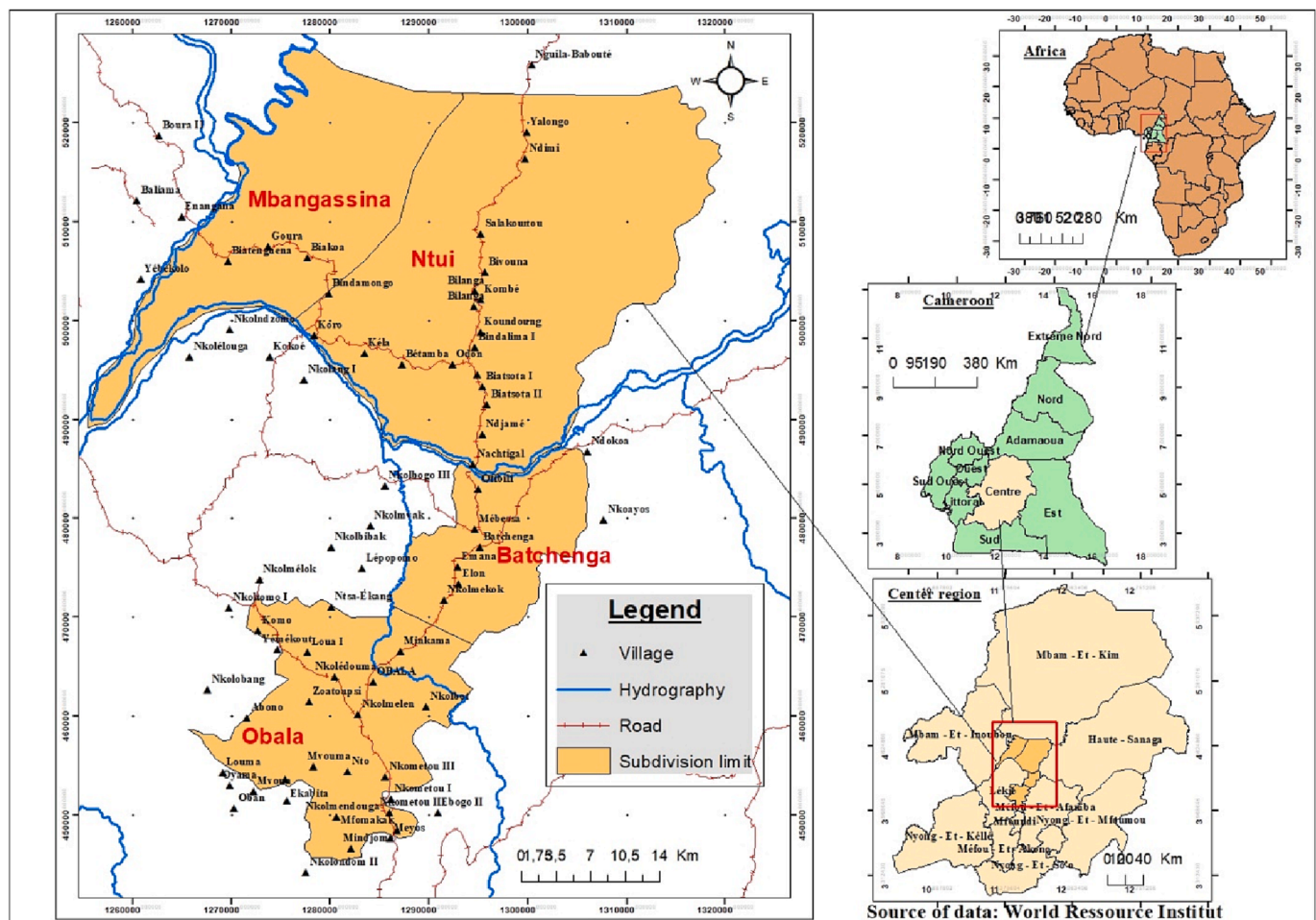


Fig. 2. Map of the study area.

season: July to August; average temperature: 23 to 25 °C. However, various influences can significantly alter this general character. Rainfall has an equatorial distribution with a low summer minimum, with the highest rainfall from September to October and the lowest from December to January. The number of rainy days ranges from 160 to 180. Maximum temperatures are from February to April (MINEPDED, 2015). The vegetation is mainly composed of savannahs and galleries of semi-deciduous forests.

Sampling procedure

The study was conducted in the Centre Region of Cameroon, particularly in its northern quarter (Fig. 2). Over 80% of those employed in the agricultural industry are smallholder farmers, making agriculture the community's principal economic activity (Chimi et al., 2023). For the collection of primary data, field visits were made. These field trips enabled data to be collected through surveys and environmental observations. The target population was sampled from around thirty villages, selecting seventeen villages based on factors such as the density of the population, the level of socio-ethnic heterogeneity (indigenous people and migrants), the diversity of agricultural activities, and the frequency of extreme climatic events. In each of the seventeen villages, 10 to 20 heads of households were randomly selected as respondents.

Second, the northern part of the Centre Region, located in Cameroon's forest-savannah transition zone, was chosen as the principal study location. Seventeen villages were then chosen with the assistance of community-based supervisors and agricultural station chiefs, based primarily on their socioeconomic, biophysical, and agroecological qualities. This choice was made to ensure that all villages in the study region were represented.

Third, Focus group discussion (FGD) is held in ten of the seventeen villages. FGD is an exploratory research tool used extensively by researchers to generate qualitative data and triangulate findings. It is a qualitative study method that requires a small homogeneous group of experienced people to discuss a study topic. It is a qualitative study method that requires a small homogeneous group of experienced people to discuss a study topic (Awazi, Tchamba, Temgoua, & Tientcheu-Avana, 2020; Awazi et al., 2020). In this study, focus group discussion was used to get information from smallholder farmers in the study sites about extreme weather events, and causes of vulnerability. These conversations took place with smallholder farmers. The 10 villages were divided into five strata (based on socioeconomic, agroecological, and biophysical factors), and each stratum had two focus group talks, for a total of ten focus groups. The focus group participants were chosen with the assistance of community supervisors and agricultural station chiefs who were better familiar with the various villages. 10 to 12 people were chosen to participate in a focus group organized by the village. The members of this focus group were selected according to age (elderly, adults, and young people), gender (men and women), membership of user groups and farmers' organizations, ethnic diversity, and the distribution between indigenous and settled migrants. The information obtained in these focus groups was transcribed. The keywords were thus obtained according to the objective of the study. These discussions made it possible to understand the realities of the different intervention environments.

Participants were chosen based on their position as smallholder farmers, agricultural experience, and familiarity with the settings. This was done to eliminate bias. In addition, key informant interviews were done. As a consequence, 40 important informants were chosen. Among them were village chiefs, cooperative executives, council managers, local leaders/managers of agricultural stations, and representatives from the agriculture, environment, and livestock ministries. Key informants were recruited based on their community status (portfolio) and familiarity with smallholder farmers and climate change. Focus group talks and interviews with key informants were conducted to get a general grasp of the situation on the ground and to get to know the family

farmers who would be the focus of the household surveys.

The number of houses (N) that would be surveyed in each village during the fourth phase was calculated using the study's target sample size, with N equal to 10, 15, and 20 in villages with more than [0–99], [100–199], and [300–399] dwellings, respectively (Bocquet, 2000). The entire hamlet was sampled using a systematic or interval sampling strategy. As part of this sampling procedure, the number of households in the space (R) between the two households to be interviewed is calculated (N). The necessary spacing was estimated using the formula $R = P/N$ (PAR, 2018).

Where N represents the total number of families to be questioned, R represents the number of households that fill the gap between the two households to be interviewed, and P represents the total number of households in the village.

A preliminary interview was conducted with each Community Chief and the Multipurpose Community Health Worker(s) (MCW) in charge of his or her region to determine the number of households present in the village. Each respondent functioned as the farm's leader based on their origin, gender, age, and period of residency. An independent farm was required for non-origin responses. For the surveys, 17 localities in the research region were chosen based on the location of the agricultural zones (dryland and/or floodplain). The sample size was set at 180 agricultural households.

The number of smallholder farmers examined in each village was determined by the size of the village and was overseen by agricultural station managers and community supervisors who were more familiar with the unique villages. Thus, 180 smallholder agricultural households were sampled from the 17 communities chosen. Even though villages were chosen based on socioeconomic, agroecological, and biophysical characteristics, certain villages had a higher percentage of farmers than others.

Vulnerability assessment procedure

The vulnerability framework developed by the Intergovernmental Panel on Climate Change (IPCC, 2014) was adapted for this study. According to this notion, the three essential elements that affect susceptibility to climatic variability and change are exposure, sensitivity, and adaptability capability.

The following variables were used to assess smallholder farmers' vulnerability to climate variability and change: (i) change in rainfall over a 10- to 30-year period; (ii) changes in drought over the same time; (iii) changes in temperature over the same period; and (iv) changes in the frequency of recurring extreme weather events (field flooding, heat, and cold waves). It was considered that the more extreme weather events there are and how frequently they occur, the more exposed smallholder farmers are to climate change and variation.

The ability to irrigate the area, the type of oil utilized, and the farming style employed are all indicators of susceptibility to climate variability and change (crops grown). It was assumed that rural populations with low irrigation potential, poor soil types, and a higher proportion of farmers using farming systems would be more vulnerable to climate variability and change than rural populations with high irrigation potential, rich soil types, and a lower proportion of small farmers using farming systems.

Four indicators were utilized to assess adaptive capacity. The social capital indicator included labor force composition and participation in a farmers' association. The number of men in the home, membership in a farmer field school, access to agricultural training, and education level were all indicators of human capital. Annual household income of more than 9,272,000 XFA, access to credit in a microfinance/bank, and other sources of income were all considered economic capital. Physical/natural capital includes 4.5 ha of viable agricultural land, a perception of soil fertility, a square of 29 ha of agricultural land, and access to mechanization. It was assumed that as social, financial, human, and physical resources rose, so did adaptation capacity. In contrast, when

social, financial, human, and physical capital dwindles, so does adaptive capacity. It should be noted that the many capitals used to assess adaptation capacity were derived from the literature, focus groups, key informant interviews, and farmers' assessments.

As a result, there should be less exposure, reduced sensitivity, and higher adaptive capability to reduce smallholder farmers' vulnerability to negative climate fluctuation and change.

Method of analysis

Four processes were employed for this evaluation: (i) identifying the vulnerability components; (ii) identifying and calculating the indicators; (iii) computing the indices of the key vulnerability components; and (iv) evaluating the vulnerability of the communities.

a. Identification of vulnerability components

The vulnerability components for the three vulnerability criteria were chosen through literature study and field interactions. The sensitivity factor components were picked from three options (irrigation potential, soil type, and main crops). Extreme occurrences, rainfall fluctuation, temperature, and drought were used as exposure factors. Physical/natural, social, economic, and human adaptation are the four components of adaptable aptitude (Table 1).

Table 1
Components and sub-components of vulnerability.

Indicators	Sub-indicators	Authors
Irrigation potential	% of people who do not use irrigation	(Bangalore et al., 2019; Sujakhu et al., 2019)
Type of soil	% of respondents with fertile soils of a person growing <i>Manihot esculentus</i> , <i>Ipomoea batatas</i> , <i>Arachis hypogea</i> , <i>Zea mays</i> , <i>Dioscorea</i> spp., and <i>Theobroma cacao</i>	
Main crops	% of respondents who noticed a heat wave	(Maharjan et al., 2017)
Extreme event	Respondents who noticed a change in drought 10–30 years	(Thao et al., 2019), (Ray et al., 2018)
	% of respondents who observed cold waves	(He et al., 2021)
	% of respondents who observed flooding at least once	(Thao et al., 2019), (Sa-adthien et al., 2020)
Precipitation	of respondents who noticed a variation in rainfall 10–30 years	Sa-adthien, S., Tanpichai, P., Jai-aree, A., 2020.
Temperature	% of respondents who noticed a variation in temperature between 10 and 30 years	(Thao et al., 2019), (Ray et al., 2018)
Physical/Natural	% of respondents with a useful agricultural area ≥ 4.5	(Leartlam et al., 2021)
	Number of respondents with a UAA square ≥ 29	(Ho et al., 2022)
	Several respondents with access to mechanization.	(Ho et al., 2022)
Social	Member of a cooperative	(Sujakhu et al., 2019)
	% of respondents so the number of members working in EAF	(Ho et al., 2022), (Bangalore et al., 2019)
	Member of farmers' association	(Sujakhu et al., 2019)
Economic	% of respondents who have an annual income greater than 9272*1000	
	% of respondents who have credit in a microfinance/bank	(Hoang et al., 2020), (Sujakhu et al., 2019)
	% of respondents with multiple sources of income	(Thao et al., 2019), (Ho et al., 2022)
Human	Number of men	(Ho et al., 2022), (Adu et al., 2018)
	% of respondents with at least primary education	(Ho et al., 2022), (Adu et al., 2018)
	Farm school (educational farm)	
	% of people with agricultural training	(Ho et al., 2022), (Bangalore et al., 2019)

b. Identification and calculation of indicators

To achieve this, the index of each sub-component was calculated using the following formula from (Hahn et al., 2009).

$$I_{sc} = \frac{Sd - S_{min}}{S_{max} - S_{min}} \quad (1)$$

With: I_{sc} : sub-component of the different villages; Sd : percentages of respondents; and S_{min} and S_{max} : respective minimum and maximum values of each determined sub-component used for data collection in the subdivisions.

c. Calculation of the indices of the major components of vulnerability

At this level, equal weighting is calculated for all vulnerabilities, and the major components are moderated according to the following formula (Hahn et al., 2009):

$$I_{sc} = \frac{\sum_{i=1}^n I_{sc}}{n} \quad (2)$$

With: M : major component; n : number of subcomponents of each major component; and I_{sc} : represents the subcomponents.

d. Obtaining community vulnerability results.

For this purpose, the equal weighting was calculated using the following formula:

$$I_c = \frac{\sum_{i=1}^n M_i}{\sum nm} \times 100 \quad (3)$$

With: I_c : Component index; M_i : Percentage index of different major components of the boroughs; and nm : Total of all major components.

After vulnerability weighting and indicator moderation, the vulnerability index is calculated using the equation developed by (Gehendra, 2012):

$$V = (E \times S) / AC \quad (4)$$

The vulnerability of each surveyed individual is categorized using four classes: low, medium, high, and very high (Table 2).

A farmer survey was utilized to quantify and assess the indicators to determine the vulnerability of family farms to climatic variability and change. For qualitative indicators, Likert scales were used in compliance or order with the indicator. The data was coded using SPSS (IBM) version 25.0. To normalize all indicators to a scale of 1 to 4, the Min-Max normalization approach was used. Following that was the equal weighting of these indicators (Sullivan et al., 2002). The indications were then integrated using basic arithmetic means of the normalized (z) values for the individual vulnerability components to establish the vulnerability index for each component. The Livelihood Vulnerability Index was used to measure the level of vulnerability of family farms (LVI). Finally, the composite vulnerability index was constructed by averaging the values of each component.

Data collection

Both primary and secondary data were gathered for this

Table 2
Distribution of the different classes of vulnerability.

Vulnerability Index	Class
$V \leq 1$	Low
$1 < V \leq 2$	Medium
$2 < V < 4$	High
$V \geq 4$	Very high

investigation.

To collect primary data on smallholder farmers' opinions of climate variability and change, as well as their sensitivity to its consequences, 180 farm leaders from seventeen communities in the northern part of the Centre Region were polled. As a supplement, information from focus groups and key informant interviews was incorporated into this survey. Data from key informants and focus groups validated the veracity of the information obtained from the household surveys.

For the household surveys on smallholder farmers' perceptions of climate variability and change, as well as the causes of vulnerability to climate variability and change, farm leaders were asked about their experiences with climate variability and change over the last 30 years, as well as the causes of vulnerability to climate variability and change.

What have you noticed about the changing of the seasons? What are your thoughts on rainfall, temperature, and drought in the last 10–30 years? Several questions were addressed to farm leaders to understand more about family farmers' experiences with climatic variability and change over the last 30 years. Total precipitation was assessed using a Likert scale with three options: rising, decreasing, or no change. The temperature was assessed using a three-point Likert scale: high, unchanged, and low. Drought was evaluated using a Likert scale with three options: long, short, and unchanged.

Climate data were acquired from secondary sources. The climatic data was gathered via the "Climate data from power Larc NASA (Power Data Access Viewer)" webpage. These were used to assess the degree of climatic element fluctuation and change (precipitation and temperature). The information acquired from a single location per locale was sufficient to represent the entire study region because the weather and climate in the study area are fairly stable (with only small differences in agro-climatology).

Data analysis

Using Microsoft Excel, temperature and rainfall data from the online resource "Climate data from Power Larc NASA (Power Data Access Viewer)" were normalized and viewed as temperature and rainfall curves.

The data from the household survey were used to generate the exposure, sensitivity, and adaptive ability indexes. Each index was constructed by adding all of the scores and multiplying them by the weights assigned. Data on farmers' perceptions of climate variability and change, as well as the factors that contribute to their vulnerability to it, were coded and imputed in Microsoft Excel 2022, SPSS version 27.0, XLStat 2022.2.1.1294, and RStudio 2022.07.1–554, which perform descriptive, bivariate, multivariate, and inferential statistical analyses.

Descriptive statistics, frequency distributions, means, mean deviations, and percentage indices were calculated. Spearman's correlation, *t*-test, Fisher's exact test, Kruskal-Wallis test, and binomial logistic regression were the key inferential statistics produced. The statistical tests Spearman's rho, *t*-test, and Fisher's exact were used to determine the current relationship between smallholder farmers' vulnerability to climate fluctuation and change and the numerous continuous and discontinuous explanatory variables proposed.

It should be noted that the linked formula was utilized to calculate the index of smallholder susceptibility to climate change and fluctuation. This resulted in the use of (Fongnzossie et al., 2018)'s classification. Susceptibility was classified into two categories: "high" and "medium." To finish, numerous statistical tests were run on these two groupings.

The Kruskal-Wallis (H) test statistic was used to determine whether there was a significant difference in smallholder farmers' vulnerability to climate variability and change between subdivisions. The binomial logistic regression model was also used to estimate the degree of causation between smallholder farmers' vulnerability to climatic fluctuation and change and other presumed continuous and discontinuous explanatory factors.

All statistical tests were performed after the normality tests. However, because the majority of the study's variables (dependent and independent variables) were categorical or qualitative, the study primarily used non-parametric tests such as Fisher's exact statistical test and Kruskal-Wallis statistical test; Spearman's rank correlation; and a discrete choice regression model, i.e., binary logistic regression. The *t*-test and Levene's statistics were used, however, because the continuous independent variables were all normally distributed and the dependent variable was binary.

Diverse analytical approaches (*t*-test, Fisher's exact test, Kruskal-Wallis test, Spearman correlation, and binary logistic regression) were used to conduct various studies. The *t*-test and Fisher's exact test statistics were used to assess the influence of the study's independent factors (socioeconomic, institutional, and environmental variables) on the dependent variable (vulnerability). Spearman's rank correlation was used to demonstrate the degree of non-causality between the dependent variable (vulnerability) and the independent components in the study. The Kruskal-Wallis statistical test was used to evaluate the degree of variability in the susceptibility of smallholder farmers to climate fluctuation and change across several subdivisions. The degree of causation between the dependent variable (vulnerability) and the independent variables was demonstrated using binary logistic regression.

The data collection methodology used in studies such Fongnzossie et al. (2018), Funwi et al. (2020), and Rurinda et al. (2014) are somewhat similar; however, the data analysis methodology used in this work is distinct since it mostly employs inferential statistical techniques. Inferential statistical approaches were generally used to obtain more technically and scientifically sound results since, unlike descriptive statistical techniques, they allow for inference. Awazi et al. (2020) also utilized the chi-square test. In the current investigation, Fisher's exact test was used. The Fisher exact test is an exact test that can be performed with smaller sample sizes (1,000) (returns an exact *p*-value). This test can be used in place of the chi-square test when more than 20% of the cells have frequencies of <5. In the current study, Fisher's exact test was employed with a sample size of 180. This paper also calculated the vulnerability index. Awazi et al. (2020) examined farmers' attitudes to determine their susceptibility.

The output of the data analysis permits the presentation of the results in terms of calculating the vulnerability index by emphasizing their contribution to local adaptation.

Results

Profile of farmers.

Socioeconomic profile of farmers

The findings show that there is a difference between the four subdivisions, with men accounting for 73.3 percent of heads of farms (FTs) and women accounting for 26.7 percent (*p*-value = 0.008). 55.56 percent of the FTs are not members of the Common Initiative Group or a cooperative. Because the calculated *p*-value (*p*-value = 0.0002) is less than the significance level $\alpha = 0.05$, there is no independent association between locales and membership in a farming group. Furthermore, the *p*-values (Fisher's exact test) for the no and yes modalities in Mbangassina, Ntui, and Obala are significant at the $\alpha = 0.05$ level (0.040 and 0.040, 0.0001 and 0.0001, respectively). In the subdivision of Batchenga, on the other hand, there is no significant difference

Table 3

P-values (test exact de fisher) membership in a farmer's organization \ subdivision.

Membership in a farmer's organization	Batchenga	Mbangassina	Ntui	Obala
No	1,000	0,040	0,040	<0.0001
Yes	1,000	0,040	0,040	<0.0001

between farmers who are members of a farmers' organization and those who are not (Table 3).

The values displayed in red are significant at the $\alpha = 0.05$ threshold.

According to the statistics, while 17.8 percent of respondents lack formal education, 82.3 percent can read and write. 42.8 percent of those polled have finished at least primary school. A higher degree is held by 4.45 percent of farm managers, which is a very modest percentage. Furthermore, there is no difference between the places because the determined p-value is bigger than $\alpha = 0.05$. There is a conspicuous lack of these facilities, with only 1% of all institutions in the three subdivisions being higher education facilities. The socio-demographic profile demonstrates considerable differences in these subdivisions as well.

The majority of farm managers (57.77 percent) say they have formal agricultural training. Because the estimated p-value (0.82) is greater than $\alpha = 0.05$, the localities are independent for this variable. This is typically done in agricultural schools (educational farms). As a result, with a p-value of <0.0001 , 60% of respondents believe they are affiliated with a farmer's school. When asked if they could get credit through microfinance or banks, 63.88 percent said yes. Location affects reality (p-value = 0.078). The computed p-value above $\alpha = 0.05$ indicates significance. These farmers make a living through several means. Aside from agriculture, they normally have three additional sources of income, with a maximum of six and a minimum of 1.

According to socio-economic studies, the average age of the 17 villages is 49.42 ± 0.93 years, showing that young people do not have easy access to land and do not inherit when they are young. In farming, the average number of years is 21.1 ± 70.18 . In a normal home, there are 8 people. Furthermore, the sample shows that 69.44 percent of FTs are also accountable to other people. There are usually four of them. 85 percent of the 180 farmers surveyed say they are primarily farmers (84 percent of farmers and 1 percent of retired civil servants converted into farmers).

Agriculture is the principal source of income for households in the study region, which has an average area of 4.56 ± 0.21 ha. Agriculture is followed by the petty trade sector (6%) and jobs in public administration (4 percent). The average monthly household income in the research area is $777,472 \pm 67,510.90$ XFA.

The average yearly salary is $932,975 \pm 81,130.72$ XFA, with salaries ranging from 450,000 to 49,300,000 XFA. There is a significant difference (p-value = 0.007) at the yearly income limit of 5%. Farmers pay more attention to some crops. Cocoa has the highest turnover rate (59.44 percent), followed by cassava, plantain, yam, maize, and cucumber (32.21 percent), and watermelon, rice, and beans (8.55%). The p-value is 0.035, which is less than the α , suggesting that the most popular theory's locales differ. This supposition generates an average annual revenue of $6,846,788 \pm 667,497$ XFA. There is a difference between the four locations since the calculated p-value is smaller than the significance criterion of $\alpha = 0.05$.

Production system

The fields used have an average area of 4.55 ± 0.21 ha and range in size from 0.75 ha to 17 ha. Because the calculated p-value is smaller than $\alpha = 0.05$, the threshold for significance, there is a significant difference between the localities and the useable agricultural area variable. The minimum and maximum area for the principal crop is 0.25 ha and 15 ha, respectively, with a total average of 3.12 ± 0.2 ha for the four subdivisions. At the 5% cutoff, there is a significant difference in the values of the four subdivisions (p-value = 0.0002).

According to the findings, a farmer normally cultivates 0.37 ± 0.03 ha of *Zea mays* (maize), 0.46 ± 0.03 ha of *Manihot esculenta* (cassava), 0.19 ± 0.01 ha of *Arachis hypogaea* (groundnut), 0.16 ± 0.01 ha of *Ipomoea batatas* (sweet potato), and 0.28 ± 0.03 ha *Dioscorea* sp. (yams). Additional crops related to the latter include *Musa* spp. (sweet banana), *Cucumeroopsis mannii* (cucumber), *Xanthosoma* sp. (macabo), *Sesamum*

indicum (sesame), *Vigna subterranea* (voandzou), and various fruit trees. Speculation On 7 acres of land in the Batchenga subdivision, just a few individuals produce *Oryza sativa* (rice). The areas dedicated to maize, cassava, and market garden crops, on the other hand, stand out in the subdivisions of Batchenga and Obala, with Ntui coming in second for cocoa and plantain and Mbangassina coming in third for sweet potato. In 75% of cases, these crops are produced on ferritic/hydromorphic soils, and in 25% of cases, on ferritic/clay soils.

In terms of soil fertility perception, 64.44 percent of farmers say soil fertility is unchanged. It has slightly decreased in Batchenga. At the 5% level, this variable and the various locations reveal a significant difference (p-value = 0.0001). 52.78 percent allowed agricultural residues to remain in situ to allow the soil to naturally recover. This practice is common in Mbangassina (67 percent) and Ntui (64.44 percent). Because the computed p-value is greater than 0.05, subdivisions are unrelated to one another. Organic amendments are used by 62.22 percent of the population (chicken droppings, pig dung). Because the estimated p-value is less than $\alpha = 0.05$, the significance criterion, there is a link between the four communes for this parameter. The majority of farm owners prefer not to use irrigation (99.44 percent). P-value = 0.38, which is greater than the 5% limit. This practice is used by only a few farmers in Batchenga. Chemical fertilizers are rarely utilized on farms (74.78 percent). Market gardeners, on the other hand, use them to boost crop yield.

According to the research, 71.11 percent of respondents believe that obtaining agricultural mechanization with tractors is tough. On the other hand, 17.78 percent say it is simple. Mechanization, according to 11.11 percent of respondents, is not available where they live. Because the determined p-value (p-value < 0.0001) is less than the significance level $\alpha = 0.05$, there is a correlation between location and access to mechanization. The p-values (Fisher's exact test) demonstrate that the modalities tough (<0.0001), easy (0.001), and non-existent (0.002) are all statistically significant for the commune of Batchenga. Ntui's challenging modality is significant (p-value = 0.023).

Variability of climatic parameters

Variations in temperature

The mean temperature changed between 1981 and 2021 (Fig. 3). Between 1998 and 2004, the four subdivisions experienced very substantial mean annual temperature differences (r greater than 50 percent). 2019 was the warmest year on record for the Mbangassina subdivision. The locations are interdependent (R^2 greater than 0.5).

Variations in precipitation

For several years, precipitation has been decreasing in the studied area. The most prominent precipitation anomalies occurred in 1990, 1991, 1997, 1999, 2003, 2004, 2005, 2008, 2009, 2011, 2014, 2015, and 2019 (Fig. 4). It was in 1991 when there were noteworthy changes in the average monthly rainfall. The average monthly rainfall in 1982 was quite variable. A precipitation decrease was seen in 13 of the 40 years studied, indicating that many other years had below-average precipitation totals. This means that the rainfall anomalies have a negative trend line, implying that rainfall has been erratic and scarce over the last 40 years. The boroughs aren't all that different from one another.

Perception of climatic factors

Local perceptions of climate variability indicators

Almost all of the locals, or 89.44 percent of the sample, agree that climatic variability exists. Because the calculated p-value is bigger than the significance level $\alpha = 0.05$, there is no link between the subdivisions. These differences can be noticed in the irregular timing of the dry and rainy seasons, rising temperatures, increased wind frequency, and the introduction of invasive species in crops (such as locusts and

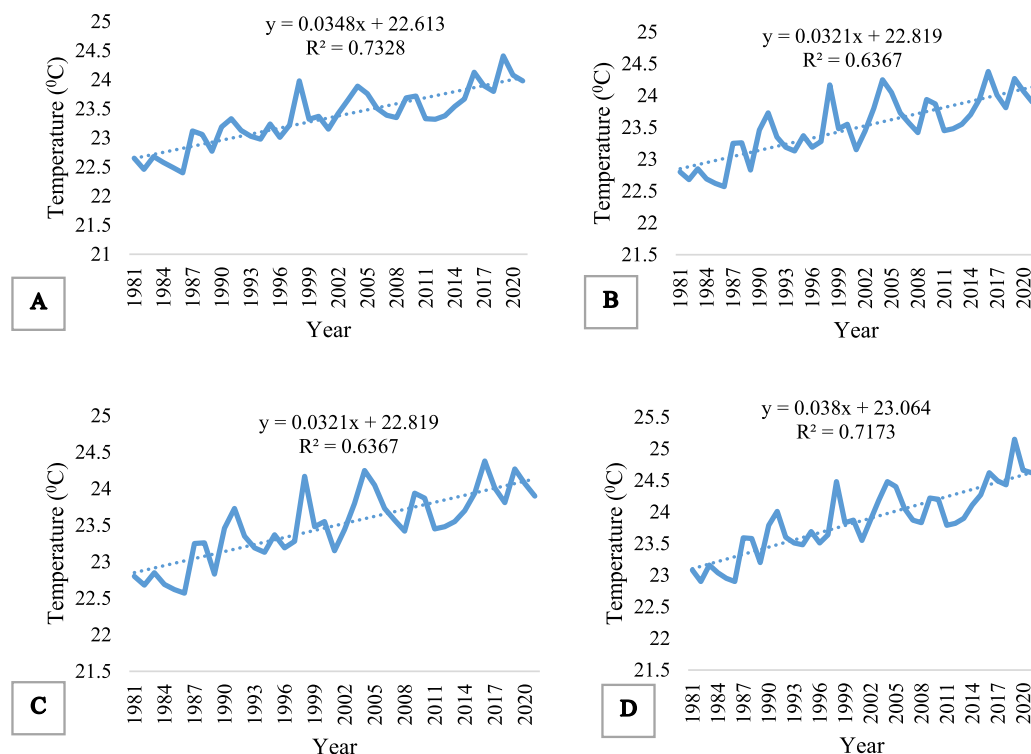


Fig. 3. Variation in temperature between 1981 and 2021 (A: Obala, B: Batchenga, C: Ntui, D: Mbangassina) (Source: Climate data from power Larc NASA (Power Data Access Viewer)).

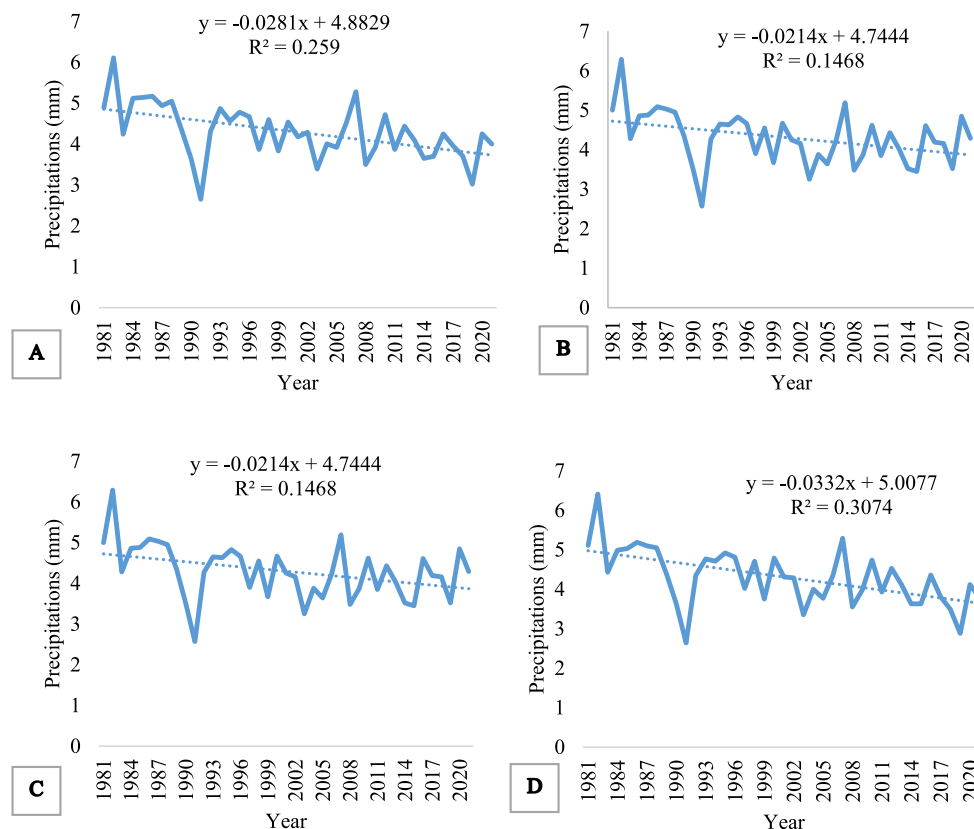


Fig. 4. Variation in rainfall between 1981 and 2021 (A: Obala, B: Batchenga, C: Ntui, D: Mbangassina) (Source: Climate data from power Larc NASA (Power Data Access Viewer)).

caterpillars). According to the respondents, these variances are to blame for 49.3 percent of the deforestation of the research area's few unique forest galleries, 25 percent of people not adhering to traditional beliefs promoted social norms, and 25.7 percent of people experiencing punishment for violating gods.

Similarly, polls show that the agricultural economy, with its seasonal cycle, is one of the most impacted by climate change as a result of rising temperatures, increased variability of rainy and dry seasons, and rising strong winds. As a result, 25.56 percent of respondents indicated rains arrive later than usual, and 41.11 percent said variable rainy seasons are a symptom of climate change in their location. 18.89 percent of respondents said the drought is severe and persistent, 14.44 percent said they saw patches of rain in the middle of the dry season, and more individuals said it is regular and very windy. There is a correlation between locations and the occurrence of dc (p -value < 0.0001) since the estimated p -value is below the significance level $\alpha = 0.05$.

Extreme events

The majority of respondents (48.33 percent) believe the last ten years have seen the coldest waves on record. Because the predicted p -value (0.56) surpasses the significance level $\alpha = 0.05$, the study's four locations are most likely unrelated. Heat waves are considered severe by the vast majority of farmers (87.77 percent). Again, because the calculated p -value (0.601) is greater than the $\alpha = 0.05$ criterion of significance, the localities are independent for this variable. Flooding in the fields destroys the majority of the crops along its path. 45.5 percent of those polled agree.

A thermal trend during 10–30 years

Most people are acutely aware of the temperature difference between the dry and wet seasons. 65 percent of respondents believe that temperatures have risen in the last 10 to 30 years, with 30.55 percent indicating no change. Because the estimated p -value is smaller than the significance level $\alpha = 0.05$, there is a dependency between locales (p -value < 0.0001). Fisher's exact test results for significance by modality show that temperatures are high in Batchenga, Mbangassina, and Ntui, with p -values of 0.004, 0.047, and 0.019, respectively. Obala has a significant value for the no-change modality (0.025), and Batchenga has a significant value for the reduced modality again at the 5% threshold.

Frequency and duration of the dry season during 10–30 years

According to 66.11 percent of respondents, regardless of gender, the duration and frequency of the dry season have altered in the area over the last 10 to 30 years. Drought frequency has increased over the last 10 to 30 years, according to 66.11 percent of those polled, and they also mentioned the advent and spread of caterpillars that devour cocoa leaves, as well as bushfires that have ravaged plantations since 2013. Because the estimated p -value is smaller than the criterion for significance, $\alpha = 0.05$, there is a dependency between the examination sites. The p -values (Fisher's exact test) for distinct modalities show significant values at the $\alpha = 0.05$ cutoff. Batchenga's high and low modalities had p -values of 0.018 and 0.004, respectively. At Ntui, only the high modality is notable (p -value = 0.029). In Obala, the no-change modality is significant (p -value = 0.025) at Fisher's test limit of 5%.

Frequency and magnitude of rainfall during 10–30 years

The amount of precipitation has decreased, according to nearly all respondents (76.67 percent). It had risen, according to 12.78 percent of respondents. The remaining 10.56 percent were undecided. According to studies of the independence test of χ^2 at 5%, there is no obvious variation among subdivisions. This drop has been detected due to a change in rainfall over the last 10 to 30 years. "It rains hard one year, but it doesn't rain the same amount the next year," one respondent stated. It should be noted that if it does not rain in September, October, or November, we frequently have a lot of rain in January and February. The amount of rain has decreased dramatically and is not dropping evenly.

Only 7.78 percent of respondents believe the changes are beneficial, while 51.11 percent believe they are horrible and 41.11 percent believe they are acceptable, and the 0.05 chi-square test suggests that locations are independent.

Local adaptation measures/strategies

In response to perceptions of climatic fluctuation and change, family farmers developed adaptation mechanisms. The most commonly employed local adaptation strategies are bridging/mulching (95.57 percent), crop association (93.3 percent), and crop rotation (92.78 percent) (Table 4).

Vulnerability profile of the different subdivisions

Vulnerability components, particularly exposure, sensitivity, and adaptation, were arranged into indicators. According to the findings, family farms in the research areas are not particularly sensitive to climate change. Thus, the Batchenga subdivision (13.4 percent) is the most susceptible, followed by Ntui (13.5 percent), Mbangassina (13.5 percent), and Obala (13.5 percent) (13.4 percent). In terms of exposure, family farms in these places are less vulnerable to climatic change to varied degrees. The Obala subdivision contains the fewest family farms (5.8 percent), followed by Batchenga (9.5 percent), Mbangassina (19 percent), and Ntui (19 percent) (21 percent). (19.2 percentage points in terms of adaptive capabilities, family farms in Obala (17.2 percent) outperform those in Ntui (15 percent), Mbangassina (10.8 percent), and Batchenga (10.6 percent) (Fig. 5).

Extreme events and labor have the largest influence on vulnerability in Ntui, with index values of 0.51 and 0.64, respectively. In contrast, the main crops, extreme occurrences, and social potential all affect the vulnerability of family farms in Batchenga, Mbangassina, and Obala (Table 5). A growing reliance on rainfed agriculture, which is becoming increasingly unreliable as a result of global climate change, will result in a lower share of irrigated land.

The distribution of the vulnerability index is disparate according to the different villages of the study area. According to this map, each village has its realities ranging from low to very high (Fig. 6). The combination of these different vulnerability indexes made it possible to produce the indexes for the different subdivisions.

According to the data, family farms in Obala (1.1) have the lowest vulnerability score, followed by those in Batchenga (2.16), Ntui (2.17), and Mbangassina (2.99). According to the findings, whereas family farms in Batchenga, Ntui, and Mbangassina have high sensitivity indices to climate variations and changes, those in Obala are just moderately vulnerable (Fig. 7).

Table 4
Local adaption measures.

Local adaptation measures/strategies	Adoption rate (%)
Abandonment/adoption of new crops and/or varieties**	57.56
Association of crops***	93.33
Crop rotation***	75.50
Mounding***	95.57
Decrease in the area sown*	17.22
Crop rotation***	92.78
Early seeding**	61.11
Early planting**	62.78
Late seeding**	68.89
Use of short cycle varieties**	69.44
Fallow land**	54.60

*** (very common); ** (common); * (less common).

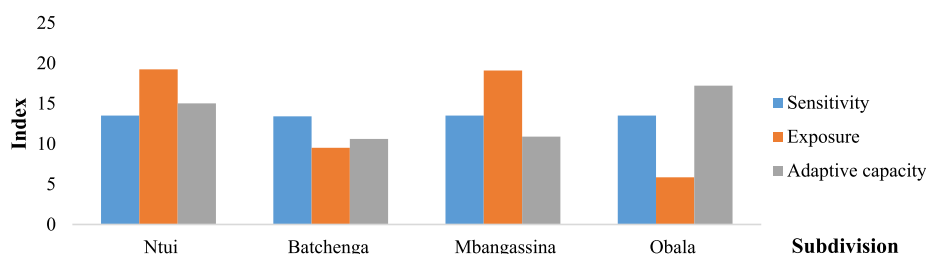


Fig. 5. Vulnerability components of family farms in the localities.

Table 5

Value of the main components of vulnerability in family farms.

Contributing factors	Major component	M Ntui	M Batchenga	M Mbangassina	M Obala
Sensitivity	Irrigation potential	0.45	0.44	0.45	0.45
	Type of soil	0.45	0.45	0.45	0.45
	Rainfed crop	0.45	0.49	0.45	0.45
Exposure	Extreme events	0.51	0.32	0.48	0.17
	Precipitation	0.41	0.35	0.42	0.41
	Temperature	0.97	0.27	0.95	0.21
Adaptive capacity	Physical/Natural	0.28	0.32	0.36	0.42
	Social	0.28	0.22	0.16	0.75
	Economic	0.28	0.30	0.29	0.29
	Human	0.64	0.21	0.26	0.25
LVI		0.47	0.33	0.43	0.36

Factors influencing smallholder farmers' vulnerability to climate variability and change

Correlation between explanatory variables and the index of smallholder farmers' vulnerability to adverse climate variability and change.

After analyzing the association between twenty-seven explanatory variables and smallholder farmers' sensitivity to adverse climate conditions, a negative link was discovered between vulnerability and ten of the study's hypothesized explanatory variables. The links between the two variables revealed a positive relationship.

Explanatory variables were *Theobroma cacao* (cor = -0.176, $p < 0.05$), *Musa* spp. (cor = -0.167, $p < 0.05$), *Ipomoea batatas* (cor = -0.018, $p < 0.05$), *Dioscorea* sp. (cor = -0.151, $p < 0.05$), rainfall (cor = -0.250, $p < 0.01$), and soil fertility (cor = -0.297, $p < 0.01$). The sensitivity of smallholder farmers to climate variability and change is positively connected with explanatory variables such as temperature (cor = 0.251, $p < 0.01$) and drought (cor = 0.186, $p < 0.05$), implying that an increase in these explanatory variables will likely increase this vulnerability.

Non-causal relationship between explanatory variables and smallholder farmers' vulnerability to adverse climate variability and change

Non-causal relationship between continuous explanatory variables and smallholder farmers' vulnerability to adverse climate variability and change. The F-test results of Levene revealed a significant non-causal correlation between four continuous explanatory factors and the sensitivity of smallholder farmers to climate change ($p < 0.05$) (Table 6). Smallholder farmers' vulnerability to climate variability and change is significantly correlated with continuous explanatory variables such as annual income ($F = 3.03$, $p < 0.1$), useful agricultural area ($F = 3.88$, $p < 0.1$), different sources of income ($F = 6.65$, $p < 0.05$), and monthly agricultural training frequency ($F = 4.00$, $p < 0.05$). This demonstrates that a viable agricultural region, several sources of income, agricultural training frequency, and annual revenue all have a substantial impact on how exposed smallholder farmers are to climatic fluctuation and change.

Non-causal relationship between discontinuous explanatory variables and smallholder farmers' vulnerability to adverse climate variation and change. Fisher's exact test results revealed a significant causal association between five discontinuous explanatory variables and smallholder farmers' sensitivity to climate change ($p < 0.05$) (Table 7). This demonstrates that dryness during these 10–30 years, soil fertility due to *Dioscorea* spp., and rainfall during these 10–30 years all significantly contribute to smallholder farmers' vulnerability to unfavorable climate variability and change.

Ranking of smallholder farmers' vulnerability to climate variability and change by subdivision. Four transitional forest-savanna areas in Cameroon's central region were researched to assess climate change sensitivity and determine whether there was a significant difference in smallholder farmers' vulnerability to climate change.

The Kruskal-Wallis test (H-test) revealed that the sensitivity of smallholder farmers in the various communities to climate change varies significantly ($X^2 = 179$, $p\text{-value} = 2.2e^{-16}$). This indicates how significant local disparities in smallholder farmers' vulnerability are. However, the thematic ranking demonstrates that smallholder farmers in Mbangassina (IV = 2.99), Ntui (IV = 2.17), and Batchenga (IV = 2.16) are significantly more vulnerable than those in Obala (IV = 1.12). Despite being in the same agroecological zone, the research region is defined by minor differences in socioeconomic and infrastructure conditions, implying that each of the places has its distinct characteristics.

A causal relationship between explanatory variables and smallholder farmers' vulnerability to adverse climate variability and change.

In the binomial logistic regression model, five of the six explanatory factors had statistically significant inverse causal associations with smallholder farmers' sensitivity to unfavorable climate change. The drought factor had a significant positive causal relationship (Table 8).

According to the model, useful agricultural area ($\beta = -0.348$, $p < 0.0001$), soil fertility ($\beta = -0.568$, $p < 0.05$), *Dioscorea* spp. ($\beta = -0.926$, $p < 0.05$), precipitation during these 10 to 30 years ($\beta = -0.582$, $p < 0.05$), and annual income ($\beta = -0.002$, $p < 0.01$) all contributed to lessening smallholder farmers' vulnerability to unfavorable climate variability and change. This illustrates that the vulnerability of smallholder farmers to unfavorable climate variability and change decreases when available agricultural land, soil fertility, *Dioscorea* spp., rainfall, and annual income growth during the next 10–30 years. Drought, on the other hand, enhanced smallholder farmers' susceptibility to negative climate fluctuation and change ($\beta = 0.906$, $p < 0.05$). This depicts how drought increases people's vulnerability.

It must be acknowledged that the results of this model stand up when the Likelihood Ratio X^2 , the Nagelkerke R^2 , and the number of correctly classified cases are considered. The X^2 likelihood ratio (6, $n = 180 = 250.75$, $p < 0.05$) indicates that the model is statistically significant and has strong explanatory power. The model predicted up to 74.1 percent of the variation in smallholder farmers' susceptibility to unfavorable climate fluctuation and change, according to the Nagelkerke R^2 (0.741). Furthermore, the model correctly detected up to 79.4 percent of the susceptibility of smallholder farmers to negative climate fluctuation and change.

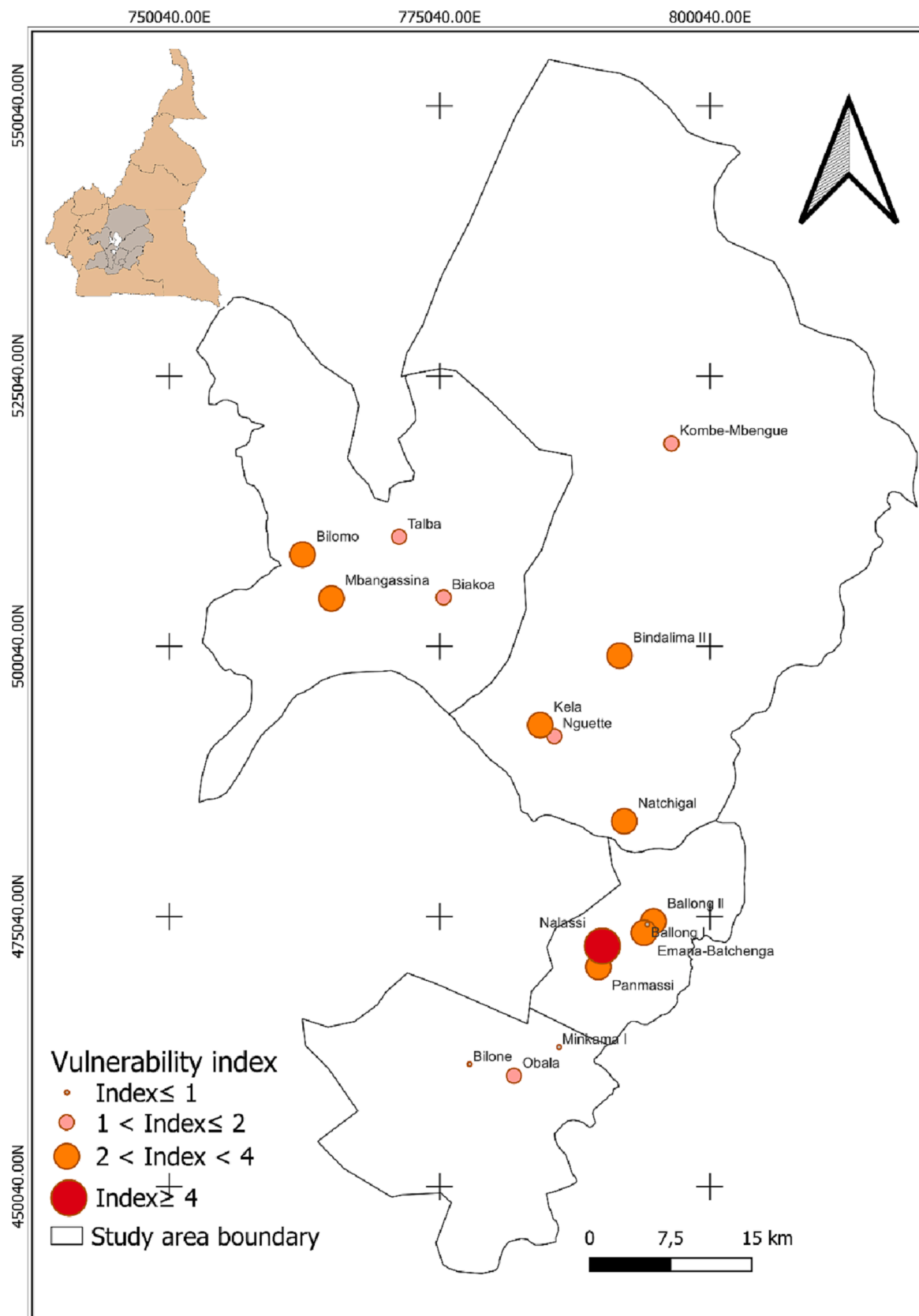


Fig. 6. Map explaining the distribution of vulnerability index in the areas (17 villages) of investigations.

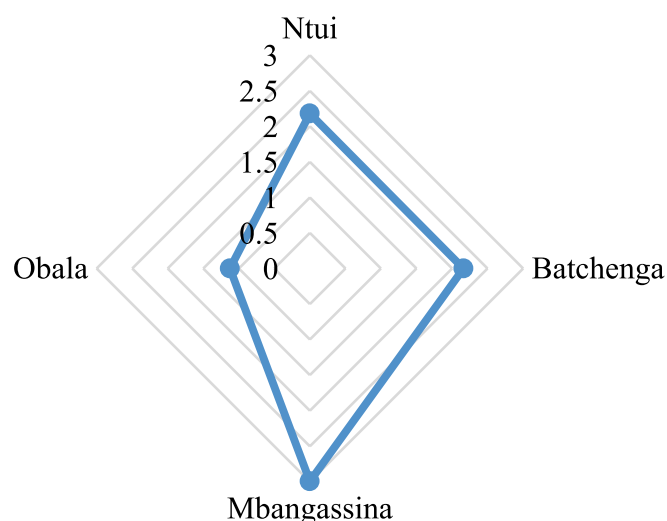


Fig. 7. Radar diagram showing the level of vulnerability of family farms in the Obala, Batchenga, Ntui, and Mbangassina subdivisions.

Overall, the results highlight the need to re-discuss the importance of determining vulnerability indices and identifying the determinants that constitute them for viable adaptation measures for family farmers.

Discussion

Variations and changes in climatic elements

The correlation between family farmers' perspectives and the examined climate factors demonstrates that fluctuations and changes in climate parameters occur in the northern portion of Cameroon's Central Region (temperature and rainfall Awazi et al. (2019), Chimi et al. (2022), Azibo et al. (2016), and Gur et al. (2015) have all reported high levels of variability in climate parameters over the past decades; however, little research has been done to date to evaluate the degree of variations and changes in climate parameters by integrating data and farmers' perceptions and relating them to the concept of vulnerability. The findings of this study are consistent with those of Awazi et al. (2020), who performed research in Cameroon's western area. Similarly, Awazi et al. (2022) demonstrated that temperatures, rainfall, and rainy days varied markedly, with increasing temperatures, erratic rainfall, and fewer rainy days in the northwest region of Cameroon. Despite working for 15 years, their findings fill a knowledge gap because climate change cannot be officially acknowledged until 30 years of observation.

The average temperature fluctuations were examined between 1981 and 2021. The four areas saw very significant mean annual temperature changes between 1998 and 2004. The year 2019 is the hottest on record for Mbangassina. These various findings are identical to those of the second national climate change communication (NDC) (MINEPDED, 2021). Indeed, temperatures are increasing with a decrease in 2018 and

2021. The trend of increasing average temperature is concerning for the semi-arid South Cameroon plateau, according to Abossolo et al. (2017), Tchindjang, (2012), and MINEPDED (2021); these findings are similar to those reported in the current study. In addition, Tchindjang, (2012), and MINEPDED (2021), demonstrated that in the agroecological forest zone, the average temperature oscillated from 23.5 in 1974 to 25.3° in 2005, a difference of 1.80 °C over 40 years for an annual average of 24.4 °C. With 0.45° of temperature increase per decade, it can be said that the temperature in the forest agroecological zone has increased by 1.84% per decade. Farmers in all four subdivisions are experiencing heat waves as a result of global change. MINEPDED (2021) discovered the same outcomes. In addition to flooding, landslides, and erosion, these will occur. Based on all of the information gathered and assessed, the South Cameroon Plateau looks to be the least damaged, although caution is still required owing to deforestation, logging, and mining, all of which jeopardize conservation and can exacerbate threats.

Furthermore, rainfall has been decreasing over the last few decades. The most significant precipitation anomalies were reported in 1990, 1991, 1997, 1999, 2003, 2004, 2005, 2008, 2009, 2011, 2014, 2015, and 2019. The average amount of rainfall in different months varied significantly during the year 1991. In 1982, the average monthly rainfall varied significantly. Thirteen of the forty years investigated saw drop-in precipitation, indicating that many other years had below-average

Table 7

Fisher exact test statistics show a non-causal relationship between vulnerability to climate change and discontinuous explanatory variables.

Qualitative variable	Fisher's Exact Test	
	p-value	Odds ratio
IRR	1	0
<i>Arachis hypogea</i>	0.813	1.263
<i>Dioscorea</i> spp.	0.04534**	0.550
<i>Ipomoea batatas</i>	0.12268	0.443
<i>Manihot esculentus</i>	0.3488	0.656
<i>Musa</i> spp.	0.3151	0.675
<i>Theobroma cacao</i>	0.2414	0.575
<i>Zea mays</i>	0.1946	4.661
S30	0.04257**	/
VAC	0.6006	1.573
ERO	0.3266	0.531
VAF	0.3031	1.468
P30	0.02919**	/
T30	0.14257	/
SOF	0.03186**	/
MEC	0.5798	/
MOP	0.4483	1.674
ACR	0.722	1.175
EPA	0.7396	0.733

Signif. code: 0.05 ***. IRR: irrigation practice; S30: drought variations from 10 to 30 years; VAC: heat wave; ERO: road condition; VAF: cold wave; P30: rainfall variations from 10 to 30 years; T30: temperature variations from 10 to 30 years; SOF: soil fertility; MEC: access to mechanization; MOP: a member of a farmer organization; ARC: access to climatic information; EPA: a member of a farmer school.

Table 6

Independent sample test statistic showing a non-causal relationship between vulnerability to climate change and continuous explanatory variables.

Variable	t-test for equality of means				Levene's test for equality of variance	
	t	df	p-value	Mean diff.	F value	Pr (>F)
FOA	-0.78896	165	0.4313	The true difference in means between groups is not equal to the 99% confidence interval	4.002	0.04709**
INO	-0.33737	178	0.7362		0.0745	0.7852
NHO	-0.47638	178	0.6344		0	0.9944
REA	0.44577*	178	0.06563		3.0376	0.08308*
SAU	-2.8386**	178	0.00506		3.8894	0.05014*
SRE	-1.8032*	178	0.07305		6.6531	0.01071**

Signif. codes : 0.05 *** 0.1 **. FOA: training in agriculture (number of times/month); INO: Field flooding (number of times/year); NHO: Number of family members working on the farm; REA: agricultural income; SAU: useful agricultural area; SRE: sources of income.

Table 8

Binomial logistic regression predicting smallholder farmers' vulnerability to climate change based on six explanatory variables.

Explanatory variables	Coefficient (β)	Sig.	Wald	ddl	Exp (β)	CI for Exp. (β) 95%	
						Lower	Upper
SOF	-0.568*	0.048	3.903	1	1.765	1.005	3.101
<i>Dioscorea</i> spp.	-0.926*	0.021	5.360	1	2.525	1.153	5.531
S30	0.906*	0.013	6.131	1	0.404	0.197	0.828
P30	-0.582*	0.041	3.360	1	1.789	0.960	3.334
SAU	-0.349*	0.000	15.786	1	1.417	1.193	1.683
REA	-0.002*	0.013	6.169	1	1.000	1.000	1.000
Constant	-4.507*	0.001	10.658	1	0.011	/	/
-2 Log-likelihood	169,161						
Likelihood ratio X^2	250.75**	0,038					
Nagelkerke R^2	0,741						
Number of cases correctly classified	79,4 %						
N	180						

*, ** significant at the 5% and 1% probability levels respectively. S30: drought variations from 10 to 30 years; P30: rainfall variations from 10 to 30 years; REA: agricultural income; SAU: useful agricultural area; SOF: soil fertility.

rainfall quantities. This implies that the rainfall anomalies have a negative trend line, showing that rainfall has been scant and unpredictable over the last 40 years. These conclusions are consistent with those presented by UNDP (2008) and confirmed by the MINEPDED (2021), which emphasizes the decreasing trend in average rainfall. In addition, according to Tchindjang, (2012), and MINEPDED (2021), the agro-ecological forest zone with bimodal rainfall constitutes a homogeneous environment where the evolution of average annual precipitation is regressive but quite significant if we stick to the trend. This agroecological zone has recorded an overall reduction of 11.95% in 60 years; i.e. a decrease in average precipitation of 2% per decade over the past six decades.

All in all, temperatures are rising in the study area with a decline between 2018 and 2021 depending on the emission scenario. Precipitation is on the rise. These findings were also made by MINEPDED (2021) in its revised version of NDC. He went further by predicting the decline in precipitation from 2030.

Smallholder farmers' perceptions of sources of vulnerability to climate variability and change

Family farmers discovered numerous signals of climate change and varying susceptibility. All of these farmers recognized various climate change vulnerability indicators, demonstrating that family farmers' susceptibility to the detrimental effects of climate variability and change is accounted for by several indicators. Farmers are vulnerable to the effects of climate variability and change, according to studies in Cameroon by Molua, (2006), in Zimbabwe by Rurinda et al. (2014), in Ethiopia by Deressa et al. (2011), Temesgen et al., (2014), and Tessema et al. (2013), but few studies have looked at smallholder farmers' perceptions of climate variability and change vulnerability factors. Awazi et al. (2020) focused on how smallholder farmers perceive various vulnerabilities to climatic variability and change, closing a crucial information gap. The current study's findings support this. However, the phenomenon of deforestation would also be taken into account in this forest-savannah transition zone. Indeed, demographic pressure and the industrious nature of the population have led to the transformation of forests and savannah into plantations, thus reducing the wealth of marketable species and non-timber forest products (NTFPs).

Based on estimations of vulnerability components and their index, farmers in these areas are moderately vulnerable for some and very vulnerable for others, depending on how smallholder farmers evaluate their level of sensitivity to the adversities of climate fluctuation and change. The majority of small-scale farmers, according to Awazi et al. (2020), see themselves as severely vulnerable. Even though they did not compute the vulnerability index to compare with farmers' perceptions of vulnerability, the results are comparable. Although research from

Fongnzossie et al. (2018), Funwi et al. (2020), Kasulo et al. (2013), Belaine et al. (2013), Tessema et al. (2013), Burney et al. (2014), Rurinda et al. (2014), Temesgen et al. (2014), and Feleke (2015) indicated that smallholder farmers are vulnerable to climate change challenges, little the findings of this study provided evidence of this ignorance in the northern part of the Centre Region.

These data demonstrate farmers' sensitivity to the effects of climatic threats. These findings are consistent with the findings of the MINEPDED (2021), which said that the agricultural sector in Cameroon will be the most affected by climate change due to its high sensitivity to water supply, erosion, and flooding.

Determinants of smallholder farmers' vulnerability to climate variability and change

Smallholder farmers' sensitivity to climate variation and change has been researched in Cameroon, Africa, and the tropics (Awazi et al., 2019; Molua, 2006; Gbetibouo et al., 2010; Deressa et al., 2011; Yaro, 2013; Rurinda et al., 2014). However, very little of this research has employed quantitative approaches extensively and completely to assess the factors that render smallholder farmers sensitive to climate variation and change. The research of Awazi et al. (2020) in western Cameroon aimed to fill this knowledge gap. According to their findings, three major types of elements - climate-related factors, socioeconomic factors, and institutional factors - were the principal reasons for smallholder farmers' sensitivity to climatic variability and change. These factors have also been emphasized in the current study. In addition, Awazi et al. (2022) showed that the main agroforestry practices that significantly contributed to reducing smallholder farmers' vulnerability to climate change were Taungya, trees on cropland, trees on pasture, home gardens with livestock, and coffee-based agroforestry in the northwest region of Cameroon.

Temperature and rainfall, the two most important climatic characteristics, are the primary vulnerabilities when it comes to climate-related variables that define how vulnerable smallholder farmers are to climate fluctuations and changes, according to Awazi et al. (2020). Furthermore, Chimi et al. (2022) established a compelling case in their study in the Ntui region that the agricultural calendar is disrupted due to high levels of temperature and rainfall unpredictability in recent years, making it increasingly difficult for farmers to plan the agricultural season. Farmers' local knowledge of weather patterns has been challenged as a result of high levels of rainfall, temperature swings, and extreme heat events, making it nearly impossible for them to forecast when the agricultural season will begin and end (Awazi et al., 2020; Chimi et al., 2022). Several studies have found significant levels of fluctuation in climate indices (particularly temperature and rainfall) in Cameroon in recent years (Chimi et al., 2022; Awazi et al., 2019; Gur et al., 2015;

Azibo et al., 2016; Tume and Fogwe, 2018). According to Awazi et al. (2020), climate parameter variations and changes play a key role in smallholder farmers' vulnerability to unfavorable climate variations and changes. The current research does not contradict these findings.

Several studies in Cameroon and Africa have examined some of these characteristics as drivers of vulnerability to climate change, focusing on the socioeconomic and institutional factors that influence smallholder farmers' susceptibility to climate variation and change (Funwi et al., 2020; Belaine et al., 2013; Smit and Wandel, 2006; Challinor et al., 2007; Gbetibouo et al., 2010; Kasulo et al., 2013; Temesgen et al., 2014; Tessema et al., 2013; Burney et al., 2014; Rurinda et al., 2014; Feleke, 2015). The most recent study, by Awazi et al. (2020), assessed the sensitivity of smallholder farmers to climate variability and change, filling in the gaps left by previous studies. Even though Fisher's exact test, which is more appropriate for such investigations, was not used in their work in favor of the χ^2 test. This study's findings have helped to shed light on this statistical difference.

One of the few studies conducted in Cameroon that extensively used quantitative approaches (inferential statistics and binary logistic regression) to demonstrate the significance of socioeconomic and institutional determinants in smallholder farmers' sensitivity to climate variability and change (Awazi et al., 2020). Furthermore, Awazi et al. (2020), Awazi et al. (2020) in his work examines the determinants of smallholder farmers' practice of agroforestry in the face of climate variability and change; and assesses the contributions of different agroforestry practices in reducing the vulnerability of smallholder farmers to climate variability and change, showing that the existence of a statistically significant non-causal relationship between several explanatory variables (number of farms, household size, age of household head, household income, level of education, gender, access to information, level of income, level of wealth, level of income of the household head), household income, level of education, gender, access to information, access to credit, access to land and access to extension services) and smallholder agroforestry practices in the face of climate variability and change indicate that these variables plausibly influence smallholder farmers' decisions to adopt agroforestry practices in the face of climate variability and change. According to the findings, family farms in Obala are just marginally vulnerable to climatic variability and change, whereas those in Batchenga, Ntui, and Mbangassina have considerable vulnerability indices. A significant noncausal correlation exists between vulnerability and four and five continuous and discontinuous explanatory factors, respectively. The binomial logistic regression model demonstrates statistically significant inverse causal links between five of the six explanatory factors and the sensitivity of family farmers to climate change. The drought variable has a significant positive causal relationship. This leads to the conclusion that these six explanatory variables largely impact smallholder farmers' vulnerability to climate fluctuation and change.

On the other hand, having access to information improves smallholders' decision-making capacity. Because they are more aware of current agricultural trends, more knowledgeable farmers adopt better farming practices and agricultural inputs than their less-informed peers. Furthermore, household income is important because, as compared to low-income families, higher-income households can afford better farm inputs, equipment, and food, making them less vulnerable to the negative effects of climate variability and change. Access to land is also important because it is an important and necessary component of agricultural activities. As a result, farmers with greater land can plant a wider range of crops, spreading the risk. Thus, the aforementioned socioeconomic and institutional factors are critical in reducing family farmers' susceptibility to climate fluctuation and change.

In contrast to other studies that have assessed smallholder farmers' vulnerability factors to climate change adversities using different approaches, this study emphasizes the causal and non-causal relationship between climate, socioeconomic, and institutional factors and smallholder farmers' vulnerability to unfavorable climate variations and

changes by primarily using quantitative or inferential techniques. Thus, climate, socioeconomic, and institutional factors primarily determine smallholder farmers' susceptibility to unfavorable climate fluctuation and change in Cameroon's Centre Region.

Conclusion

Family farms are especially vulnerable to the negative effects of climatic variations and changes. They are particularly vulnerable to the negative consequences of climatic variations and changes. In this regard, this article assessed the factors that influence family farmers' susceptibility to climate variability and change in the transition zone between forest and savanna in the northern part of the Centre Cameroon's Region. The study did this by combining primary data (gathered from a survey of 180 smallholder farmers) with secondary data (information on temperature and rainfall). Field observations were also conducted on these family farms in Mbangassina, Ntui, Batchenga, and Obala from January to March 2020, March to May 2021, and July to September 2021. We used statistical tools for both descriptive and inferential analysis. Over the previous ten years, small farmers were found to have experienced the highest temperatures and heat waves. Extreme droughts, which are becoming more common, and falling rainfall totals were thought to be the primary contributors to climate sensitivity.

This study's findings unequivocally show how family farmers interpret various meteorological factors as manifestations of climate variations and changes (rainfall, temperature, and drought). Localized effects can be felt. While family farms in Batchenga, Ntui, and Mbangassina are extremely vulnerable to climate variability and change, those in Obala are only moderately so. A significant noncausal association exists between vulnerability and four and five continuous and discontinuous explanatory factors, respectively. The binomial logistic regression model demonstrates statistically significant inverse causal relationships between five of the six explanatory factors and the susceptibility of family farmers to climate change. The drought variable has a significant positive causal relationship. This leads to the conclusion that these six explanatory variables largely determine smallholder farmers' susceptibility to climatic fluctuation and change. According to the study's findings, family farmers should be given more financial assistance and accurate climate information to reduce their vulnerability to climate fluctuation and change.

In this regard, we acknowledge that the proposed set of indicators can be supplemented by referring to additional vulnerability factors. Further research in this area could focus on the integration of the vulnerability factors studied here, taking into account aspects of different farmer exit strategies, resilience, and, ultimately, the sustainability of the farming systems in the study area. It will therefore be interesting to examine how the analysis's results differ when these factors are taken into account, to better guide the decision-making process.

Based on the findings of the study, policies to mitigate the vulnerability of family farmers to climate variability and change should focus on the five of the six explanatory factors and the sensitivity of family farmers to climate change. In addition, based on traditional knowledge and know-how, policies focused on providing farmers with agroclimatic warning systems.

Declaration of Competing 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 paper.

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Data that has been analyzed without participant identity may be available on request.

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