The Drivers of Vulnerability to Climate Change for Banana Growers in Tanzania

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Abstract

Bananas are a key staple food and cash crop in Tanzania, supporting millions of smallholder farmers with food security and income. However, its production is increasingly constrained by climate change, pests and diseases, soil degradation, and market fluctuations, which threaten both crop output and household welfare. This study examined the vulnerability of banana growers to climate change, and its key drivers. Using the first three waves (2008/09, 2010/11 and 2012.13) of the Tanzania National Panel Survey data (TNPS), a vulnerability index was constructed through principal component analysis (PCA), while drivers of vulnerability were established using a fixed effects model. The results from the PCA show that 89.34% of banana-growing households are highly vulnerable, primarily due to low adaptive capacity. The average vulnerability index for the entire period covered by this study was -56.28, which is considered high; and is mainly attributed to drought and flood shocks, plot slope, and soil erosion. The fixed effects analysis revealed that household education spending and banana sales value significantly reduce vulnerability. In contrast, higher productivity, rising average temperatures, and year fixed effects were found to exacerbate vulnerability. Based on these findings, key policy options include enhancing access to education, agricultural extension services, and good markets; as well as promoting climate-smart agricultural practices. Such measures are vital for building resilience and securing the sustainably of banana-dependent livelihoods.

Keywords: *banana, drivers of vulnerability, climate change, panel data, PCA*

JEL Classification: O13, Q54, Q12

1. Introduction

Bananas are one of the most important staple food crops globally and play a central role in food security and livelihoods. Bananas and plantains rank among the top ten crops worldwide, positioned behind maize, rice, wheat, cassava, and potatoes; but ahead of sorghum, millet, and sweet potatoes (Calberto et al., 2015). In developing countries, bananas are the fourth most important crop after rice, wheat, and maize in terms of production (Lucas & Jomanga, 2021). Beyond subsistence, bananas are a major export commodity in countries such as Ecuador and Costa Rica, generating significant income and employment opportunities (Ferreira et al., 2018).

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In Tanzania, bananas serve as both a staple food and a key cash crop; with demand steadily rising due to population growth, urbanisation, and changing consumption habits. Despite this importance, banana productivity remains critically low. Yields among smallholder farmers average only 6.25 tonnes per hectare; far below the potential of 60–80 tonnes per hectare (FAO, 2012; Lucas & Jomanga, 2021; Shell Foundation, 2023). This underperformance is attributed to factors such as persistent drought, declining soil fertility, poor crop management, pests and diseases, limited genetic diversity, and various socio-economic constraints (Chabi et al., 2018; FAO, 2012). Farmers' limited access to credit, agricultural technologies, and extension services further constrain production efficiency (Mgbenka & Mbah, 2016).

Banana farming in Tanzania is predominantly rain-fed, making it highly sensitive to climatic variability. Although banana plants can withstand water stress for extended periods, prolonged drought and extreme temperatures above 35°C significantly reduce yields (Thornton & Cramer, 2012). Banana yields in areas with annual rainfall below 1,100mm may decline by up to 65% compared to regions with enough rainfall that ranges between 1,100mm and 2,000mm per annum (van Asten et al., 2011). Given that over 95% of crops in Tanzania—and other Sub-Saharan African (SSA) countries—are rain-fed, with less than 5% of land under irrigation (Abrams, 2018; Burney et al., 2013; Sheahan & Barrett, 2017), the sector is highly exposed to climate shocks. SSA is among the world's most vulnerable regions to climate change, experiencing nearly one-third of global droughts (IMF, 2020).

This exposure has far-reaching implications for household welfare, as smallholder farmers rely heavily on bananas for both food and income; yet have limited adaptive capacity to cope with climate shocks (McDowell & Hess, 2012). Farmers' vulnerability varies within and across households depending on roles, responsibilities, and exposure to climate shocks (Kakota et al., 2011; Iqbal et al., 2015). The drivers of vulnerability include droughts, floods, storms, pests, and other climate-related hazards that directly impact productivity and food security (Sujakhu et al., 2018). However, the specific drivers differ by location, farming system, and climatic context (Adger et al., 2007; Cano & Campos, 2024). For example, the factors that make semi-arid farmers vulnerable to drought in Africa may not be the same as those affecting farmers in flood-prone areas elsewhere (Brooks et al., 2005; Lombe et al., 2024).

Given the sensitivity of banana production to climate-induced stresses and the high stakes for household welfare, understanding the drivers of vulnerability is crucial. Yet, in Tanzania, little empirical research has addressed the vulnerability of banana farmers to climate change using panel data. While related studies exist in countries with similar contexts (Deressa et al., 2008; Lokonon, 2019; Sujakhu et al., 2018), most of these studies rely on cross-sectional or time-series data. This study, therefore, fills a critical gap by establishing the specific drivers of vulnerability to climate change among banana-growing households in Tanzania using nationally representative panel data.

2. Theoretical Perspective

This study employs the theory of environmental externality in its analysis. The environmental externality theory posits that individual or collective actions often have unintended consequences—positive or negative—on others; or on the environment, which are not reflected in market prices. These externalities are critical in agricultural systems, as farming households and practices directly affect natural resources, ecosystems, and climate resilience. For instance, overuse of fertilisers or pesticides to increase banana yields may degrade soil quality, thereby intensifying households' sensitivity to climatic shocks (Asumadu-Sarkodie & Owusu, 2016; Rahman et al., 2016). Conversely, sustainable practices—such as intercropping, agroforestry, an increase in income, and irrigation adoption—can reduce negative externalities, and enhance resilience (Jalal et al., 2021).

Literature on vulnerability to climate change identifies three common methods that are usually used in vulnerability assessments. One of the common methods is econometric, followed by the indicator method, and lastly, the simulation method. By applying the econometric method, household-level data are used to assess levels of household vulnerability to climate change impacts. The econometric method is inclined to measure a loss of welfare due to recurring climate change shocks (Hoddinott & Quisumbing, 2010).

Using the indicator method, a set of possible vulnerability indicators is selected and thoroughly incorporated to establish the levels of households' vulnerability. There are several approaches used to understand the importance of each indicator. These include principal component analysis (PCA) (Ochieng & Hepelwa, 2018); an association of current climate shocks and previous catastrophic events (Brooks et al., 2005); application of fuzzy logic; and expert judgment (Chiang & Lei, 2016). The challenge of the indicator method is that there is no agreed-upon way of establishing weights for the indicators used. On the other hand, simulation methods create and analyse a digital prototype of a physical model to predict its performance in the real world. Crop simulation models are an example.

Approaches to household vulnerability analysis consider variations in the characteristics of people in a community. People's differences in a community explain the variations in vulnerability levels amongst them or their households. This study blends socioeconomic and biophysical approaches to vulnerability, and econometric analysis, to assess the drivers of vulnerability to climate change among banana growers in Tanzania. The approach is deemed valuable, especially for policy-related studies, as it can provide clear climate-related policy options (Füssel, 2007).

3. Empirical Evidence

Different approaches and methods have been used to assess vulnerability to climate change in various aspects of households, resulting in mixed outcomes. For instance, Demeke et al. (2011) examined the impact of rainfall shocks on food security and vulnerability among smallholders in rural Ethiopia, using panel data. By classifying households as less secure and more secure, the study found that the more secure households tend to have males and heads who can read and write, more employed members, larger livestock holdings, higher farm outputs due to better use of available rainfall, membership in community savings groups, and a tendency to apply chemical fertilisers on their farms. The fixed effects regression results indicated that rainfall shocks significantly influence household food security over time. Factors such as household size, the age of the household head, participation in local savings groups, non-farm employment, input use like fertiliser, and ownership of farm animals: all were found to positively affect household food security (ibid.).

Another related study is by Sujakhu et al. (2018), who sought the drivers of vulnerability in Asia using cross-sectional data. The study found that a head's education, practicing irrigation, having a non-farm income, and using modern technologies: all correlate to adaptive capacity. Lokonon (2019) assessed farmers' vulnerability to climate distress in Benin using household data by applying indices and ordinary least squares regression (OLS) methods. The index results revealed a vulnerability of 57.43% of the farm households, of which 31.74% were found to be very vulnerable. Furthermore, the study indicates that moderate adaptive capacity does not entail the highest exposure and sensitivity as preconditions for the highest vulnerability. The econometric estimations indicate that the levels of vulnerability increase uniquely depending on the type of climate distress. Ironically, floods were reported as valuable to farmers as they reduce vulnerability (ibid.).

A study by Deressa et al. (2008) examined farmers' vulnerability to climate change in Ethiopia using various indicators related to Ethiopia's agriculture. The study found that regions that are minimally developed and characterised as semi-arid or arid are the most vulnerable to climate change shocks. On their part, Mkonda and He (2018) assessed livelihood vulnerability in Kongwa District; a semi-arid zone of central Tanzania. The study utilised multiple methods for data collection and analysis, such as surveys, key informant interviews, discussions, and direct observation. The findings revealed that climate stress had negatively affected soil quality, vegetation, and crop yields; while also accelerating environmental degradation. Given that most people relied heavily on these resources, their livelihoods had become increasingly vulnerable.

The current study uses a panel dataset to model the vulnerability of banana growers in Tanzania to climate change, unlike many existing studies that use cross-sectional data, which do not control for the endogeneity problem that leads to estimation bias. The study used nationally representative data, which gives the results that can be unambiguously generalised to all banana growers in the country. Unlike other studies, this study focused on a single perennial crop, specifically bananas; a crop that is harvested throughout the year. It contributes to the literature by empirically demonstrating the vulnerability of banana-growing households to climate shocks, such as drought throughout the year and across years. Correspondingly, the data used in this study also provide an edge to control for a household's time-invariant characteristics (fixed effects), like the ability and response to unobservable shocks: an advantage that is missed when other types of data are used. Using these data, the study estimates the evolution of a household's adaptive capacity, sensitivity, and exposure to climate shocks in the three waves; and tells which households are more vulnerable among the banana-growing households.

4. Methodology

4.1 Generating Household Vulnerability Index

The study used the principal component analysis (PCA) to estimate household vulnerability to climate change index. This study followed a straightforward measure of the household vulnerability index (HVI), which encompasses the main components of vulnerability to climate change—i.e., adaptive capacity, sensitivity, and exposure (IPCC, 2007)—and aligned it in the context of households that grow bananas in Tanzania. The PCA enabled the allocation of distinct weights to each kind of vulnerability indicator using factor loadings.

Assuming the first set of correlated indicator variables $(x_1 , x_2, x_3, \dots , x_n)$, non-correlated indices—known as principal components (PCs)—are created, and they are linearly assigned weights from the first indicator variables (Hair et al., 2010). The kth principal component is represented as:

$$PC_k = \sum_{i=1}^{n} w_{ki} x_i \qquad (1)$$

whereby, PC_k represents the k^{th} principal component, and w_{ki} stands for the weight given to the indicator variable x_i.

Accordingly, the first principal component (PC_1) explains the largest variation of the data. This makes PC_1 possess the largest eigenvalue, and therefore a larger percentage of variance. The next principal component (PC_2) accounts for the remaining variation, but is short of PC_1; while the subsequent components explain the remaining variability.

Because the study relies on three waves of household panel data, it is necessary to construct a vulnerability index that remains comparable across time. As per Demeke et al. (2011), the data were pooled, and the principal components were calculated on the aggregate data. The resultant weight was then attached to variable values across each wave. Equation 2 was used to establish a non-standardized index of household vulnerability (*NSI_HVI*). The proportion of variation accounted for by component i to the total variation is the weight assigned to each component i in setting up the vulnerability index. According to Hair et al. (2010), this approach enables the vulnerability index obtained to be comparable across time (Hair et al., 2010). Equation 2 reads:

$$NSI_{HVI} = \sum_{i=1}^{n} \frac{V_i}{TV} * PC_i \qquad (2)$$

Where: NSI_HVI is the non-standardised household vulnerability index; n is the number of components maintained; V_i is the percentage of variation accounted by component i; TV is the total variation in the data accounted by n components kept; and PC_i is the i_{th} component.

Equation 2 yields a non-standardized vulnerability index that has positive and negative values. The household vulnerability index was then calculated as the net effect of adaptive capacity, sensitivity, and exposure:

$$Vulnerability = Adaptive\ capacity - (Exposure + Sensitivity) \qquad (3)$$

To achieve household vulnerability indices that span from 0 to 100 for each indicator in the vulnerability equation, equation 4 was used:

$$HVI = \frac{NS_{HVI} + (-)minNS_{HVI}}{maxNS_{HVI} + (-)minNS_{HVI}} * 100 \qquad (4)$$

A similar approach was applied by Ochieng and Hepelwa (2018). After combining *HVI* from adaptive capacity, sensitivity, and exposure to form a vulnerability index, households with a vulnerability index value of, say, below zero, are vulnerable; and households with a vulnerability index above 0 are perceived as less vulnerable. Histogram bin width was used to classify the levels of household vulnerability. Equation 5 was used to generate the ultimate vulnerability index from adaptive capacity, exposure, and sensitivity:

$$VI = HVI_{ad} - (HVI_{ex} + HVI_{se}) \qquad (5)$$

Where: *VI* is the vulnerability index; HVI_{ad} is the household vulnerability index for adaptive capacity; HVI_{ex} is the household vulnerability index for exposure; and HVI_{se} is the household vulnerability index for sensitivity.

The sampling adequacy was tested using the Kaiser-Meyer-Olkin (KMO) measure. The standard KMO should be greater than 0.5 (Hair et al., 2010). Also, Bartlett's test for sphericity was used to test the correlation matrix using the null hypothesis that the variables are not intercorrelated. If the null hypothesis is rejected, then using PCA is justified.

According to Hair et al. (2010), component loadings of 0.3 are suitable because they have a practical significance, and the sample size for this study is greater than 350. The varimax rotation approach was implemented instead of the promax rotation. The varimax rotation was chosen because it improves the component structure considerably, where the loadings are improved for almost every variable. The loadings are more closely aligned to the objective of having a high loading on only a single component, and one variable (V_1) has a cross-loading (Hair et al., 2010).

Table 1 shows the variables used for the construction of the household vulnerability index from PCA. These variables were derived from existing studies on vulnerability to climate change that largely focused on farming households. To calculate the direction of the relationship in vulnerability indicators (i.e., their sign), a negative value was assigned to both sensitivity and exposure, while adaptive capacity indicators were assigned a positive sign.

Table 1: Variables for Construction of PCA

Adaptive Capacity	Sensitivity	Exposure
Use of pesticides	Chronic disease	Drought shock
Use of irrigation	Plot steepness	Floods shock
Livestock ownership	Agriculture dependency	Crop disease
Radio ownership	Severe water shortage	Extreme rainfall dummy
Mobile phone ownership	Erosion	Extreme temperature dummy
Credit access	Planted below the year 2000	
Intercropping		
Non-agricultural		
Planted in the last 12 months		
Ownership of land		

Source: Existing vulnerability to climate change literature

The 'planted in the last 12 months' variable is a dummy variable that shows whether a household used more recently available improved banana planting materials. Using improved planting materials enhances household adaptive capacity (Larsen, 2015). In addition, 'planted below the year 2000' is a dummy variable that shows whether a household used traditional or improved banana planting materials. Using traditional planting materials makes banana plants more sensitive to climate shocks (Larsen, 2015).

4.2 Model Specification

The environmental externality hypothesis follows the definition of vulnerability to climate change by IPCC (2007). Vulnerability to climate change—as a function of exposure, sensitivity, and adaptive capacity—was modelled around the fixed effects (FE) and random effects (RE) models. FE and RE models can explain or model time-based and individual differences, and they can control for the incidences of missing or unobserved variables. In determining the drivers of household vulnerability to climate change, a panel econometric model was specified as follows:

$$Y_{it} = \beta_0 + \beta_1 X_{it} + \rho T_t + \alpha_i + \mu_{it} \tag{6}$$

Where: Y_{it} is an outcome variable for household i at time t in this study; Y_{it} is the household vulnerability index established using PCA; X_{it} is a vector of explanatory variables for household i at time t; β is a vector of coefficients; α_i represents unobserved household-specific effects, which are assumed to be fixed over time and vary across household i; T_t is the time-fixed effect, which represents the time data were collected; and μ_{it} is the idiosyncratic error term.

The assumption that defines the relationship between the explanatory variables (X_{it}) and unobserved household effects (α_i) differentiates the fixed effects from the random effects models. Using the fixed effects approach, α_i is regarded as non-random; with this regard, (X_{it}) and α_i are correlated. The random effects approach assumes that X_{it} is not correlated with α_i, and this makes the error term bear its effect (Wooldridge, 2002). An important difference between fixed and random effects is whether the unobserved individual effect incorporates traits that are correlated with the regressors in the model, and not whether these effects are stochastic or not (Greene, 2012).

Also, the study used a Hausman test to see if there is a correlation between X_{it} and α_i so that the correct model is specified. If correlation in large samples does not exist, the estimates of fixed effects and those of random effects are the same (Hill et al., 2011). We also tested for the presence of autocorrelation and heteroscedasticity in the model specified. To decide whether to include time-fixed effects in the model, a joint test was conducted to find out whether dummies for all years are equal to zero; and if they are equal to zero, then time-fixed effects would not be included in the model (Wooldridge, 2002).

Table 2 summarises the study's prior expectations. Banana productivity is expected to correlate negatively with household vulnerability, as an increase in banana productivity paves the way for banana value chain participation, which enhances a household's adaptive capacity. Other variables and prior expectations are also summarised in Table 2.

Table 2: Description of Variables Used in the Study

Variable	**Description of variable**	**Sign**
Vulnerabilty_index	A measure of household vulnerability to climate change	+/-
Lnproductivity	Total amount of bananas harvested per acre (Kg/)	-
Age	Age of the household head in years	+/-
Lnbananasold_value	Total value of bananas sold in Tanzanian shillings	-
Lnbanaplts_number	Number of banana plants on a plot	+/-
Hhsize	Number of persons living in a household	+/-
Area	Size of banana plot in acres	+/-
LneducaR	Annual expenditure in education in real terms	-
Average_rainfall	Average annual rainfall	+/-
Average_temp	Average annual temperature	+
Extension1	1 if have access to the government extension service	-

Source: Existing vulnerability to climate change literature

4.3 Data Type and Sample Size

This paper employs the Tanzania National Panel Survey (TNPS) from 2008 to 2013. The first wave of the data was collected between October 2008 and September 2009; the second wave was conducted from October 2010 to September 2011; and the third wave was conducted from October 2012 to September 2013. The study used 104 households from 2008; 241 households from

2010; and 274 households from the 2012 waves. The total number of observations across all waves was 619 households in Tanzania (Mainland and Zanzibar), which led the study to an unbalanced panel dataset.

The optimum rainfall for banana growth is 1000–2000mm per year. To achieve good yields, a well-distributed rainfall of 200–220mm/month is required throughout the year (MOALF et al., 2019). On the other hand, the most favourable temperature range for banana growth is 20–30^{0}C; and exposure to temperatures outside this range for a long time reduces banana production per hectare (Thornton & Cramer, 2012). Temperature and rainfall data were matched to favourable conditions (temperature and rainfall) for growing bananas, and if the data fall outside the favourable range, extreme rainfall or temperature is recorded and given 1; while if they fall within the favourable range, a 0 value is given and makes a dummy variable.

5. Results and Discussion

5.1 Principal Component Analysis

The analysis of PCA maintained four principal components for adaptive capacity, three principal components for sensitivity, and two for exposure based on the Kaiser Criterion and scree plot. Principal components (PC_1, PC_2, PC_3,…….PC_n) are unit-length linear combinations of the original variables (Erhardt et al., 2016). They linearly combine the original variables to maximise the variance explained by the data. The maintained components account for the variance in the dataset for 52.06% of adaptive capacity, 55.77% of sensitivity, and 63.17% of exposure. The percentages were achieved by summing the percentages of variance accounted for by each component in adaptive capacity, sensitivity, and exposure variables. The sampling adequacy and Bartlett's sphericity test were run, and the results were that the Kaiser-Meyer-Olkin statistics were 0.531 for adaptive capacity, 0.519 for sensitivity, and 0.522 for exposure: which are all fairly acceptable. The p-value for Bartlett's sphericity test was 0.000 for adaptive capacity, sensitivity, and exposure; this suggesting the existence of a correlation between the variables in use, and thus validates an application of PCA in the construction of household vulnerability index.

By default, the PCA results in this study are displayed for loadings that are above 0.3 in absolute value. For every principal component maintained, there is at least one variable that it represents. The results of the PCA for adaptive capacity (Table 3) show that the first component (PC_1) accounted for 15.15% of the total variation. This means households that adapt are associated with the use of mobile phones, non-agriculture, have a radio, and own livestock which are the primary source of organic manure used by farmers. The second component (PC_2) explains about 13.0% of the total variation. This means that intercropping and household ownership of land are associated with household food security. The third component (PC_3) accounts for 12.53% of the total variation. It explains the variation in the use of irrigation and planting banana plants in the last 12 months. This can be explained as the use of improved seeds and technology.

Table 3: PCA Results for Adaptive Capacity: Varimax Rotation Component Matrix

Variable	PC_1	PC_2	PC_3	PC_4
Mobile phone ownership	0.6103			
Use of irrigation			0.6860	
Livestock ownership	0.4176			
Non agriculture	0.3270			
Use of pesticides				0.6958
Radio ownership	0.5839			
Credit access				0.6947
Intercropping		-0.6161		
Planted in the last 12 months			0.6947	
Ownership of land		0.6709		
Percent of variance (54.11%)	15.15%	13.00%	12.53%	11.38%

Source: Authors' computation from TNPS data

Component four (PC_4) accounts for 11.38% of the variance in the use of pesticides and credit access. It demonstrates a household's ability to cope with banana production shocks; and diversifying the risk of crop failure through the use of pesticides and access to credit. Table 3 also shows the variables with higher loadings along the first component in adaptive capacity.

These results on household adaptive capacity are in line with those found by Demeke et al. (2011), who noted that ownership of livestock enables a household to carry out farm activities timely, thereby enhancing food security and adaptation to climate change. The findings also corroborate those of Deressa et al. (2008), who found that adaptive capacity is associated with relatively higher access to technology and household irrigation potential in one of the areas in Ethiopia.

The PCA results for sensitivity (Table 4) show that the first component (PC_1) accounted for 20.51% of the total variation. It tells that most sensitive households to climate change are associated with having steep banana plots that have experienced soil erosion. The second component (PC_2) explains about 18.24% of the total variation. This variation is associated with chronic disease and having banana plants planted before 2000. Households that have a member suffering from chronic disease have less time to work on farms as more time is used in caring for the sick, which makes that particular household more sensitive to climate change. The third component (PC_3) explains about 17.02% of the variation. It means that households that are sensitive to climate change are associated with dependence on agriculture, and are also faced with a problem of severe water shortage. Table 4 also shows the variables with higher loadings along the first component for sensitivity.

These findings support those of Deressa et al. (2008) who inferred that the vulnerability of an area is mainly associated with lower levels of development by lacking necessary social services such as health services and water; and also with high dependence on agriculture.

Table 4: PCA Results for Sensitivity: Varimax Rotation Component Matrix

Variable	PC_1	PC_2	PC_3
Chronic disease		0.6936	
Plot steepness	0.6978		
Agriculture dependency			0.7396
Severe water shortage			0.6366
Erosion	0.7062		
Planted below 2000 year		-0.7050	
Percent of variance (55.77%)	20.51%	18.24%	17.02%

Source: Authors' computation from TNPS data

Table 5 provides the PCA estimates for exposure. The first component (PC_1) accounted for 40.73% of the total variation. The component is highly associated with household shocks. It means that banana-growing households that are exposed to climate change are associated with drought and flood shocks. The last component maintained in exposure is component two (PC_2), which accounts for 22.45% of the total variation. Households associated with incidences of crop diseases and extreme rainfall and temperature are well exposed to climate change. These findings echo those of Deressa et al. (2008), who reported that the vulnerability of an area is associated with a high frequency of drought and floods.

Table 5: PCA Results for Exposure: Varimax Rotation Component Matrix

Variable	PC_1	PC_2
Drought shock	0.6691	
Crop disease		-0.3410
Floods shock	0.6595	
Extreme rainfall dummy		0.6660
Extreme temperature dummy		0.6599
Percent of variance (63.17%)	40.73%	22.45%

Source: Authors' computation from TNPS data

On the classification of banana growing households to vulnerability levels, lower values of the vulnerability index show more vulnerability, and higher values depict less vulnerability (more adaptive capacity). Most of the banana-growing households (89.34%) are cumulatively highly vulnerable to climate change shocks, 8.24% are vulnerable as their status can change anytime to highly vulnerable or less vulnerable, and only 2.42% of the sample households are less vulnerable.

Figure 1 depicts the levels of household vulnerability from the PCA results. The classification was made by organizing the data in 10 intervals of the same bin width. Then, those with a vulnerability index lower than -10 are considered highly vulnerable to climate change shocks, and households with an index that lies between -10 and +10 are classified as vulnerable. A household whose index

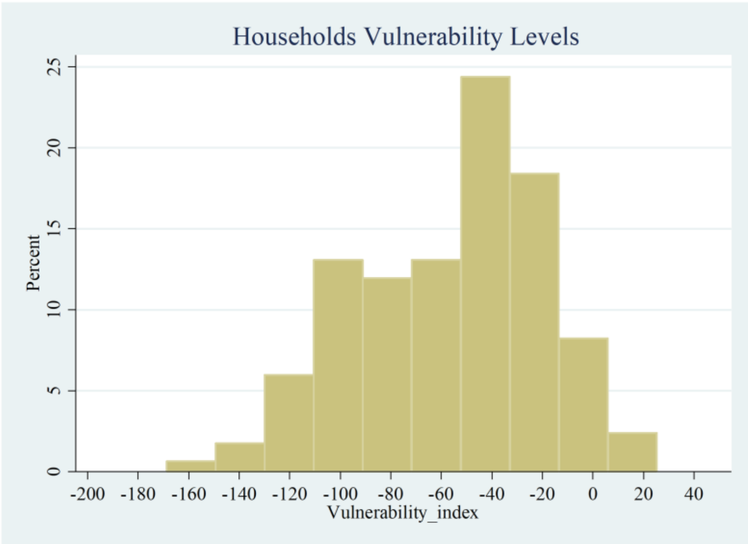

Figure 1: Household Vulnerability Levels

Source: Authors' computation from TNPS Data 2008-2013

is above +10 is considered less vulnerable to climate change shocks. The same classification was used by Lokonon (2019), who revealed that more than half of the sampled farm households were vulnerable to climate shocks; and more than a quarter of them were very vulnerable to climate shocks.

5.2 *Descriptive Statistics*

Table 6 shows the descriptive statistics of the variables used in this study. The table reports sample mean values, standard deviation, and minimum and maximum values for the variables used.

Table 6: Descriptive Statistics

Variable	Obs	Mean	Std	Min	Max
Vulnerability_index	619	-56.28	36.64	-168.84	25.49
Productivity	619	446.58	985.01	8	12600
Age	619	52.07	16.17	21	107
Bananasold_value	619	124664.1	260718.5	1500	2640000
Bananaplants_number	619	436.09	919.00	10	8800
Hhsize	619	5.50	2.68	1	19
Area (acres)	619	2.89	1.31	0.25	25
EducaR	619	179536.8	533062	0	7003812
Average_rainfall	619	826.41	286.39	345	1652
Average_temp	619	220.45	28.49	165	278
Extension1	619	0.12	0.32	0	1

Source: Authors' computation from TNPS Data 2008-2013

The descriptive statistics in Table 6 show that the average vulnerability index for households is -56.28, which depicts high vulnerability according to the levels made from the histogram bin width. The average banana productivity is 446.58kg per acre. Households were made up of heads with an average of 52 years. The average value of bananas sold was TZS124,664.1. The average number of banana plants available on a plot was 436.1 banana trees. Also, the average household size was 5.5 occupants per household. This average is higher than 4.8 and 4.3 occupants per household in the 2012 and 2022 Population and Housing Census reports, respectively (URT, 2024). This difference in household size is attributed to either the sampled banana growing regions having higher household size, or an increase in awareness of family planning in the past decade that is associated with urbanisation.

The average banana plot area was 1.17ha (2.9 acres), which is less than the national average farm size for smallholder farmers in Tanzania of 2.7ha (6.5 acres) per household (NBS, 2021). On average, households spent TZS179,536.8 annually on education. The average annual rainfall was 826.4mm, while the annual average temperature was 22.05^{0}C. Households that receive government extension services were found to be 12% of the study's observations.

5.3 Econometric Analysis

The drivers for vulnerability to climate change for banana growers were estimated using both fixed effects and random effects models. The results were compared using the Hausman test with the null hypothesis that the unobserved household effects are not correlated with the explanatory variables included in the model. Following the analysis, the null hypothesis was rejected (Prob>chi2 = 0.0075). This means that the unobserved effect and the explanatory variables are correlated; hence, a random effect model produces inconsistent results, and the fixed effects model should be used. Therefore, here we report the fixed effects (FE) model computed results. We carried out a test of whether time is needed in a fixed effects model using the null hypothesis that all years' coefficients are jointly equal to zero. The null hypothesis was rejected (Prob>F = 0.0230), hence time was included in the FE model. In addition, a test for nonlinearity in age was carried out to find whether age squared needs to be included in the model. The test result indicates that age is linear; thus, age squared was not included in the model (Prob > chi2 = 0.6299).

The model was used to determine whether the problem of autocorrelation exists. The Wooldridge test for autocorrelation in panel data (Wooldridge, 2002) was employed to assess the presence of serial correlation. The null hypothesis test states that there is no first-order autocorrelation, while the alternative hypothesis indicates the presence of autocorrelation. The test fails to reject the no autocorrelation hypothesis (Prob > F = 0.7637). To make sure efficient estimates are attained, vce(robust) standard errors were used; specifying vce(robust) yields the same standard errors as specifying vce(*cluster id*) (Wooldridge, 2013). The model was significant (Prob > F = 0.0000), implying that the variables jointly explained the variation in the vulnerability index. This confirms the plausibility of the model. The results obtained are presented in Table 7.

Table 7: Drivers of Vulnerability to Climate Change for Banana Growers

Vulnerability Index (Dependent variable)	Fixed effects
Lnproductivity	6.342***
	(1.861)
Age	-0.934
	(3.811)
Lnbananasold_value	-4.064**
	(1.694)
Lnbananaplants_number	3.055
	(1.999)
Hhsize	2.309
	(1.837)
Area	0.074
	(0.948)
LneducaR	-1.680***
	(0.648)
Average_rainfall	-0.011
	(0.101)
Average_temp	4.789*
	(2.570)
Extension1	-7.191
	(5.410)
2010 year	23.62**
	(10.39)
2012 year	29.63*
	(17.48)
Constant	-1,079
	(688.0)
Observations	619
R-squared	0.189
F-Test	3.98***

Note: Robust standard errors in parentheses
***, **; *: Significant at the 1%, 5%; 10% respectively
Source: Authors' estimation based on NPS data 2008-2010

Ironically, an increase in banana productivity is associated with household vulnerability to climate change positively and significantly at a 1% level of significance. This sounds like counterintuitive results implying that an increase in banana productivity by one unit increases the vulnerability of a household by 6.34 points. A possible explanation is that an increase in food crop production correlates with an increase in agricultural land expansion, and unsustainable intensive use of inputs like pesticides and other resources that enhance productivity. Assuming a fixed household banana plot, increased use of variable production inputs such as pesticides, inorganic fertilizers, and other enhancers may initially boost productivity but eventually lead to soil quality decline, resulting in diminishing marginal returns on banana production in the short-run. This makes households vulnerable to climate change in the long-run.

Moreover, an increase in banana productivity may increase the emission of greenhouse gases; an increase that will correlate positively with household vulnerability. In addition, farming methods employed by farmers—such as burning farmlands to clear the land, drying of wetlands, intensive use of agrochemicals like pesticides and inorganic fertilizers, keeping livestock (the main source of organic fertilizer for bananas) that produce methane, and employing fossil fuel in the agricultural production process: all these increase household vulnerability. Similar results were reported by Asumadu-Sarkodie and Owusu (2016), and Rahman et al. (2016).

Income received from bananas sold was found to be negatively related to household vulnerability at a 5% level of significance. The value of bananas sold decreases household vulnerability to climate change by 4.06 points. This may be because when households sell bananas, they earn income which is used to improve dietary requirements, construct or repair houses, acquire better inputs to enhance banana production, and pay for different fees: all of which enhance a household's adaptive capacity. This finding matches those of Challinor et al. (2014).

Household annual expenditure in education had a negative relationship with vulnerability at a 1% significance level. Each additional spending on education by a household reduces a household's vulnerability to climate change by 1.68 points. A possible explanation is that household spending on education generates household members who have a higher chance to work off-farm, resulting in less dependency on agriculture, particularly banana production and other activities, which could trigger negative externality to the environment. Correspondingly, households with high education expenditure are likely to have higher income, which in turn reduces their vulnerability. These results correspond to those found by Lutz et al. (2014), who suggested that more funds should be channelled into education investment for efficient and effective climate funding.

Moreover, the average annual temperature has a positive coefficient, and is statistically significant at a 10% level of significance. According to the results, a unit increase in temperature increases the vulnerability of a household to climate change by 4.79 points. It shows that as the average annual temperature increases, a household's vulnerability to climate change would increase. This may be because an increase in temperature can directly affect plants and animals, wells and other sources of water, shift in weather patterns, and cause a rise in sea levels. The warmer the planet gets, the more serious the impacts on households' welfare and the entire environment. The results support those of Opiyo et al. (2014) and Jalal et al. (2021), who reported a positive relationship between household vulnerability and temperature.

For the years fixed effects, the household vulnerability to climate change in 2010 was 23.62 points at a 5% significance level, and in 2012 it was 29.63 points at a 10% significance level. This may be explained mainly by low levels of households' adaptive capacity. Furthermore, there are annual temperature, precipitation, and drought extremes that are probably getting worse; which lead to irregular and unpredictable banana yields that make households more vulnerable every year.

6. Conclusion and Policy Implications

This study set out to assess the vulnerability of banana growers in Tanzania to climate change using panel data. The findings reveal that a majority (89.34%) of banana growers are highly vulnerable; and the average vulnerability index for the three waves (2008 to 2013) was -56.28, which demonstrates the presence of high vulnerability of banana farming households. This high vulnerability index was associated mainly with drought and flood shocks, plot steepness, and soil erosion. Factors such as productivity, value of bananas sold, and household expenditures on education: all significantly influence the vulnerability of households. Notably—and contrary to expectations—increased productivity was associated with heightened vulnerability; underscoring the complexity of climate-agriculture interactions. However, income from bananas, to a certain extent, offset the vulnerability of banana growers. Climatic variables, particularly temperature, were also found to play a significant role in shaping vulnerability outcomes. These results align with those of previous studies conducted in other developing countries, such as Ethiopia and Benin; while also highlighting unique country-specific dynamics. The findings reinforce the environmental externality theory by demonstrating how production increases, without corresponding climate resilient measures, may exacerbate rather than reduce farmers' exposure to climate risks.

The study contributes to the existing body of knowledge by focusing on banana growers, a group that has received relatively little scholarly attention despite the crop's importance for food security and livelihoods in Tanzania. By applying a panel data analysis, it provides a robust evidence that can guide policy and practice.

The implications of the findings are that, first, there is a need for targeted policies and interventions that promote climate-smart agricultural practices such as the use of improved planting materials, mulching, soil erosion control technologies, and the use of irrigation. Second, interventions that strengthen extension services, expand access to education and skills, as well as access to good banana markets are equally important. All these interventions will lead to a sustainable banana production due to a conserved environment and access to a higher value of the produce.

The analysis in this study focused exclusively on banana-growing households; therefore, the findings cannot be generalised to households cultivating other crops in Tanzania. This is because bananas possess unique characteristics, such as being perennial, propagated vegetatively rather than by seed, and are highly perishable. Therefore, it will be interesting to have a study that focuses on other crops such as maize, rice, wheat, and cassava to assesses the drivers of households' vulnerability to climate change in these crops. Also, the method used in the study to measure household vulnerability to climate change has to be tested in different settings to justify its robustness in measuring household vulnerability to climate change. Hence, this study should be taken as a harbinger for future research.

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