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Assessing the contribution of climate-smart agricultural practices to the resilience of maize farmers in Bungoma County, Kenya

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Abstract

Climate variability threatens farmers' livelihoods. Efforts to address climate stress recognise climate-smart agriculture (CSA) as a promising approach to minimising the damage caused by increasing weather variability. However, the effect of CSA practices on the resilience of maize farmers in the face of climate variability is not well understood. This study assesses the effects of CSA practices on the resilience of maize farmers. Using primary data from 250 randomly sampled maize farmers in Kenya, a resilience index was generated and then analysed using a structural equation model. The results show that CSA practices increase the resilience of farmers, suggesting enhanced resilience to climate variability. CSA practices improve farmers' food security and welfare, and their adoption should be promoted.

Key words: climate-smart agricultural practices; resilience index; stress; structural equation model

1. Introduction

Africa remains particularly sensitive to the effects of climate change and climatic variability because of its low adaptive capacity (Carter *et al*. 2005). Africa's agriculture is being affected negatively by climate change, as evidenced by continuing low crop yields (Oloo 2013). Sub-Saharan Africa (SSA) is experiencing a rise in average temperatures in both water and land areas, extremes of heat in many populated regions, and the likelihood of floods and droughts in many regions (IPCC 2018). Climate change is expected to have a damaging effect on crop production in SSA, greatly affecting the way of life of small-scale farmers (Lobell *et al*. 2011).

Food insecurity has remained high in SSA since 2000, when the United Nations (UN) published its Millennium Development Goals, followed later by the modified version, the Sustainable Development Goals (Herman & Lal 2008). In SSA, per capita maize production has not kept up with population growth over the last 40 years (Smale & Jayne 2003). In the last few decades, maize production has been affected by inconsistent rainfall and changing temperatures. The droughts of the 1990s and 2000s significantly decreased maize production, leading to famine in various parts of SSA

(Msowoya *et al*. 2016). Meeting the food demand in SSA, which relies mostly on rain-fed smallholder agriculture (Nata *et al*. 2014), will likely remain a dream unless major efforts are implemented to reverse the current unfavourable trends in productivity.

Approaches are needed that reduce the variability in yield due to climate change. The use of climate-smart agricultural practices has been found to mitigate the negative effects of climate change by increasing crop yields and incomes and making production systems more adaptive and resilient (Palombi & Sessa 2013). Some agricultural practices and technologies contribute to the reduction of greenhouse gas emissions and sequester carbon in agricultural biomass and soils (McCarthy *et al*. 2011). Climate-smart agriculture facilitates a transition to agriculture and food systems that are more sustainable, productive and climate-friendly (Siminyu *et al*. 2020). Maize-legume intercropping and the application of organic manure have been identified as potential approaches for dealing with the effects of climate change on maize production. A study by Berre *et al*. (2016) found that maize-legume intercropping is the most suitable climate-smart agriculture (CSA) practices for the maize-producing regions of Kenya and that it helps to increase crop diversification, while at the same time providing a cover crop to prevent soil erosion. Crop yields depend largely on the availability of nitrogen at the critical stages of plant growth, and legumes form nodules on their roots that house nitrogen-fixing symbioses with rhizobial bacteria that fix nitrogen from the air for use by the plant (Giller 2001). Organic fertilisers such as manure and compost are essential for increasing soil carbon content, improving soil fertility, accelerating the build-up of fertility, and maintaining soil moisture (Liu & Zhou 2017). Therefore, using organic fertilisers is a climate-smart agricultural practice for sustainable food production (Chauhan *et al*. 2012). CSA practices make maize production more sustainable and make farmers more resilient to shocks (Palombi & Sessa 2013). According to Arslan *et al*. (2017), the influence of organic fertiliser and maize-legume intercropping on maize productivity simultaneously helps to regulate weather shocks. Farmers in regions where precipitation in the cropping season is highly variable and temperatures unpredictably high had significantly low maize yields (Arslan *et al*. 2017).

Resilience has emerged as a lens for examining how a socioecological system (SES) responds to shocks and stresses or perturbations, such as those linked to climate change (Choptiany *et al*. 2015). Resilience is the capacity of a structure to absorb shocks and to restructure towards a more stable state (The Resilience Alliance 2010). Shocks and stresses cannot be avoided, so attention has to be paid to enhancing the resilience of the affected (Mosel & Levine, 2014). Resilience research through different disciplines shows that, historically, individuals and systems have the ability to manage and overcome encounters of hostile events efficiently (Choptiany *et al*. 2015*)*. Development organisations are developing and promoting approaches for households to manage hostile events in agriculture. However, in many scenarios, their investments often focus on reducing short-term risks but avoid building long-term adaptation strategies (Muricho *et al*. 2019). Climate-smart agricultural practices increase sustainability and make farmers more resilient to reduced and more irregular crop yields caused by climate variability (Palombi & Sessa 2013).

According to d'Errico and Di Giuseppe (2018), resilience is a dynamic concept. The capacity to absorb shocks and restructure should be captured to better analyse the long-term effect of shocks and the related coping strategies. Reducing short-term consumption is one short-term coping strategy. In measuring resilience, all possible pathways should be captured in the face of shocks. Faced with a shock, a number of coping strategies need to be applied, including the adoption of new livelihood strategies and the smoothing of assets and consumption. A dynamic analytical framework that covers both negative and positive shocks is crucial for gaining a better understanding of the livelihood strategies of a household affected by shocks. The study of d'Errico and Di Giuseppe (2018) analysed the empirical evidence of what drives changes in the resilience capacity of a system. According to their study, the resilience capacity of a system includes the possible measures that can be taken to deal with stresses or shocks. Their paper applied econometric methods to estimate households' resilience, and they adopted a change matrix to estimate how resilience varies over time. They also provided an evidence-based analysis of the main drivers of resilience. Their study recommends that policies to enhance resilience should connect development and humanitarian involvements by demonstrating how long-term viewpoints can lead to an increase in capacity for resilience. In the long term, the strategies could lead to a decrease or increase in output. Any change in output affects resilience capacity, which may influence the future capacity to react to shocks.

Climatic variability and low soil fertility stand out as the main causes of low maize yields in Kenya, including in Bungoma County, our study area (Wabwoba 2017). According to Mumo *et al*. (2018), maize yields in the county are reducing significantly, at a rate of 0.07 tons/ha/decade, with a high inter-annual variation. The drop is attributed to a significant reduction in seasonal precipitation and rising temperatures (Mumo *et al*. 2018). To tackle such challenges, Black *et al*. (2011) recommend using investments, innovations and deliberate efforts to empower the world's most vulnerable populations by constructing a global food system that adapts to climate change and ensures food security, thus reducing poverty while minimising greenhouse gas emissions and sustaining the natural resource base.

Efforts to address climate-related stress in agriculture recognise CSA as a promising approach. However, the effect of CSA practices on the resilience of farmers so that they can continue to produce maize with yields that are driven by climate variability is not known. This study analyses the effect of the CSA practices of maize-legume intercropping, the use of organic fertiliser, and the planting of high-yielding certified maize varieties on the resilience of farmers. The study tests the hypothesis that CSA practices enhance the resilience of maize farmers to the yield variability brought about by climate change. It contributes to knowledge by analysing how yield variability could decrease, suggesting enhanced resilience to climate variability. It generates a maize farmer resilience index and uses a structural equation model to analyse the factors, including CSA practices, that affect the resilience of maize-farming households.

2. Materials and methods

2.1 Analytical framework

This study used the structural equation model (SEM) to analyse farmers' increased resilience to climate change as a result of using CSA practices. There are three main advantages to using the SEM (Alan 2013). Firstly, the SEM makes it possible to identify direct and indirect effects. Direct effects refer to the direct relationship between the dependent (latent) variable and the independent variables related to it. The indirect effect takes place when one variable has an influence on another variable through a third dependent or independent variable. An indirect effect indicates, for example, that the age of a household head could have an indirect effect on the resilience capacity index (RCI). The second advantage is the possibility of having multiple indicators that explain the latent variable. It is possible to evaluate the effect of single indicators on the dependent variable, taking into account other indicators. The third advantage is that measurement errors can be included in the model, which is the main difference compared with using path analysis. Path analysis includes an error term in the prediction, but unfortunately does not control for measurement error during the process. The SEM analysis, in accounting for measurement errors, provides a better understanding of how well the model predicts the actual outcome, minimising the discrepancy between the covariance matrix of the observed variables and the theoretical covariance matrix predicted by the model structure (Bollen *et al*. 2010). The SEM allows for model calibration until a satisfactory level of goodness of fit is achieved.

2.2 Resilience pillars

Measuring the resilience capacity of a household needs a multidimensional tactic. The main question is which components to include in the model, and this was determined by examining the major household strategies for building resilience. All major methods to measure resilience recognise the significance of two broad groups of indicators: a natural base, and an enabling capacity for transformation and adaptation.

Some of the fundamental pillars of resilience are the following: income and food access (IFA); adaptive capacity (AC); productive assets (AST); access to basic services (ABS); and social safety nets (SSN) (d'Errico & Di Giuseppe 2018).

Income and food access are important aspects of household livelihood, as they can determine disparities in income and, consequently, in food security. IFA is denoted by the following: daily income of those employed; the average number of meals consumed per day; the amount spent on buying food items per week; and the extent of food insecurity during the months of inadequate food supply (d'Errico & Di Giuseppe 2018).

Adaptive capacity is the ability of a household to adapt to a new situation and develop new sources of livelihood. In this study, the adaptive capacity took the dimension of the following variables: working on-farm and off-farm; level of education of the household head; using CSA practices in maize production; membership of savings or credit institutions; and sources of income for the household.

Productive assets are those that enable households to produce consumable or tradable goods. This was represented by (i) a household's total land area under maize production in the long rainy season of the year 2017, and (ii) the number of 90 kg bags of maize produced. Access to basic services, such as schools, health centres, water and electricity, and nearby markets, is a fundamental aspect of resilience.

Social safety nets include both formal and informal transfers; access to transfers, whether cash or in kind, represents a major source of poverty alleviation in many developing countries. The social safety nets are represented in our model by two variables: provision of farm labour and borrowing from neighbours.

2.3 Sampling and data collection

Farmers in Bungoma County are experiencing the effects of climate change on agriculture through changes in temperature and precipitation. These changes directly affect crop production and the distribution of agroecological zones, runoff and water availability, which influence crop production (Oloo 2013). Crop yields for smallholder farmers become smaller each season (Oloo 2013). Agricultural stakeholders should support and promote sustainable practices for increased productivity that help farmers adapt to and mitigate the effects of climate change (County Government of Bungoma 2018). Through the Kenya Agricultural Carbon Project (KACP), the non-governmental organisation (NGO) Vi Agroforestry trains farmers in Bungoma County in different CSA practices, including agroforestry, the use of cover crops, mulching, and the use of green manure to increase the organic content of the soil (Coe *et al*. 2014).

Data was collected in Bungoma County, Kenya using multistage sampling. In the first stage, Bungoma County was purposively selected because of the popularity of maize farming and the active intervention by Vi Agroforestry in promoting CSA practices. In the second stage, a list of villages in the county was generated, and ten villages were selected proportionate to size: villages with the highest number of maize farmers were selected. The third stage involved listing maize farmers within each of the selected villages, followed by randomly sampling of 25 farmers in each village. The selected farmers were visited in April 2018 by trained enumerators for computer-assisted personal interviews (CAPI) using a pretested, semi-structured questionnaire programmed in open data kit (ODK). Data was collected on household characteristics, maize production and sales, postharvest losses, amount of money spent on food, type of safety nets used, causes of inadequate food supply and related coping strategies, practices applied to cushion against future maize losses, expenditure on food, kinds of shock due to climate change in maize production, and what was done to manage the shocks.

2.4 Estimating resilience

The Resilience Index Measurement and Analysis (RIMA) approach is focused on two related analyses of resilience: capacity and structure. The aim of the analysis of the Resilience Structure Matrix (RSM) is to identify the causes of resilience. It first assesses the observed variable weights, then identifies their comparative input in determining the pillars, and finally assesses the weights of the pillars in their contribution to determining the Resilience Capacity Index. The analysis of the RCI compares the resilience index across different households (male-headed vs. female-headed; urban vs. rural; or regional-level differences). According to the Food and Agriculture Organization ([FAO] 2013), this is probably to understand which profiles show a higher or lower capacity of coping with stressors and shocks.

As discussed above, resilience is considered an unobservable index that is calculated as a function of five pillars: income and food access (IFA); adaptive capacity (AC); assets (AST); access to basic services (ABS); and social safety nets (SSN):

$$R_{i,t} = \mathrm{f}\left(IFA_{i,t}, AC_{i,t,}AST_{i,t,}ABS_{i,t,}SSN_{i,t,}\right) + \acute{\varepsilon}_{i,t} \quad (1)$$

The resilience index of the i^{th} household depends on the levels of IFA, ABS, AST, SSN and AC at time t, plus the error term.

A two-step estimation is involved in the procedure. In the first step, an estimation is made of the factor analysis of the resilience pillars, which is subsequently employed in the estimation of household resilience capacity. During factor extraction, the shared variance of the variables is separated from their unique variance and error variance to reveal the underlying factor structure; only shared variance appears in the solution. A sufficient number of factors are considered to make sure that they account for at least 95% of the explained variance (Preacher *et al*. 2013).

Despite a large number of latent variable models, Resilience Index Measurement and Analysis adopts a structural equation model that includes the correlation between residual errors and several formal statistical tests and fit indices.

The maize resilience index that was generated in this study is a weighted sum of the factors. Table 1 shows the variables used to generate the maize resilience index. As the Kaiser-Meyer-Olkin (KMO) values are close to zero, it means that there are numerous partial correlations compared to the sum of correlations. There are widespread correlations, which are a big problem for factor analysis. KMO values between 0.7 and 1 indicate that the sampling is adequate (Muricho *et al*. 2019).

Table 1: Variables used to generate the maize farmer resilience index

Variable	Percentage	Mean	Std. Deviation
Amount spent per week on food in Ksh		2103	802.9
Number of 90 kg bags of maize produced		16.2	10.4
Number of 90 kg bags of maize consumed		6.4	3.9
Number of 90 kg bags of maize sold		10.2	6.9
Number of 90 kg bags of maize lost		5.9	3.8
Farm labour as the type of safety net	46		
Causes of inadequate food supply (poor harvest and high prices).	49		
Borrowing from neighbours as a coping strategy	54		
Using CSA practices as a coping strategy	51		
Using animal manure as fertiliser to cushion against future losses	82		
Expenditure on food reduced in the last six months	62		
State of household income reduced in the last six months	62		
Crop pests and disease as a kind of shock experienced by the farmer	72		
On-farm and off-farm casual jobs to manage shocks	51		
Adapting CSA practices to manage shocks better in the future	60		
Number of observations = 224 Chi-square = 1 447.2; degrees of freedom = 153, P-value = 0.000; H_0 – variables are not intercorrelated Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy = 0.72; extraction method: principal component analysis			

Source: Survey data

According to Latif *et al*. (2018), the main objective of principal component analysis (PCA) is to transform variables into smaller sets of linear combinations. It consists of the following steps: data matrix construction; creation of standardised variables; correlation matrix calculation and determination of eigenvectors; panel component (PC) selection; and presentation of the results (Latif *et al*. 2018). This study generated a maize farmer resilience index (MFRI), which is a weighted index of all the fifteen maize farmer indicators in the PCA. The index provides a relative weighted index that contains the variables used in the study. Table 2 shows the PCA analysis for the MFRI.

Table 2: Results of the principal component analysis (PCA) eigenvalues of the observed matrix

Component	Eigenvalue	Difference	Proportion	Cumulative
Component 1	3.325	0.942	0.222	0.222
Component 2	2.383	0.896	0.159	0.381
Component 3	1.487	0.132	0.099	0.480
Component 4	1.355	0.166	0.090	0.570
Component 5	1.189	0.181	0.079	0.649
Component 6	1.008	0.093	0.067	0.716
Component 7	0.914	0.138	0.061	0.777
Component 8	0.776	0.109	0.052	0.829
Component 9	0.667	0.130	0.045	0.874
Component 10	0.537	0.028	0.036	0.909
Component 11	0.509	0.153	0.034	0.943
Component 12	0.356	0.110	0.024	0.967
Component 13	0.246	0.050	0.016	0.984
Component 14	0.196	0.145	0.013	0.997
Component 15	0.051	0.000	0.003	1.000

Source: Survey data

The maximum eigenvalues of the observed matrix are 3.325 for the first factor, 2.383 for the second factor, and 1.487 for the third factor, with a decreasing trend up to 0.051 for the fifteenth factor, which is the lowest (Table 2). The proportional variation for the first factor is 22.2% and for the second factor it is 15.9%. In Table 3, this study presents the eigenvectors indicating the first six principal component factor loadings. All the principal component factor loadings have negative values with considerable lowest values, except for Component 1.

Table 3: Results of the principal component analysis: eigenvectors

Variable	Comp 1	Comp 2	Comp 3	Comp 4	Comp 5	Comp 6
Log amount spent per week on food in Ksh	-0.031	-0.043	-0.540	0.111	0.434	0.103
Log number of 90 kg bags of maize produced	0.523	-0.017	-0.087	0.102	0.044	0.003
Log number of 90 kg bags of maize consumed	0.485	-0.016	-0.101	0.047	0.056	0.102
Log number of 90 kg bags of maize sold	0.507	0.000	-0.057	0.078	0.020	-0.076
Log number of 90 kg bags of maize lost	0.402	0.028	0.093	0.037	-0.244	-0.142
Farm labour as the type of safety net	-0.057	0.050	0.537	0.178	0.236	-0.335
Causes of inadequate food supply (poor harvest and high prices)	-0.117	0.291	-0.391	-0.173	-0.016	-0.054
Borrowing from neighbours as a coping strategy	0.140	0.059	0.260	-0.496	0.344	-0.349
Using CSA practices as a coping strategy	0.119	0.517	0.045	0.026	0.063	0.094
Using animal manure as fertiliser to cushion against future losses	-0.010	-0.077	0.197	0.366	0.139	0.189
Reduced expenditure on food in the last six months	0.046	0.145	0.223	-0.212	-0.525	0.484
State of household income reduced in the last six months	0.036	0.051	0.259	0.163	0.454	0.588
Crop pests and diseases as a kind of shock experienced by the farmer	-0.064	0.113	-0.069	0.646	-0.247	-0.300
On-farm and off-farm casual jobs to manage shocks	-0.044	-0.569	0.066	0.086	-0.074	0.050
Adapting CSA practices to manage shocks better in the future	0.107	-0.523	-0.066	-0.172	-0.033	0.018

Source: Survey data

3. Analysing the resilience of maize farmers using CSA practices

To test the contribution of climate-smart agricultural practices to the resilience of farmers statistically, and in particular the contribution of maize-legume intercropping and using manure as fertiliser, a structural equation modelling (SEM) with a latent (unobserved) variable was estimated. The study first identified the latent variable structuring the model and its constituent indicators. Then the model was validated by the construction of the latent variable using factor analysis and, finally, an SEM was built and tested by assigning the relevant relationships between the latent variables. The structural equation model was built and tested in Stata 13 by assigning the relevant interaction among the unobserved variables.

3.1 Latent variables and indicators

With one latent variable at a probability level of 0.05, the recommended minimum sample size is 200 (Wolf *et al*. 2013); a minimum sample size of 200 will develop the model structure, and a minimum sample size of 87 will detect the effect of the model (MacCallum & Austin 2000). This study identified and extracted the food security (FS) latent variable expressing the resilience of farmers who were intercropping maize with legumes and using manure fertiliser.

The food security (FS) latent variable was measured by the following three indicators: the average number of meals consumed in a day when the household was food secure (FS1); the average number of meals the household consumed in a day when it was food insecure (FS2); and the amount spent on food per week when the household did not have any mature crops on the farm (FS3). Variables FS1 and FS2 took values from one to four: one showed that the household had no meals in a day, implying that it was food insecure; four meant that the household had four meals in a day, implying that it was food secure (Clover 2003). Climate change and related variabilities such as droughts and floods tend to reduce food production and increase shortages in households, leading to a reduction in the number of meals taken per day to two instead of three or four, as was common 10 years ago (Saronga *et al*. 2016). FS3 is a continuous variable. When nearly all the household income is being spent on food, a household is prone to severe food insecurity (Chinnakali *et al*. 2014).

As a test of the validity of the latent variable, this study undertook factor analysis with varimax rotation. Each set of variables was loaded onto a separate factor, and only one factor was retained and taken to represent the food security latent variable. The individual factor analyses extracted a single factor, with all variable loadings above 0.7, which is above the 0.5 recommended value threshold (Toma *et al*. 2008), generating a maize farmer resilience index. This established that the choice of observed variables was reliable by their empirical significance.

3.2 Latent variable modelling with a structural equation model

A structural equation model (SEM) was used to analyse farmers' resilience, with the resilience index generated used as the dependent variable. The relationships between behaviours and attitudes are well understood using the SEM, which is used in investigating the linkages among variables (Toma *et al*. 2008).

This study built and tested the SEM by assigning the relevant relationships in the latent variable. The basic structural equation model has two parts: the measurement model, identifying the interactions among the latent variables and their constituent pointers, and the SEM, designating the causal interactions among the latent variables (Toma *et al* 2008).

The model is defined in matrix terms by the three equations below:

- the SEM: $\eta = B\eta + \Gamma\xi + \zeta$,
- the model that measures y: $y = \Lambda y\eta + \varepsilon$, and (2)
- the model that measures x: $x = \Lambda x\xi + \delta$,

where: η is an mx1 random vector of endogenous latent variables; ξ is an nx1 random vector of exogenous latent variables; B is an mxm matrix of coefficients of the η variables in the structural model; Γ is an mxn matrix of coefficients of the ξ variables in the structural model; ζ is an mx1 vector of equation errors (random disturbances) in the structural model; y is a px1 vector of endogenous variables; x is a qx1 vector of predictors or exogenous variables; $y\Lambda$ is a pxm matrix of coefficients of the regression of y on η; $x\Lambda$ is a qxn matrix of coefficients of the regression of x on ξ; ε is a px1 vector of measurement errors in y; and δ is a qx1 vector of measurement errors in x.

The structural equation model takes into account the direct and indirect causal relationships among constructs, meaning that one causal relationship may be strengthened or offset by another.

4. Results and discussion

4.1 Demographic characteristics of the farmers

The participating household heads had an average of 10 years of schooling. There was a positive correlation between the MFRI and the education of the household heads (see Table 4). According to Paltasingh and Goyari (2018), education is an important factor in the adoption of technology and significantly increases the adoption of farm technologies, and hence productivity levels.

Table 4: Correlation coefficient

	MFRI	Education	Age	Gender	Income
MFRI	1.00				
Education	0.37	1.00			
Age	0.14	0.32	1.00		
Gender	0.03	0.04	0.09	1.00	
Income	0.29	0.14	-0.03	0.01	1.00

Source: Survey data

Among the households, 84% intercropped maize with legumes and 31% applied manure to the maize crop. Intercropping maize with legumes increases the accumulation of nitrogen in the soil and crop residues, leading to sustainable crop production (Punyalue *et al*. 2018). Using animal manure as fertiliser helps to maintain crop productivity, decreases environmental degradation, and keeps the soil healthy (Chauhan *et al*. 2012). The adoption of CSA practices and improved maize varieties improves the welfare and enhances the crop productivity of the farming community (Wossen *et al*. 2017).

The sampled farmers experienced the following types of shock: crop pests and diseases (72%); drought (16%); and soil erosion (12%). Constraints in crop production that increased the shocks to farmers included pest resistance, water depletion, soil nutrient depletion, soil and water contamination, and the emergence of new pests and diseases (Reynolds *et al*. 2015). In Africa, the effects of climate change will cause the pervasiveness of crop pests and diseases to vary, hence agricultural production will be at risk (Smith 2015). All the farmers had noticed reduced rainfall and prolonged drought in the region.

4.2 Maize farmers' resilience

4.2.1 Percentage distribution of household resilience

This study generated a household resilience index related to maize. The resilience index was rescaled to lie between 0 and 1. When a household had a rescaled resilience index nearing 1, the household was said to be resilient. Farmers used climate-smart agricultural practices because of their potential to enhance food security and the resilience of the farming system (Khatri-Chhetri *et al*. 2017). The resilience indices calculated were distributed as shown in the kernel density estimation (Figure 1). Most households had a resilience index distribution of between 0.34 and 0.66, showing a medium resilience capacity, with the remaining farmers having a resilience index of between 0 and 0.33, and only a few farmers had a resilience index between 0.67 and 1.

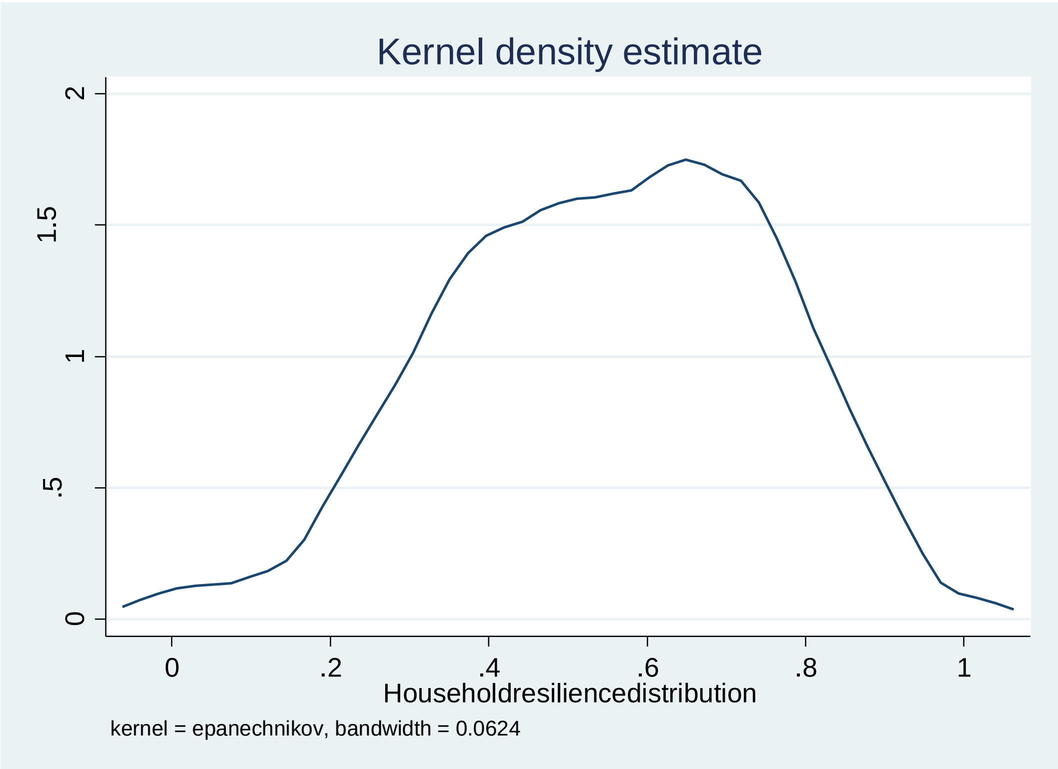

Figure 1: Distribution of household resilience
Source: Survey data

Bartlett's score of sphericity had a *p*-value of 0.000, which is highly significant at 1%. Hence the study rejected the null hypothesis, as the variables were intercorrelated. With a 0.72 KMO measure of sampling adequacy above the recommended 0.5 minimum, unbiased inferences can be drawn from the indices constructed with the variables.

An SEM model was used to analyse the maize resilience index generated. The optimal estimated model includes one exogenous latent variable, namely food security (FS), predicted by the average number of meals consumed in a day when the household was food secure (FS1), the average number of meals the household had in a day when it was food insecure (FS2), and the amount spent per week on food when the household did not have any mature crops on the farm (FS3) (see Figure 2). The model has an adequate fit according to the measures of absolute, incremental and parsimonious fit (Toma *et al*. 2008). A combination of technological, policy and institutional solutions will help in managing the climate-related risks of vulnerable farming communities (Shiferaw *et al*. 2014).

The study analysed the SEM in a two-step procedure – measurement model and structural model. The results of the measurement model showed that the set loadings of indicators for the latent variable were statistically significant. The coefficients of FS1, FS2 and FS3 were above the recommended minimum value of 0.20, and therefore supported the theoretical basis for the assignment of indicators to the construct (Toma *et al*. 2008).

The goodness of fit of the SEM for this study was tested by the overall model fit (Worthington & Whittaker 2006), which confirmed whether the model fitted the experimental data (MacCallum & Austin 2000). The dimensions of the variables were correlated with the food security latent variable, and the factor loadings or correlation score, as shown above the arrows in Figure 2 (FAO 2013), represent how the variable is weighted with the factor.

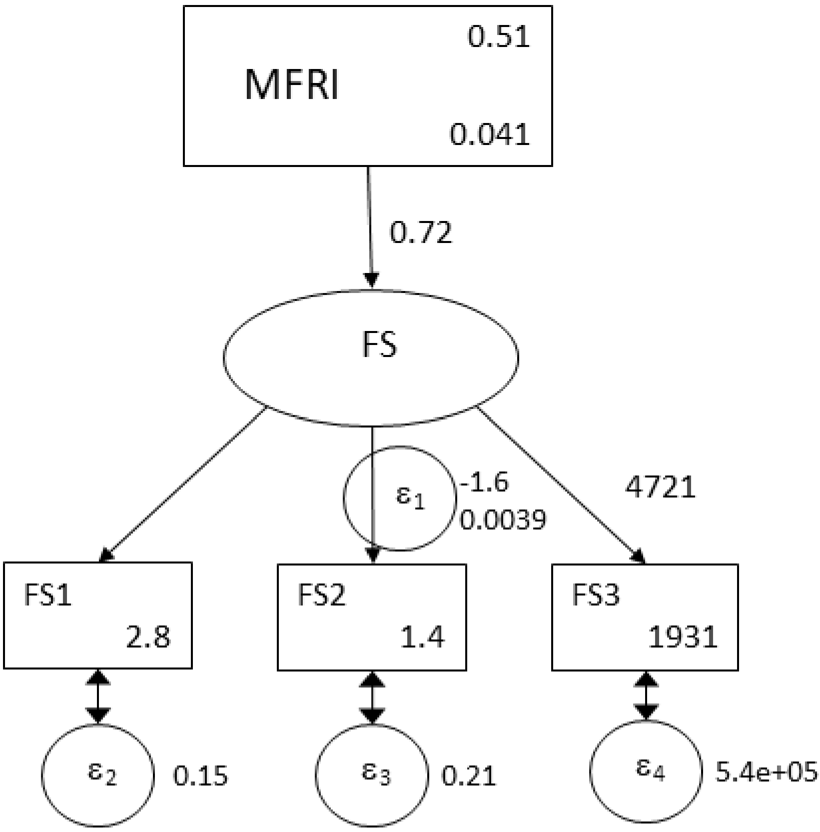

Figure 2: Path diagram for the estimated SEM
Source: Survey data
Notes: FS – food security; MFRI – maize farmer resilience index

With a Chi-square value of 0.16 and a very high p-value of 0.9843 for the test, it holds that there is no significant difference in the covariance matrices of the observed and the estimated models, therefore indicating excellent fit. The root mean square error of approximation (RMSEA) was 0.07, the comparative fit index (CFI) was 0.97, and the Tucker-Lewis index (TLI) was 0.91, all indicating a good model fit for the data (Pituch & Stevens 2016; Stegmann 2017) (Table 5). The overall SEM was significant, with a low log likelihood of -2 267 and a Chi-square value of 5.7 (MacMallum & Austin 2000).

Table 5: SEM estimation

Resilience index	Coefficient	Z	R^2
FS1	0.87***	96.42	0.99
FS2	0.47***	41.03	0.88
FS3	0.74***	39.59	0.87
Root mean squared error of approximation = 0.07 Comparative fit index = 0.97 Tucker-Lewis index = 0.91			

This study therefore rejects the null hypothesis and concludes that both maize-legume intercropping and the use of manure as fertiliser enhance the resilience of farmers. Environmentally friendly practices in crop production cushion food security from the increasing weather shocks, as observed elsewhere (Arslan *et al*. 2017).

5. Conclusion and policy implications

This paper presents the findings of a study on the contribution of CSA practices to the resilience of maize farmers. The study generated a resilience index from the household data collected to identify where the farmers fell on a resilience score between 0 and 1 after using CSA practices. With a 0.72 KMO measure of sampling adequacy above the recommended 0.6 minimum, the study concluded that maize farmers affected by climate variability were more resilient when they used CSA practices.

To analyse the maize household resilience index, the study used a structural equation model (SEM), which was significant. The results indicate that both maize-legume intercropping and the use of manure as fertiliser reduce the variance in maize yields, suggesting that they enhance the resilience of maize farmers. In conclusion, these findings call for stakeholders in the agricultural sector to train and encourage farmers to use climate-smart agricultural practices in their crop production. This will help farmers to sustain their livelihoods in an environment of variable yields.

These findings imply that CSA practices are welfare-enhancing and underscore the need to promote their wide-scale adoption among farmers.

6. Need for further research

There are very few studies that focus on how farmers become resilient when they use climate-smart agricultural practices in crop production. This study assessed the effects of CSA practices on the resilience of maize farmers in the face of climate variability.

More research needs to be done on how farmers become resilient when they use climate-smart agricultural practices when producing different crops on the farm.

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