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Effect of climate-smart agricultural practices on household food security in smallholder production systems: micro-level evidence from Kenya

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Abstract

Background: Climate change in Sub-Saharan Africa has had a negative impact on agricultural production leading to food insecurity. Climate-smart agricultural (CSA) practices have the potential to reverse this trend because of its triple potential benefits of improved productivity and high income, reduction or removal of greenhouse gases and improved household food security. Hence, we empirically find the determinants of choice and the effect of CSAs on household food security among smallholder farmers in Kenya.

Methods: Primary data were collected in Teso North Sub-county, Busia County of Kenya, among smallholder farmers. CSA practices used by farmers were grouped by principal component analysis and linked to food security by multinomial endogenous switching regression model.

Results: With the application of principal component analysis, we clustered the CSA practices into 4 components: crop management, field management, farm risk reduction and soil management practices. We find that the greatest effect of CSA adoption by smallholder farmers on food security is when they use a larger package that contains all the four categories of practices. Adopters of this package were 56.83% more food secure in terms of HFCS and 25.44% in terms of HDDS. This package mitigates upon the impacts of climate change as well as enhancing nutrient availability in the soils for higher productivity. Further, adoption of this package was positively influenced by gender of the household head, farm size and value of productive farm assets.

Conclusions: CSAs have the potential to alleviate food insecurity among smallholder farmers if used in combinations and to a larger extend. To enhance adoption, land fragmentation should be discouraged through civic education and provision of alternative income-generating activities for farmers to benefit when practiced on relatively bigger land. Farmers should be sensitized on the need to invest in farm productive assets in order to absorb the risks of climate change while enhancing adoption of CSA practices.

Keywords: Climate-smart agricultural practices, Food security, Climate change, Smallholder farmers, Multinomial endogenous switching regression analysis

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Introduction

Climate change is a threat to food security systems and one of the biggest challenges in the twenty-first century [1]. The ability to contain the pace of climate change by keeping temperature rise within 2 °C threshold is now curtailed, and the global population will have to deal with its consequences [2]. This is in the context that agricultural production systems are expected to produce food for the global population that is projected to be 9.1 billion people by 2050 and above 10 billion by the year 2100 [3]. According to [4], agricultural systems should be transformed to increase the productive capacity and stability in the wake of climate change. Climate change has already caused significant impacts on water resources, human health and food security [1]. The steady rise in temperature and irregular rainfall patterns affect agricultural production with the attendant decline in crop and livestock production.

In Sub-Saharan Africa (SSA), poverty reduction and food security improvement are among the many challenges that governments face. These governments constantly face a trade-off between food production which generates significant amounts of green house gas (GHG) and mitigation of climate change which requires reduction in some agricultural activities [3]. For instance, ruminant production contributes a significant amount of methane gas to the atmosphere, yet it is an important exercise to meet the food demand and income for farmers [1]. Addressing these antagonistic objectives has proved challenging. Attention in the literature has mostly focused on the low and stagnant returns from African agriculture [3, 5]. Moreover, many ecosystem services, including nutrient cycling, nitrogen fixation, soil regeneration and biological control of pests and weeds, are under threat in African food production systems and have serious implications on smallholder sustainable food security [6–8]. SSA continues to significantly face declining fallow periods, with inadequate investment in sustainable intensification and veering off from diversification in favour of mono-cropping in otherwise traditionally complex farming systems [6]. The result of this trend is food insecurity brought by the low agricultural production, especially under the conditions of climate change.

Climate change in Kenya is quite evident indicated by a continuous rise in temperature [9]. Generally, irregular rainfall patterns continue to be experienced with intense downpours causing floods in many parts which appear in cycles with severe droughts. Specifically, both day and night temperatures have significantly been on a rising trend since the 1960s. For instance, the night temperature (minimum) has risen by 0.7–2.0 °C and the day temperature (maximum) by 0.2–1.3 °C, depending on the season and the region [10, 11]. Further, these unprecedented changes in climate have accompanied losses that have already been experienced in the country [10]. For instance, evidence indicates that between 1999 and 2000 droughts in Kenya caused damages equivalent to 2.4% of gross domestic product (GDP) [9]. The report further indicates that the projected annual cost of climate change impacts will be in the tune of USD 1–3 billion by the year 2030 [9].

Majority of smallholder farmers in Kenya depend on agriculture for survival [12]. Building their adaptive capacity and resilience to climate change is key to enable them protect their livelihoods and ensuring their food security. The ability to cope with the impacts of weather shocks and natural disasters brought by the effects of climate change depends largely on the household's resilience, or its capacity to absorb the impact of, and recover from, a shock [13]. One way of combatting the effects of climate change is through climate-smart agricultural (CSA) practices [1, 11, 14, 15]. Promoters of CSA adoption seek to sustainably increase agricultural productivity and incomes by building resilience through adapting to changes in climate and reducing and/or removing GHGs emissions relative to conventional practices [1]. Strengthening Adaptation and Resilience to Climate Change in Kenya Plus (StARCK+) Programme identifies poverty, weak institutions and under-investment in key sectors as the main factors which stifle Kenya's ability to cope with climate change.

Climate change is a serious threat to local food production and family well-being resulting in malnutrition, hunger and persistent poverty in many regions of Kenya [16]. Despite the multiple benefits of CSAs and the deliberate efforts by the government and development partners to encourage farmers to invest in them, there is still a lack of evidence on farmers' incentives, conditioning factors that hinder or accelerate usage and impact of CSAs on food security status. Thus, an improved understanding of farmers' adoption behaviour and the potential welfare effects in terms of food security is important in informing the strategies policy makers and other development partners could champion in enhancing usage and effectiveness of CSA practices in smallholder production systems.

Based on the foregoing, the objectives of this study are twofold. We first seek to determine the factors that influence the choice of CSA practices in smallholder production systems. Secondly, we explore the effect of the CSA practices on household food security. To achieve these objectives, we use a micro-level data set of smallholder farmers in Kenya. This paper contributes to the literature as follows. First, we group the CSA practices based on usage by farmers in a principal component analysis (PCA). This departs from use of the conventional groups used by earlier researchers [8, 17, 18] which could potentially present difficulties, especially where few or even one strategy represents the entire group leading to a weak attribution of the impacts of such groups. Secondly, we also evaluate the influence of farmer perception on soil conditions and past experiences with climate-related shocks on adoption of climate-smart agricultural practices. Lastly, we link smallholder farmer's usage of CSA practices with household food security status to provide micro-level evidence. A multinomial endogenous switching treatment effects approach is used to control for selection bias while determining the impact of CSAs on food security. This is demonstrated using data from a cross-sectional survey of rural smallholders who participate in agricultural production amidst the challenges of climate change.

Methodology

Study area

This study was conducted in Teso North Sub-county, Busia County in Kenya. The area was selected for study because of its high potential for food production in the entire Busia County which is attributed to its better soils but under threat of massive soil degradation. It lies on the Northern part of Busia County and has six wards (Malaba Central, Malaba South, Malaba North, Ang'urai South, Ang'urai North, and Ang'urai East) and covers an area of 261 km^2 with a population of 117,947 [16]. The Sub-county has two main rivers Malakisi and Malaba on the northern part. The dry season with scattered rains falls from December to February. The Sub-county receives an annual rainfall of between 760 mm and 2000 mm. [16] indicates that 50% of the rainfall falls during the long rain season which is at its peak between late March and late May, while 25% falls during the short rains between August and October. The annual mean maximum and minimum temperatures range between 26 and 30 and 14 and 22 °C, respectively.

The Sub-county has experienced environmental degradation including loss of quality and quantity of natural biodiversity, soil erosion and flooding which poses a threat to its food production potential. As stated in the county's integrated development plan, varying rainfall patterns have affected both land preparation and good production leading to lower yields [16]. There is also a remarkable decline in water volumes in rivers, wells, pans, and springs with the average distance to watering point averaging at 1.5 km.

The data used for this study were obtained from a farm household survey carried out between May and July 2016 by well-trained enumerators. The sample for this study was drawn from smallholder farmers in Teso North Sub-county. Multistage sampling procedure was employed to select respondents, whereby in stage one, Teso North Sub-county was purposively selected based on its high food production potential in the entire Busia County. In stage two, three wards (Malaba South, Malaba North and Ang'urai South) were randomly selected from the six wards in Teso North Sub-county. Finally, in the last stage, simple random sampling was used to select 384 farmers for the interview from a source list acquired from the office of County Director of Agriculture using a pretested interview schedule. The interview schedule was administered through face-to-face interviews by well-trained enumerators.

Analytical framework

First, CSA practices used in Teso North were identified and grouped into heterogeneous principal clusters by the use of principal component analysis. The components were rotated using orthogonal rotation (varimax method) [19, 20] so that smaller number of highly correlated practices would be put under each component for easy interpretation and generalization about a group. The result of the rotation was 4 principal components from a possible 14 extracted with eigenvalues > 1 following the [21] criterion. Principal component analysis was useful in reducing the dimensionality of data without loss of much information. This was important as it allowed determination of the relationship between practices based on usage and subsequent analysis by fitting the groups into the model and reaching conclusions. The approach is superior to the use of conventional grouping of practices which would make it difficult to conclude about a group in cases where few practices could represent the entire group.

The practices were grouped using principal component analysis with iteration and varimax rotation in the model represented as shown below:

$$\begin{aligned} Y_1 &= a_{11}x_{12} + a_{12}x_2 + \cdots + a_{1n}x_n \\ &\cdot \quad \cdot \\ Y_j &= a_{j1}x_{j1} + a_{j2}x_2 + \cdots + a_{jn}x_n \end{aligned} \tag{1}$$

where $Y_1,\ldots Y_j$ = principal components which are uncorrelated, $a_1 - a_\mathrm{n}$ = correlation coefficient, $X_1,\ldots X_j$ = factors influencing choice of a particular strategy. The CSA practices identified and grouped through a principal component analysis are presented in Table 1. Selection of these practices prior to the field study was guided by the successful CSA practices established by a previous study done by Forum for Agricultural Research in Africa in the region [7].

After grouping the CSA practices, multinomial endogenous switching regression (MNLESR) model was then used to model the determinants of choice and effect of CSA practices on food security of smallholder farmers.

Table 1 Climate-smart agricultural practices identified to be actively used by farmers

S. No.	CSA practices
1	Use of improved crop varieties
2	Use of legumes in crop rotation
3	Use of cover crops
4	Changing planting dates
5	Efficient use of inorganic fertilizers
6	Use of terraces
7	Planting trees on crop land
8	Use of live barriers
9	Diversified crop and animal breeds
10	Irrigation
11	Use of improved livestock breeds
12	Use of organic fertilizers
13	Planting crops on tree land
14	Use of mulching

Food security status of the respondents was measured using Household Food Consumption Score (HFCS) and Household Dietary Diversity Scores which are measures of dietary diversity and quality.

In the first stage, farm households were assumed to face a choice of 7 mutually exclusive combinations/packages for responses to changes in mean temperature and rainfall (climate change). In the second stage, MNLESR econometric model was used to investigate the effect of different CSA practices on food security status.

Stage 1: Multinomial adoption selection model

At this stage, multinomial logit was used to determine the determinants of choice of CSA packages. Farmers were assumed to maximize their food security status, Y_i by comparing the revenue provided by 7(M) alternative CSA strategies. The requirement for farmer i to choose any strategy, j over other alternatives M is that $Y_{ij} > Y_{iM} \quad M \neq j$, that is, j provides higher expected food security than any other strategy. Y_{ij}^* is a latent variable that represents the expected food security level which is influenced by the observed household, plot characteristics, climate shocks and unobserved features expressed as follows:

$$Y_{ij}^* = X_i\beta_j + \varepsilon_{ij}. \tag{2}$$

X_i captures the observed exogenous variables (household and plot characteristics), while the error term ε_{ij} captures unobserved characteristics. The covariate vector X_i is assumed to be uncorrelated with the idiosyncratic unobserved stochastic component ε_{ij}, that is, $E(\varepsilon_{ij}|X_i) = 0$, whereby error terms ε_{ij} are assumed to be identically Gumbel distributed and independent, that is, under the independent irrelevant alternatives (IIA) hypothesis. The selection model (2) leads to a multinomial logit model [22] where the probability of choosing strategy $j(p_{ij})$ is:

$$p_{ij} = p(\varepsilon_{ij} < 0|X_i) = \frac{\exp(X_i\beta_j)}{\sum_{M=1}^{j}\exp(X_i\beta_M)}. \tag{3}$$

Stage 2: Multinomial endogenous switching regression model

Here, endogenous switching regression (ESR) was used to investigate the impact of each response packages on food security by applying [23] selection bias correction model. Farm households face a total of 7 regimes with regime $j=1$ being the reference category (non-responsive). The food security status equation for each possible regime is defined as:

$$\begin{array}{lll} \text{Regime } 1 & Q_{i1} = z_i\alpha_1 + \mu_{i1} & \text{if } i = 1 \\ \vdots & \vdots & \\ \text{Regime } j & Q_{ij} = z_i\alpha_j + \mu_{ij} & \text{if } i = j \end{array}. \tag{4}$$

From the above equation, Q_{ij}*'s* represent the food security status, Z_i represents a set of exogenous variables (that is, household, plot, location characteristics, institutional variables and climate shocks), and the ith farmer in regime j and the error terms μ_{ij}*'s* are distributed with $E(\mu_{ij}|x, z)=0$ and $\text{var}(\mu_{ij}|x,z) = \sigma_j^2$. Q_{ij} is observed if, and only if, CSA strategy j is used, which occurs when $Y_{ij}^* > \max_{M\neq 1}(Y_{im})$; if the error terms in (3) and (4) are not independent, OLS estimates for Eq. (4) were biased. A consistent estimation of α_j requires inclusion of the selection correction terms of the alternative choices in Eq. (3). MNLESR assumes the following linearity assumption: $E(\mu_{ij}|\varepsilon_{i1}\ldots\varepsilon_{ij}) = \sigma_j\sum_{m\neq j}^{j} r_j(\varepsilon_{im} - E(\varepsilon_{im}))$. By construction, the correlation between the error terms in (3) and (4) was zero.

Using the above assumption, Eq. (3) can be expressed as follows:

$$\begin{array}{lll} \text{Regime } 1 & Q_{i1} = z_i\alpha_1 + \sigma_1\lambda_1 + \omega_{i1} & \text{if } i = 1 \\ \vdots & \vdots & \\ \text{Regime } j & Q_{ij} = z_i\alpha_j + \sigma_j\lambda_j + \omega_{ij} & \text{if } i = j \end{array}. \tag{5}$$

σ_j is the covariance between ε's and μ's, while λ_j is the inverse Mills ratio computed from the estimated probabilities in Eq. (5) as follows:

$$\lambda_j = \sum_{m\neq j}^{j}\rho_j\left[\frac{p_{im}In(p_{im})}{1-p_{im}} + In(p_{ij})\right]. \tag{6}$$

ρ in the above equation represents the correlation coefficient of ε's and μ's, while ω_{ij} are error terms with an expected value of zero. In the multinomial choice setting expressed earlier, there were $j-1$ selection correction terms, one for each alternative CSA practice. The standard errors in Eq. (5) were bootstrapped to account for the heteroskedasticity arising from the generated regressors given by λ_j.

Estimation of average treatment effects

At this point, a counterfactual analysis was performed to examine average treatment effects (ATT) by comparing the expected outcomes of adopters with and without adoption of a particular CSA strategy. ATT in the actual and counterfactual scenarios were determined as follows [8, 17]:

Food security status with adoption/usage

$$E(Q_{i2}|i=2) = z_i\alpha_2 + \sigma_2\lambda_2 \tag{7a}$$

$$E(Q_{ij}\big|i=j) = z_i\alpha_j + \sigma_j\lambda_j. \tag{7b}$$

Food security status without adoption (counterfactual)

$$E(Q_{i1}|i=2) = z_i\alpha_1 + \sigma_1\lambda_2 \tag{8a}$$

$$E(Q_{i1}\big|i=j) = z_i\alpha_1 + \sigma_1\lambda_j. \tag{8b}$$

ATT can be defined as the difference between (7a) and (8a) which is given by:

$$\begin{aligned} ATT &= E(Q_{i2}|i=2) - E(Q_{i1}|i=2) \\ &= z_i(\alpha_2\alpha_1) + \lambda_2(\rho_2-\rho_1). \end{aligned} \tag{9}$$

The right-hand side indicates the expected change in adopters' mean food security status, if adopters' characteristics had the same return as non-adopters, for instance, if adopters had the same characteristics as non-adopters, while λ_j is the selection term that captured all potential effects of difference in unobserved variables.

Variables used in econometric analysis are presented in Table 2 and were derived from review of past studies [7, 8: 14, 24: 17].

Measurement of food security

To measure food security status of the farm households, Household Food Consumption Score (HFCS) and Household Dietary Diversity Scores were used as proxies for food security of farmers. These tools were developed by WFP and are commonly used as proxies for access to food [25]. HFCS is a weighted score based on dietary diversity, food frequency and the nutritional importance of food groups consumed. The HFCS of a household is calculated by multiplying the frequency of foods consumed within 7 days with the weighting of each food group. The weighting of food groups was determined by WFP according to the nutrition density of the food group

Table 2 Variables used in econometric analysis

Variable	Description	Measurement	Mean	SD
FOODSEC	Food security status of the household	Food consumption score	63.22	19.24
		Household Dietary Diversity Score	6.73	1.65
AGE	Age in years of the household head	Continuous	46.51	14.69
GENDER	Gender of the household head	Dummy = 1 if male 0 = female	0.77	–
EDUC	Years of education of the household head	Discrete	10.00	4.45
H/SIZE	# of household size	Discrete	6.87	2.61
OFF-FARM	Participation in off-farm employment	Dummy = 1 if yes 0 = otherwise	0.44	–
ASSETS	Value of productive farm assets	Continuous	62,965.81	63,951.31
LAND	Owned farm size in acres	Continuous	2.54	1.57
TERRAIN	Terrain of the land	1 = sloppy 0 = otherwise	0.52	–
S/FERTILITY	Level of soil fertility	1 = poor 2 = medium 3 = fertile	1.70	–
EROSION	Severity of soil erosion	1 = severe 2 = moderate 3 = low	2.06	–
FLOOD	If household experienced floods in the last 5 years	Dummy = 1 yes 0 = otherwise	0.39	–
RAINS	If the household experienced insufficient rains in the last 5 years	Dummy = 1 yes 0 = otherwise	0.71	–
H/STRMS	If the farm household experienced hailstorms in the last 5 years	Dummy = 1 yes 0 = otherwise	0.63	–
DISTNCE	Walking time in minutes to the input and output market	Continuous	52.36	37.45
EXTN	Number of annual contacts with extension agents	Discrete	5.50	3.70
GRPMSHIP	If the household head is a member of a farmer-related group or association	Dummy = 1 if a member 0 = otherwise	0.66	–
CREDIT	Whether household received credit	Dummy = 1 if yes 0 = otherwise	0.60	–

[26, 27]. Appendix 1 presents the various food components used to determine the HFCS. HDDS is similar to HFCS with slight differences in the components of the various food clusters. While HFCS takes into account food items consumed within 7 days, the HDDS takes into account food items consumed within the last 24 h. Appendix 2 shows food group and weights for determination of HDDS. The two indicators measure food diversity which is strongly correlated with dietary quality and adequacy [28]. While recording the food items, foods taken during ceremonies and major occasions were skipped to reduce the bias that would have arisen in capturing such meals. Thus, for both the indicators such days were dropped.

Results and discussion

Principal component analysis (PCA)

Table 3 contains principal components (PCs) and the coefficients of linear combinations called loadings. A visual inspection of Table 3 reveals that the four PCs explained 74.19% of total variability in the data set. The results presented in Table 3 present a good fit, indicating that the PCA results highly explained the data. The first component explained 35.65% variance and is correlated with changing crop varieties, use of legumes in crop rotation, use of cover crops, changing planting dates and efficient use of inorganic fertilizer all with positive effects (factor loadings). Thus, this component was named crop management practices.

Principal components 2, 3 and 4 accounted for 20.12, 11.08 and 7.35% variances, respectively. This means that the first four components have more importance in explaining the variance in data set. The second PC was associated with use of organic manure, planting of food crops on tree land (as part of agroforestry) and use of mulching all with positive loadings too. The third PC contained crops and livestock diversification and use of improved livestock breeds both with highly negative loadings and use of irrigation with positive loadings. Finally, the last PC was associated with use of planting trees on crop land and use of live barriers with high positive effects (loadings) and use of terraces with a high negative effect.

The communality column shows the total amount of variance of each variable retained in the four components. MacCallum et al. [29] noted that all items in PCs should have communalities of over 0.60 or an average communality of 0.7 for small sample sizes precisely below 50 to justify performing a PCA analysis. With the sample size of 384, the communalities presented in Table 3 meet the minimum criteria as they contribute more than 60% variance in the PCs. For the interpretation of the PCs, variables with high factor loadings and high communalities were considered from the varimax rotation [19, 30].

Table 4 presents the descriptive statistics of composition of each component (climate-smart strategies). The most commonly used component was of crop management practices with 96.09% of farmers using at least a unit of this component. This component comprised of practices such as: use of improved crop varieties, use of

Table 3 Loadings of the four components for CSA compositions

Strategies	Comp1	Comp2	Comp3	Comp4	Communality
Changing crop varieties	0.5467	− 0.3965	0.2579	− 0.2853	0.6040
Use of legumes in crop rotation	0.6491	− 0.3903	0.2574	− 0.2224	0.6894
Use of cover crops	0.6257	− 0.3138	− 0.2292	− 0.1559	0.6344
Changing planting dates	0.5223	− 0.3779	0.3280	− 0.2981	0.6121
Crop and livestock diversification	0.3910	0.3482	− 0.4904	0.3216	0.6180
Use of organic manure	0.2550	0.6522	− 0.3156	− 0.3036	0.5086
Efficient use of inorganic fertilizer	0.5537	0.2032	0.3940	− 0.3311	0.6127
Use of terraces	0.2485	0.3343	− 0.3243	− 0.6249	0.6691
Irrigation	0.3816	0.3986	0.4546	0.2423	0.6283
Trees on crop land	0.2459	− 0.3013	− 0.4518	0.6024	0.7183
Food crops on tree land	0.3202	0.6198	0.3715	0.3424	0.7419
Use of live barriers	0.3190	− 0.3308	− 0.3845	0.5146	0.6238
Mulching	0.2811	0.5512	0.3483	0.3819	0.6500
Use of improved livestock breeds	0.2510	0.3794	− 0.7011	− 0.1492	0.7207
Eigenvalues	4.9160	2.8161	1.5505	1.0287	
Eigenvalues % contribution	35.6543	20.1153	11.0751	7.3479	
Cumulative %	35.6543	55.7696	66.8447	74.1926	

Table 4 List of climate-smart strategies

Group	Percentage of users	Components
Crop management practices (C)	96.09%	Use of improved crop varieties
		Use of legumes in crop rotation
		Use of cover crops
		Changing planting dates
		Efficient use of inorganic fertilizers
General field management practices (F)	81.51%	Use of terraces
		Planting trees on crop land
		Use of live barriers
Farm risk reduction practices (R)	39.84%	Diversified crop and animal breeds
		Irrigation
		Use of improved livestock breeds
Soil conservation practices (S)	22.92%	Use of organic fertilizers
		Planting food crops on tree land
		Use of mulching

legumes in crop rotation, use of cover crops, changing planting dates and efficient use of inorganic fertilizers. The second most used component was of general field management practices for soil erosion control used by 81.51% of farmers. This component entailed of use of terraces and contour bunds, planting trees on cropland and use of live barriers.

Farm risk reduction measures were only used by 39.84% of farmers. The practices in this component included: crop and livestock diversification, irrigation and use of improved livestock breeds. Finally, the least used component comprised of specific soil conservation practices which included: use of organic manure, planting crops on tree land and application of mulching. This component was used by 22.92% of farmers.

Econometric results

The determinants of choice of CSA packages are given followed by their impact on food security. CSA practices can be adopted in a wide range of different combinations, and this has implication on household's food security status. Given the set of available packages, understanding what drives an individual to select specific packages is important for policy direction.

Table 5 presents different packages (combinations), whereby 7 out of 16 possible combinations/packages were used by farmers. Few farmers (3.6%) were non-users/non-adopters of any CSA package. About 2.6% of farmers used package $C_1F_0R_1S_0$. This package comprised of crop management practices and farm risk reduction measures only. Another 4.4% used package $C_1F_0R_1S_1$ that had crop management, farm risk reduction measures and soil management practices. Further, 7.0% of farmers used package $C_1F_1R_0S_1$ that contained crop management, field management and soil conservation practices. Another 8.3% of farmers used package $C_1F_0R_0S_0$ that contained only crop management practices. Approximately 12% of farmers used package $C_1F_1R_1S_1$ with all the four groups of CSA strategies. About 21% used package $C_1F_1R_1S_0$ that contained crop management, general field management for soil erosion control and farm risk reduction practices only).

The largest share of farmers (41.1%) used a package $C_1F_1R_0S_0$ that had crop management and general field management for soil erosion control. This reveals the efforts of many subsistence farmers to achieve food production despite the challenges of land degradation caused by soil erosion. This observation is similar to the findings of [7] which suggested that farmers in the region executed such responsive strategies for survival amidst challenges of climate change. A keen look at Table 5 reveals that all users of CSA practices (96.4% of all farmers) used packages that included at least a crop management practice. This observation demonstrates the need of most farmers to meet their basic crop production for food generation.

Determinants of choice of specific CSA packages

This section describes the factors that influence choice of CSA packages and then followed by quantification of the effect of using packages on food security status of farmers in the last stage. This was achieved using the multinomial endogenous switching regression (MNLESR) model which is a two-stage regression analysis model. The first stage of the MNLESR is the multinomial logit model which determines factors that influence the choice of CSA packages. This is an important stage as it guides on the necessary interventions to improve the adoption of CSA packages. In the second stage, the impact of usage of CSA packages on household food security was determined. The marginal effects from the MNL model that measured the expected change in the probability of a particular choice being made with respect to a unit change in an independent variable are reported in Table 6.

Non-use of all practices ($C_0F_0R_0S_0$) was the base category compared to other seven packages (refer to Table 5 for the packages) used by farmers. The results show seven sets of parameter estimates, one for each mutually exclusive combination of strategies. The Wald test that all regression coefficients are jointly equal to zero is rejected [χ^2 (119) = 445.52; p = 0.000]. Thus, the results show that

Table 5 Specification of CSA strategy combinations to form the packages

Choice (j)	Binary quadruplicate	C = crop management		F = field management		R = risk reduction		S = specific soil management		Frequency	Percentage
		C_0	C_1	F_0	F_1	R_0	R_1	S_0	S_1		
1	$C_0F_0R_0S_0$	✓		✓		✓		✓		14.0	3.60
2	$C_0F_0R_0S_1$	✓		✓		✓			✓	0.00	0.00
3	$C_0F_0R_1S_1$	✓		✓			✓		✓	0.00	0.00
4	$C_0F_1R_1S_1$	✓			✓		✓		✓	0.00	0.00
5	$C_1F_1R_1S_1$		✓		✓		✓		✓	45.0	11.7
6	$C_1F_1R_1S_0$		✓		✓		✓	✓		82.0	21.1
7	$C_1F_1R_0S_0$		✓		✓	✓		✓		157	41.1
8	$C_1F_0R_0S_0$		✓	✓		✓		✓		32.0	8.30
9	$C_0F_1R_0S_1$	✓			✓	✓			✓	0.00	0.00
10	$C_1F_0R_1S_0$		✓	✓			✓	✓		10.0	2.60
11	$C_1F_0R_0S_1$		✓	✓		✓			✓	0.00	0.00
12	$C_0F_1R_0S_0$	✓			✓	✓		✓		0.00	0.00
13	$C_0F_1R_1S_0$	✓			✓		✓	✓		0.00	0.00
14	$C_0F_0R_1S_0$	✓		✓			✓	✓		0.00	0.00
15	$C_1F_0R_1S_1$		✓	✓			✓		✓	17.0	4.40
16	$C_1F_1R_0S_1$		✓		✓	✓			✓	27.0	7.00
Total										384	100

The binary quadruplicate represents the possible CSA packages. Each element in the quadruplicate is a binary variable for a CSA combination: crop management (C), general field management for soil erosion control, farm risk reduction (R) and soil management practices (S). Subscript 1 = adoption and 0 = otherwise

the estimated coefficients differ substantially across the alternative packages.

Age of the household head was negatively associated with usage of $C_1F_0R_0S_0$ and positively associated with usage of $C_1F_1R_0S_1$ at 10% and 5% significant levels, respectively. Increase in age of the household head by one year reduced the likelihood of using package $C_1F_0R_0S_0$ by 0.19%, while increased the likelihood of using $C_1F_1R_0S_1$ by 0.16%. This indicates that as age increases, farmers shift from smaller packages to larger ones. Older farmers may be more experienced with regard to production technologies and may have accumulated more physical and social capital thus to afford larger and better packages. Contrary, [31] noted that old age had a negative relationship to adopting climate change adaptation strategies, explaining that agriculture is a labour-intensive venture which requires healthy, risk-bearing and energetic farmers. Again, older farmers may not be aware of recent innovations.

With regard to gender of the household head, male-headed households were 2.7% more likely to use package $C_1F_1R_1S_1$ that contains crop management practices, field management, farm risk reduction practices only at 5% significant level relative to $C_0F_0R_0S_0$ (non-use of any CSA practices) compared to females. Women generally face constraints in terms of accessing resources and time. This may explain the negative relationship with usage of CSA practices in this study. FARA [7] reported that gender remains a significant barrier to the adoption of CSAs by women, stemming largely from customary gender roles. They further stated in the report that women have less access than men to resources such as land, inputs, credit, education and extension services, all of which may be important to support transitions to CSA. Land ownership systems also present more entrenched barriers to female-led households. Land tenure systems in Western Kenya, for example, require women who want to adopt CSA to obtain permission from male relatives, thus derailing them [32].

Years of education of the household head negatively influenced usage of $C_1F_1R_0S_0$ which contains crop and field management practices only. One more year of education reduced the probability of using this package by 2% at 5% significance level. It could be that educated farmers opted out of this package since it does not offer risk reduction measures which could safeguard their investment against prevailing risks of climate change. This category of farmers avoided taking the risk of using this package with increase in their years of education. Similarly, [33] argues that higher levels of education tend to build the innovativeness and ability to assess risks by farmers for proper farm adjustments.

There was a positive and significant relationship between the value of productive farm assets (a proxy of

Table 6 Marginal effects estimates for the determinants CSA packages by MNL

Variables	$C_1F_0R_0S_0$ dy/dx	$C_1F_0R_1S_0$ dy/dx	$C_1F_0R_1S_1$ dy/dx	$C_1F_1R_0S_0$ dy/dx	$C_1F_1R_0S_1$ dy/dx	$C_1F_1R_1S_0$ dy/dx	$C_1F_1R_1S_1$ dy/dx
Socio-economic factors							
Age of HH	−0.0019*	0.0007	0.0015	−0.0028	0.0016**	0.0016	0.0000
Gender of HH	−0.0434	0.0045	0.0340	−0.0284	−0.0047	−0.0047	0.0271**
Years of education of HH	0.0013	0.0015	0.0033	−0.0204**	0.0019	0.0019	0.0000
Household size	0.0075	−0.0006	−0.0020	−0.0239	0.0056	0.0056	0.0004
Participation in off-farm employment	−0.0251	0.0022	0.0341	−0.0518	−0.0168	−0.0168	0.0012
Natural log of farm assets	0.0032	0.0009	−0.0045	−0.0722***	0.0014	0.0014***	0.0307*
Farm size	−0.0378***	−0.0104	−0.0268**	−0.0171	0.0110*	0.0110***	0.0013**
Farm characteristics							
Perception on terrain of land	−0.0007	0.0057	−0.0123	0.0995	−0.0177	−0.0177	0.0011
Perception Severity of soil erosion	−0.0107	−0.0342**	0.0198	−0.0452	−0.0451**	−0.0451***	0.0007
Perception of soil fertility	−0.0064	−0.0002	0.0105	0.1871***	−0.0128	−0.0128***	0.0007
Bad incidences							
Frequent floods	0.0284	−0.0266	−0.0204	0.0205	0.0330*	0.0330	0.0003
Hailstorms	0.0268	0.0052*	−0.0053	−0.0126	0.0193	0.0193	0.0006
Insufficient rains	−0.0023	0.0008	−0.0169	0.0628	−0.0311	−0.0311	0.0004
Institutional factors							
Walking time from farm to market	0.0002	−0.0003	−0.0005*	0.0011	−0.0007**	−0.0007**	0.0001
Membership to a farmer group	0.0279	0.0148	−0.0126	0.1888**	0.0221	0.0221**	0.0000
Contacts with extension agents	−0.0046	0.0021	0.0073	−0.0296***	0.0046	0.0046**	0.0002
Access to credit	−0.0461*	−0.0044	−0.0083	−0.1571**	0.0028	0.0028***	0.0001
Number of observations = 375; Wald χ^2 (119) = 445.52; p = 0.000							

$C_0F_0R_0S_0$ is the reference base category in the MNL; HH is household head

***Significant at 1% level

**Significant at 5% level

*Significant at 10% level

wealth) and usage of CSAs. Resource-endowed farmers (those with greater value of productive farm assets) were more likely to use larger packages $C_1F_1R_1S_0$ and $C_1F_1R_1S_1$ as opposed to non-use of any package. Precisely, the probability of using these packages increased by 0.14% and 3.07%, respectively, for resource-endowed farmers. It is likely that wealthier farmers have the capacity to use CSA practices, particularly expensive ones like use of improved livestock breeds and crop varieties available in these packages. Further, these assets enhance ability to absorb the risks associated with failure and the time it takes before realizing meaningful effects of using CSAs. This is consistent with [34] who noted that lack of productive assets limits the ability to adopt climate-smart practices that require huge resource allocation. Ochieng et al. [35] as well notes that wealthier households have higher capacity to invest in such measures to improve crop production. However, on the other hand the probability of using $C_1F_1R_0S_0$ reduced by 7.2% with increase in farm assets perhaps due to lack of risk reduction measures in this package.

Farm size owned positively influenced the use of packages $C_1F_0R_1S_1$, $C_1F_1R_0S_1$, $C_1F_1R_1S_0$ and $C_1F_1R_1S_1$ and negatively associated with the use of package $C_1F_0R_0S_0$. This implies that an increase in size of land by 1 acre (0.40 ha) increased the probability of using packages $C_1F_0R_1S_1$, $C_1F_1R_0S_1$, $C_1F_1R_1S_0$ and $C_1F_1R_1S_1$ by 2.7%, 1.1%, 1.1% and 0.13%, respectively, while reduced the probability of using package $C_1F_0R_0S_0$ by 3.8%. It follows therefore that farmers with larger farm size had the capacity to use larger packages as opposed to non-usage of any package. Availability of land provides opportunity for farmers to experiment these important technologies, thus influencing usage of the large packages. This result is consistent with the result of [36] who stated that bigger farm size accrues benefits of economies of scale to farmers and also provide a means of diversifying production. Users of package $C_1F_0R_0S_0$ which contains crop management practices only were less likely to use the package with increase in their farm sizes. The possible explanation could be that these farmers chose to rent out their increasing farms for other users rather than farming since this small package may not offer meaningful production in the circumstances of harsh weather. Renting in farmers may not be motivated to implement long-term packages, thus reducing the usage of CSA practices on these particular farms.

The perception of severity of soil erosion by farmers was negatively associated with the use of the following packages: $C_1F_0R_1S_0$, $C_1F_1R_0S_1$ and $C_1F_1R_1S_0$. The probability of using these packages reduced by 3.4%, 4.5% and 4.5%, respectively, for the farmers who regarded their plots as severely eroded. It appears that farmers were highly motivated to implement CSA practices on less severely eroded farms and vice versa. In essence, these farmers were not quite responsive to countering the effects of severe soil erosion but were rather discouraged by severe soil erosion in implementing CSA technologies. Contrary, [37] noted a positive relationship with adoption of many soil conservation practices with the argument that farmers were responsive to soil degradation effects brought by soil erosion.

The perception of farmers towards soil fertility of the farm had a positive and significant influence on the usage of $C_1F_1R_0S_0$ and a negative influence on the usage of $C_1F_1R_1S_0$. The likelihood of using packages $C_1F_1R_0S_0$ and $C_1F_1R_1S_0$ increased by 18.7% and reduced by 1.3%, respectively, for farmers who regarded their farms as being more fertile. This implies that farmers who regarded their farms as being more fertile were more likely to use a small package $C_1F_1R_0S_0$ as opposed to non-use of any package. This is a lean package without significant soil fertility replenishing avenues. But those who regarded their farms as being less fertile implemented a larger package $C_1F_1R_1S_0$ that contains more soil nutrient enriching practices in the risk reduction component. Manda et al. [18] argues that the propensity to adopt sustainable agricultural practices such as improved maize is expected to be greater on plots with fertile soils, because most improved maize varieties require the application of expensive inorganic fertilizers.

Factors related to past experiences with extreme weather conditions by farmers also influenced choice of CSA packages. For instance, farmers who experienced frequent floods in the past were more likely to use package $C_1F_1R_0S_1$. The probability of using this package increased by 3.3% for the farmers who experienced frequent floods in the recent past. It is likely that these farmers were keener to the flood-related shocks, thus implementing a responsive strategy to curb it with proper field and soil management to abate soil degradation. Contrary, [24] noted that adoption of improved climate change adaptation technologies such as crop rotation and drought-resistant seeds is negatively and significantly influenced by harsh conditions brought by flooding such as waterlogging and frost stress.

Past experience with hailstorms was also positively associated with the use of package $C_1F_0R_1S_0$. It was revealed that the likelihood of using this package increased by 0.52% for farmers who had experienced frequent hailstorms in the recent past. Similarly, these farmers could be implementing a responsive strategy that included farm risk reduction through diversified production means. Previous study by [38] had a contrary result where frequent hailstorms were the greatest source of production risks related to climate change that discouraged adoption of production techniques posing a threat to yield stability in rural Amhara Ethiopia.

Distance (measured by walking time) to the input and output market negatively influenced usage of CSA practices. An increase in time taken to reach the market by 1 min reduced the probability of using packages $C_1F_0R_1S_1$, $C_1F_1R_0S_1$ and $C_1F_1R_1S_0$ by 0.05, 0.07 and 0.07%, respectively. Longer distance to the market for such larger packages increases the transaction costs involved in input purchase and output sale. Teklewold et al. [8] noted that apart from affecting the access to the market, distance can also affect the accessibility of new technologies, information and credit institutions, thus having a negative relationship.

Group membership had a positive and significant influence on the usage of packages: $C_1F_1R_0S_0$ and $C_1F_1R_1S_0$. Rather than not using any package, belonging to a farmer group increased the probability of using these two packages by 18.8% and 2.2%, respectively. Farmer groups are important channels through which extension agents and other farmer service providers (like insurance) use to access farmers. Further, field management practices like construction of terraces could be possibly achieved in mobilized labour in groups. Again, through group networks, members get to exchange ideas, handle farm demonstrations and also get connections to dissemination of important research findings. Ward and Pede [39] notes that learning from the experiences of peers increases the probability of technology adoption due to the fact that farmers trust more practical experiences demonstrated by their peers since they share much in common including shared labour.

The number of contacts with extension service providers positively influenced the use of $C_1F_1R_1S_0$ and negatively influenced the use of $C_1F_1R_0S_0$. One more annual contact with extension agents increased the probability of using $C_1F_1R_1S_0$ by 0.46% but reduced the probability of using $C_1F_1R_0S_0$ by 3.0%. This suggests that extension service played a crucial role in implementation of larger packages by farmers. It further suggests that the information disseminated had inclusion of a climate change dimension that promoted the use of the larger package. However, on the other hand, reduction in probability of using $C_1F_1R_0S_0$ suggests that the goal of promoting CSA technologies by extension service agents had mixed effects. It appears that farmers who used package $C_1F_1R_0S_0$ with only crop and field management practices were sceptical about the veracity of the information and its ability to improve their production, thus opting not to use any package. This is consistent with the findings of a study in Zambia by [14] which indicated that extension agents were involved in a lot of activities that include delivering inputs and administering credit; hence, farmers may question their skills impacting on their trust and eventual decline in implementation.

Access to credit had a positive and significant influence on the use of $C_1F_1R_1S_0$ but a negative influence on the use of $C_1F_0R_0S_0$ and $C_1F_1R_0S_0$. The results indicate that farmers who received credit in the previous farming season were 0.28% more likely to use $C_1F_1R_1S_0$. Credit access enables farmers to meet costs involved in implementing CSA technologies, especially including expensive ones like use of improved livestock breeds and irrigation present in this large package. Similarly, [40] explain that credit constraints negatively influence investment in improved seed and inorganic fertilizers, suggesting that credit-constrained households are less likely to adopt CSA technologies that require cash outlays. Access to credit reduced the probability of using packages $C_1F_0R_0S_0$ and $C_1F_1R_0S_0$ by 4.6% and 15.7%, respectively. A negative influence of credit access to usage of $C_1F_0R_0S_0$ and $C_1F_1R_0S_0$ may suggest that these farmers diverted credit to fund non-farming expenses like school fees and medical, thus opting not to use any package.

Average adoption treatment effects for the CSA packages

After determining the drivers of choice of CSA packages in the first stage, treatment effects were determined in the second stage to find the effect of usage of the packages on household food security. The ordinary least squares regression of Household Food Consumption Scores (HFCS) and Household Diversity Scores (HDDS) of the households were estimated for each combination of CSA practices, taking care of the selection bias correction terms from the first stage. At this stage, treatment effects which are the most important part of this stage were reported.

Appendices 1 and 2 present the food categories for HFCS and HDDS. For interpretation, HFCS were preferred to HDDS as the latter only capture meals taken within 24 h which may not include occasional meals taken on particular days like market days within a week. However, HDDS were used for sensitivity analysis. It is also important to note that the two scores were strongly correlated (0.97) as indicated in Table 7.

Table 7 presents the average adoption effects in terms of HFCS and HDDS under actual and counterfactual conditions. In Table 7, X_1 represents the treated group (adopters) and X_2 represents untreated (non-adopters), β_1 represents treated characteristics (adoption state) and β_2 untreated characteristics (non-adoption state). The level effect is the difference in food security status as a result of usage of the specified package. The impact is as a result of the difference between treated with treatment characteristics and the untreated with untreated characteristics $(\beta_1 X_1) - (\beta_2 X_2)$. Except users of $C_1F_0R_1S_0$, $C_1F_1R_1S_0$ and $C_1F_1R_1S_1$, all the rest using other packages would be better off in the counterfactual scenarios (non-usage) suggesting availability of other better options. All packages that included farm risk reduction practices apart from $C_1F_0R_1S_1$ had a positive impact on the welfare of farmers. This implies that farmers need to manage their farm risks to be assured of improved food security in the uncertain events of climate change.

For larger packages ($C_1F_1R_0S_1$, $C_1F_1R_1S_0$ and $C_1F_1R_1S_1$), all users were more food secure compared to their counterparts who did not use CSAs in the actual scenarios. Based on these results, a complete package with crop management practices, field management practices and farm risk reduction practices and soil management ($C_1F_1R_1S_1$) had the greatest overall effect of 30.14 and 1.72 scores on the welfare of farmers estimated using both HFCS and HDDS, respectively. This implies that farmers who used this package were 56.83% and 25.44% more food secure compared to their counterparts who chose not to use any CSA practice. Thus, farmers may be more food secure if they use climate-smart technologies within this package. This package is quite comprehensive as it addresses a wider spectrum of both field and soil conditions while also mitigating upon soil degradation for production stability. In general terms, the overall result is that non-usage of this ($C_1F_1R_1S_1$) package would be irrational as farmers will be better off in terms of food security if they use this package as it addresses a wide range of climate change challenges.

Conclusions and policy implications

The results indicate that adoption rate of CSAs was still low with many farmers implementing low capital requirement practices. This may be attributed to smallholder agriculture that is resource constrained. Crop management practices were the most dominant perhaps due to their low-cost implications. This suggests the need for farmer empowerment to progressively move towards more capital-intensive practices.

A larger package which comprised of crop management, field management, risk reduction practices and

Table 7 Impact of use and non-use of CSA packages on food security estimated using HFCS of farmers by ESR

Package		HFCS			HDDS		
		Treated characteristics (β_1)	Untreated characteristics (β_2)	Impact/returns	Treated characteristics (β_1)	Untreated characteristics (β_2)	Impact/returns
$C_1F_0R_0S_0$	Treated (X_1)	49.14 (1.92)	49.52 (0.96)	− 0.38	5.31 (0.21)	6.06 (0.12)	− 0.25
	Untreated (X_2)	52.35 (2.23)	65.07 (0.80)	− 12.72	5.68 (0.019)	6.89 (0.07)	− 1.21
	Level effects	*− 3.21*	− 15.54***	− 15.93	− 0.37*	− 0.83***	− 1.58
$C_1F_0R_1S_0$	Treated	65.75 (7.24)	56.52 (2.25)	9.23	7.20 (0.55)	6.36 (0.18)	0.84
	Untreated	63.29 (3.68)	63.65 (0.78)	− 0.36	6.69 (0.31)	6.74 (0.07)	− 0.05
	Level effects	*2.46*	− 7.13***	2.1	0.51	− 0.38**	0.46
$C_1F_0R_1S_1$	Treated	61.09 (3.37)	80.84 (2.72)	− 19.75	6.56 (0.30)	6.63 (0.10)	0.07
	Untreated	57.40 (2.63)	63.82 (0.80)	− 6.42	6.25 (0.23)	6.76 (0.06)	− 0.51
	Level effects	3.69	17.02***	− 2.73	0.32	− 0.13	− 0.20
$C_1F_1R_0S_0$	Treated	55.77 (1.09)	65.81 (1.01)	− 10.04	6.14 (0.09)	7.04 (0.09)	− 0.90
	Untreated	59.44 (0.96)	69.11 (0.93)	− 9.67	6.29 (0.09)	7.18 (0.09)	− 0.89
	Level effects	− 3.67***	− 3.30***	− 13.34	− 0.15	− 0.14	− 1.04
$C_1F_1R_0S_1$	Treated	63.89 (2.18)	69.99 (0.80)	− 6.10	6.70 (0.23)	7.52 (0.09)	− 0.82
	Untreated	63.59 (1.94)	63.69 (0.83)	− 0.10	6.76 (0.07)	6.75 (0.14)	0.01
	Level effects	0.30	6.30***	0.20	− 0.05	0.76***	− 0.05
$C_1F_1R_1S_0$	Treated	74.70 (1.03)	62.72 (0.83)	11.98	7.66 (0.10)	6.35 (0.09)	1.31
	Untreated	75.75 (1.20)	60.64 (0.89)	15.11	7.90 (0.11)	6.51 (0.08)	1.39
	Level effects	− 1.05	2.08*	27.09	− 0.25**	− 0.16*	1.15
$C_1F_1R_1S_1$	Treated	83.92 (1.01)	68.04 (0.82)	15.88	8.48 (0.11)	7.06 (0.10)	1.42
	Untreated	79.09 (1.23)	53.51 (0.82)	15.58	8.19 (0.12)	6.76 (0.07)	1.43
	Level effects	*4.83****	*4.53****	30.41	0.29**	0.31***	1.72
Pairwise correlation							
	HDDS	**HFC**					
HDDS	1						
HFC	0.9652***	1					

Standard errors are in parentheses. *C* crop management, *F* field management, *R* risk reduction, *S* specific soil management

specific soil management practices ($C_1F_1R_1S_1$) had the highest impact on food security. This package is quite comprehensive as it addresses a wider spectrum of both field and soil conditions while also mitigating upon soil degradation for production stability. Thus, for farmers to benefit more from CSAs, they need to incorporate all CSAs as much as possible. Findings were that the likelihood of usage of this package was positively influenced by gender, farm size and farm assets. Its usage was more likely on larger pieces of self-owned plots, for male-headed households with more farm assets. Thus, CSAs have the potential to alleviate food insecurity among smallholder farmers if used in combinations and to a larger extend.

Farmers should then be encouraged to incorporate larger CSAs packages which comprise at least a member in each of the four categories: crop management, field management, risk reduction practices and specific soil management practices, to have a higher effect on food security status. This could be through first sensitization on the need to invest in productive farm assets to enable them absorb risks associated with climate change at the same time enhancing their ability to uptake important CSAs. The sensitization could be done in groups by extension service providers. Secondly, land fragmentation should also be discouraged through civic education and engagement in alternative income-generating activities by farmers to benefit more from CSAs when practiced on relatively bigger portions of land.

Authors' contributions
This research was conceived and developed by all the three authors listed. All authors read and approved the final manuscript and unanimously agreed to publish it in this journal. All authors read and approved the final manuscript.

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Competing interests
The authors declare that they have no competing interests.

Availability of data and materials
Data for this study are available from the Department of Agricultural Economics and Agribusiness Management at Egerton University of Kenya and the authors. Data can be accessed on special request with permission of the department and the authors.

Ethics approval and consent to participate
Ethics approval for the study was received from the Director of Agriculture in Busia Sub-county, Kenya. The farmers interviewed were also asked for consent before commencement of the interviews.

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Appendix 1
See Table 8.

Table 8 Food groups for HFCS bY WFP

Food item	Food group	Weight
Rice	Cereals and tubers	2
Wheat/other cereals		
Potato (including sweet potatoes)		
Pulses/beans/nuts	Pulses	3
Milk/milk products	Milk	4
Meat and fish	Meat and fish	4
Poultry		
Eggs		
Fish and sea food (fresh/dried)		
Dark green vegetables—leafy	Vegetables	1
Other vegetables		
Sugar/honey	Sugars	0.5
Fruits	Fruits	1
Oil	Fats and oils	0.5
Spices, tea, coffee, salt, fish power, small amounts of milk for tea	Condiments	0

The maximum FCS has a value of 112 which would be achieved if a household ate each food group every day during the last 7 days. The total scores are then compared with pre-established thresholds. Poor food consumption 0–2, borderline food consumption 28.5–42 and acceptable food consumption > 42

Appendix 2
See Table 9.

Table 9 Food groups for HDDS

Food groups	Score
Cereals	1
White tubers and roots	1
Vegetables	1
Fruits	1
Meat	1
Eggs	1
Fish and other sea food	1
Legumes, nuts and seeds	1
Milk and milk products	1
Oils and fats	1
Sweets	1
Spices, condiments and beverages	1

Dietary diversity scores are calculated by summing the number of food groups consumed in the household or by the individual respondent over the 24-h recall period out of a maximum of 12 per day

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