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Crop mix portfolio response to climate risks: evidence from smallholder farmers in Kisumu County, Kenya

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ABSTRACT
Farm households respond to market uncertainties and household demand for food commodities by diversifying their farm-level crop portfolio. However, it is unclear if farmers' crop mix also responds to unpredictable climate variability. We use primary data from 267 randomly selected respondents and apply a multinomial logit model to test the hypothesis that crop portfolio choice is an ex-ante mechanism to manage climate risks in the absence of crop insurance. The results suggest that access to information on climate variability does influence the mix of maize, cassava, sweet potato, and sorghum, which smallholder farmers in Kisumu County, Kenya grow in various combinations. Access to credit services, farm size, gender of household head, farming experience, and distance to nearest market also influence the farm-level crop mixture. These findings imply that policies geared towards incentivizing a better crop choice portfolio at the smallholder farm level should address climate variability awareness. In addition, encouraging crop-variety mixes that are tolerant to climate risks would enhance resilience in food systems among these smallholder farmers.

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Climate risks; climate-smart crops; climate variability; crop mix portfolio

1. Introduction

Variability in climate leads to uncertainties in agricultural production decisions among farm households practising rain-fed agriculture. Bezabih, Falco, and Yesuf (2011) found growing agreement among policymakers and scientists that climate variability due to climate change significantly affects farm production. Moreover, Makate et al. (2017) argued that risks associated with climate variability are made worse due to weak institutional capacities, inadequate technical skills, and financial resource constraints among smallholder farmers. Sarr and Bezabih (2013) have shown that for farmers to hedge against adverse climate risks, they need to practice proper and cost-effective risk management and coping strategies. Due to an increasing threat of climate change to food and nutrition security, there is a need to identify location-specific adaptation strategies (Abdulai 2018).

Mpandeli, Nesamvuni, and Maponya (2015) argued that it is vital to analyze the adaptive capacity of smallholder farmers to understand how variations in climatic conditions are perceived and mitigated by resource-constrained farmers. Smallholder farmers have limited information on the potential of crop diversification as a climate-smart agricultural practice. Moreover, there is scanty information in the literature on drivers influencing the decision of smallholder farmers to practice and scale up a crop diversification strategy for enhanced resilience in food systems.

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According to Hatfield, Harrison, and Banks-Leite (2018), climate variability requires farm households to adjust their crop mix portfolio and off-farm activities to improve household production and food and nutrition security. To reduce the effect of climate variability risks, Kumar et al. (2020), Altieri et al. (2015), argued that rural farm households need to engage in risk management strategies such as crop diversification to cope with unpredictable weather patterns and climate variability. Additionally, practising crop diversification by choosing climate-smart crops would better enable public and private sectors to formulate policies for crop insurance against weather risks (Khanal and Mishra 2017).

While agricultural diversification has been recognised as a needed and effective strategy to reduce crop failure among smallholder farmers in developing countries (Mulwa and Visser 2020; Birthal and Hazrana 2019; Mitter, Heumesser, and Schmid 2015; Veljanoska 2014; Khanal and Mishra 2017; Amare, Mavrotas, and Edeh 2018), we still need a better understanding of the determinants of crop mix portfolio as a climate-risk response mechanism. The choice of crop combination as a risk coping strategy to enhance resilience in food systems depends on the risk-bearing capacity of the farm household assets and farmers' level of perception of crop diversification as a climate-smart agricultural practice (Maziya et al. (2017)). Wuepper, Yesigat Ayenew, and Sauer (2018) argued that farm households could either be pushed or pulled into the practice of crop diversification as a response to climate risks due to lack of an alternative for risk coping for poor farmers. According to Nellemann and MacDevette (2009), rain-fed agriculture accounts for approximately 98% of farming activities in Kenya. This type of agriculture makes farm households more vulnerable to climate risks like temperature increase, droughts, floods, rainfall instability, and pest and disease incidences.

This study treated drought-tolerant maize (the primary staple in Kenya), along with sorghum, cassava, and sweet potato as climate-smart crops. A multinomial logit model was used to ascertain whether farm-level crop portfolio category choices are an ex-ante risk management response in the absence of crop insurance. Additionally, evidence of the multi-level combination of crop enterprise categories was tested and their determinants assessed. Findings from this study could be significant in informing policy formulation and implementation. The study could also improve smallholder farmers' adaptive capacity to climate variability for increased resiliency in agri-food systems. The rest of the paper is organised as follows: the next section presents the methodology used to attain data and the analytical techniques. In section three, we discuss the study results, and draw conclusions and implications.

2. Data and methodology

2.1 Study area

The study was conducted in 5 wards (West Kisumu, Central Kisumu, Kisumu North, North West Kisumu, and South West Kisumu) across Kisumu West Sub-County in Kisumu County (Figure 1). The Sub-County has a total area of 212.90 square kilometres with a population of 131,246 (KNBS 2010). The Sub-County has a bimodal type of rainfall pattern of long and short rains. The Sub-County lies between longitude 34° 44′ and 34° 54′ East and Latitude 0° 05′ and 0° 14′ North. The annual precipitation ranges between 1200 and 1300 mm in different sectors (County Government of Kisumu 2015). The major crops grown in the region are maize, beans, sweet potato, sorghum, and cassava, all under rain-fed conditions.

2.2 Data sources and sampling

The study was based on a cross-sectional research design whereby primary data were collected using a structured questionnaire comprised of both open- and closed-ended questions. Following Anderson et al. (2007), a sample of 267 respondents was randomly selected from all five wards to

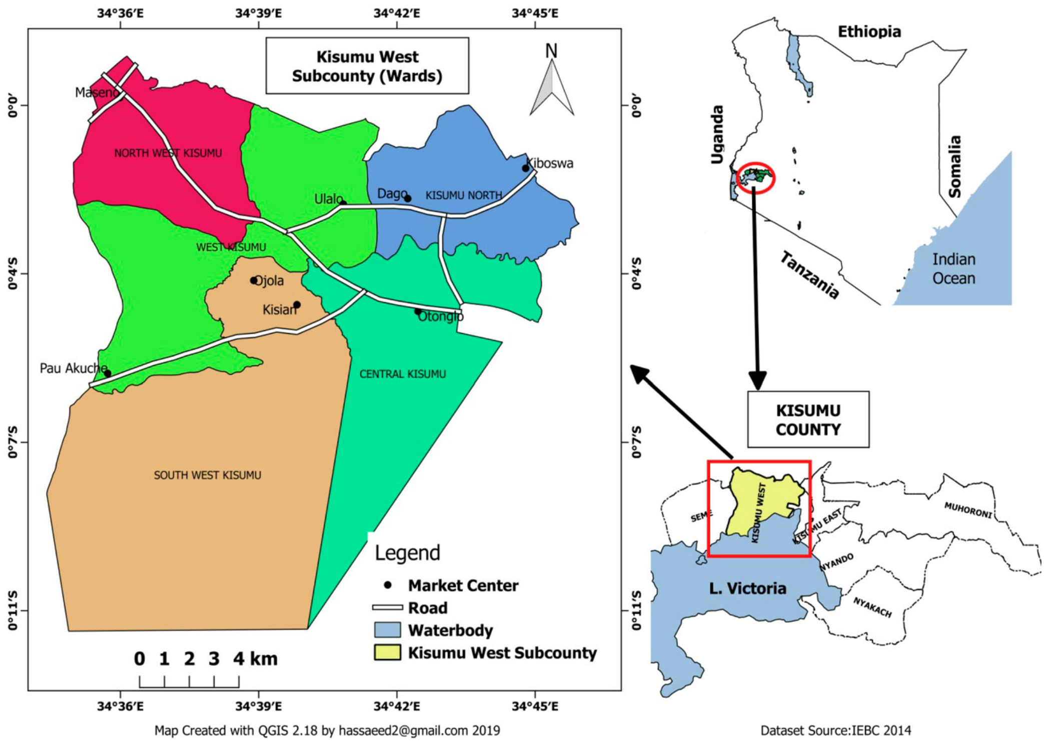

Figure 1. Map of the study area.

ensure even representation of all farmers in the study area. The sample size was distributed proportionately to the number of households per ward in Kisumu West Sub-County, as presented in Table 1.

Table 1. Proportionate sample size distribution per ward in the study area.

Wards	No. of households	Proportion (%)	Sample size
South West Kisumu	4901	17.21	46
Central Kisumu	8525	29.95	80
Kisumu North	5248	18.43	50
West Kisumu	4904	17.22	46
North West Kisumu	4896	17.19	45
Total	**28474**	**100.00**	**267**

2.3 Theory

This study is underpinned by portfolio theory (mean-variance (E-V) approach). Portfolio theory was initially developed by Markowitz (1959) and Tobin (1958), and was initially focused on financial investments. Nalley et al. (2009) define a portfolio as "a combination of items: securities, assets or other objects of interest." Nalley et al. (2009) argued that portfolio theory could be used to derive efficient outcomes by identifying a set of choices that minimises variance for a given level of expected returns or maximises expected return for a given level of variance. Under the assumptions of the EV approach, a farmers' preference ordering depends exclusively on the mean and variances of returns. The decision criterion to choose an appropriate crop mix from available possibilities is to maximise the utility of income or returns obtained from the possible crop portfolios. The utility derived depends on the return's mean and variance.

Therefore, portfolio theory is significant for this study of crop diversification as a response strategy to climate risks. Crop diversification allows producers (smallholder farmers) to allocate farm resources across various crop species and varieties with different relative risks and yields. Since different crop species respond differently to climate-related threats, there are potential risk-spreading benefits associated with producing crops under a diversified cropping system. Previous studies (Dixon et al. 2007; Nyikal and Kosura 2005) applied the theory to analyze risk preference and optimal enterprise combinations in agricultural production and to study the adoption rate of different farming practices among smallholder farmers.

According to Dury et al. (2012), selection of crop pattern or portfolio under crop diversification for agricultural areas is a typical resource allocation problem usually guided by the maximisation of expected returns or income. This return or payment depends on the farm characteristics, as well as socio-economic and institutional factors that influence the crop mix portfolio. The variability of crop productivity may depend on the postulated factors that affect the decision-making of smallholder farmers (Guariso and Recanati 2016). Therefore, based on this theory, the study evaluated determinants of crop mix portfolio as a response mechanism towards mitigating climate risk effects.

2.4 Conceptual framework

Adaptation to climate variability and the practice of crop diversification as an adaptation strategy is influenced by household characteristics, socio-cultural factors, farm characteristics, and institutional factors.

Household characteristics anticipated to affect the choice of crop portfolio included the level of education, gender, and age. For instance, based on previous studies, we hypothesised that households with highly educated members are more likely to practice crop diversification. Shah and Anbuvel 2016 and Mithiya, Mandal, and Datta 2018 found a positive relationship between education level and crop diversification.

Socio-economic factors such as access to extension services, information, and credit were also expected to influence crop mix portfolio and the extent of crop diversification. For instance, we postulated that smallholder farmers with access to credit services are more likely to practice crop diversification due to its capital and labour-intensive nature. Previous studies (Makate et al. 2016) showed a positive relationship between credit access and the practice of crop diversification.

Farm characteristics such as farm size were also expected to influence the crop combination chosen and the extent of crop diversification. For instance, we anticipated households with a large piece of land are more likely to practice crop diversification than those with a small piece of land. Previous studies have found crop diversification to be associated with larger farms. Group membership as an aspect of social capital was observed by some authors to be an essential variable influencing crop choice portfolio and the intensity of crop diversification (Mitter, Heumesser, and Schmid 2015). We hypothesised that group membership would have a positive effect on climate variability adaptation strategy and crop choice combination. Since crop diversification is thought to have food security vulnerability reducing effects, we assumed that a household would attempt to mitigate the effect of climate risks by choosing a crop portfolio that reduces production risks and enhances resilience in food systems.

The conceptual framework in Figure 2 below shows the interrelationships between the critical variables of the study.

2.5 Analytical framework

The dependent variable for this study is categorical, and so econometric models such as multinomial logit (MNL), multivariate probit (MVP), multinomial probit (MNP), and nested logit are

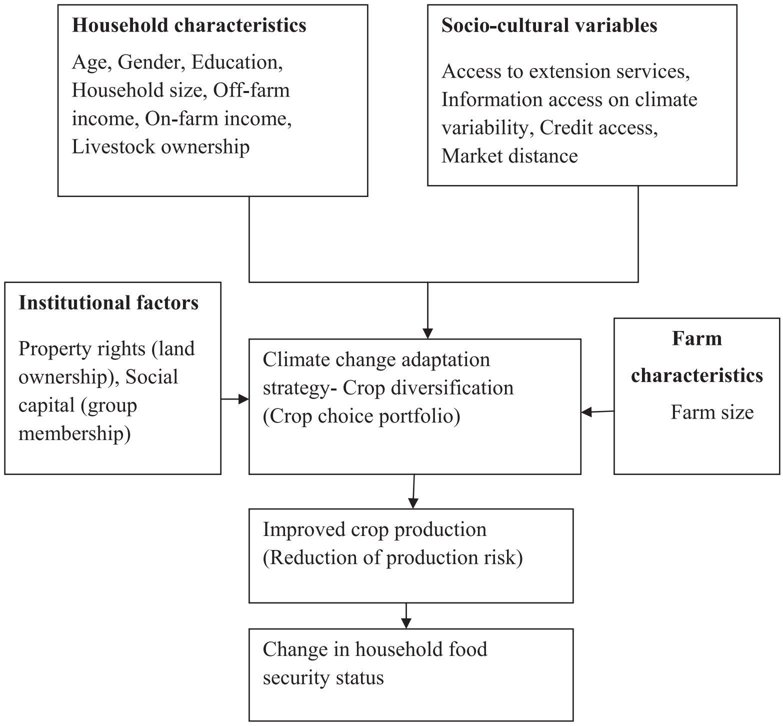

Figure 2. Conceptual framework.

appropriate. The MNP model does not require the assumption of the independence of irrelevant alternatives (IIA). However, the major limitation of the MNP model is its essential requirement of multivariate typical integral evaluation to estimate unknown parameters (Mihiretu, Okoyo, and Lemma 2019). Moreover, the MVP model may not be applicable in this case unless the dependent variable has more than two mutually dependent outcomes. Therefore, we adopted an MNL model to analyse determinants of crop mix portfolio where farmers have to choose only one product among the crop portfolios. The reason is that choice of crop portfolio is regional, soil characteristics, and preference specific.

According to Greene (2002), the advantage of the MNL model is that it permits the analysis of decisions across more than two outcomes, thus allowing the determination of choice probabilities for different categories. Most of the empirical studies similar to ours (Kumar et al. 2020; Ojo et al. 2013; Oloo, Ngigi, and Mshenga 2013; Gbetibouo, Hassan, and Ringler 2010; Wanyama et al. 2010; Deressa et al. 2009; Rahji and Fakayode 2009, Nhemachena and Hassan 2008) adopted an MNL model for their analyses.

Unbiased and consistent parameter estimates of the MNL model require the assumption of the IIA property to hold. This property states that the ratio of the probabilities of choosing any two alternatives is independent of any of the attributes in the choice set. For instance, the assumption requires that the likelihood of selecting a particular crop portfolio by a given farm household needs to be independent of the probability of choosing another. The validity of the IIA assumption was tested using the Hausman test.

We grouped farm households into nine categories based on the combination of crops chosen to respond to climate risks, as shown in Table 2.

To describe the MNL model, let $y$denotes crop portfolio categories ($j = 1, 2, 3, 4, 5, 6, 7, 8, 9$) for smallholder farmer i, and let Xdenotes a set of explanatory variables hypothesised to

Table 2. Categories of crop portfolio.

Crop portfolio	Categories
Maize only	1
Maize and Cassava	2
Maize and Sorghum	3
Maize and Sweet potatoes	4
Maize, Cassava and Sorghum	5
Maize, Cassava and Sweet potato	6
Maize, Sorghum and Sweet potato	7
Maize, Cassava, Sorghum and Sweet potato	8
Maize and other crops	9

determine the choice of crop portfolio. The general form of the MNL model is specified as:

$$\Pr = (y_i = j) = \frac{\exp(\beta_j X_i)}{1 + \sum_{j-1}^{j} \exp(\beta_j X_i)} \tag{1}$$

And to ensure identifiability,

$$\Pr = (y_i = 0) = \frac{1}{1 + \sum_{j-1}^{j} \exp(\beta_j X_i)} \tag{2}$$

where for the i^{th} farm household, y_i is the observed outcome, X_i is a vector of explanatory variables, and β_j is the unknown parameters to be estimated.

The model for this study was summarised as follows:

$$P_{ij} = \frac{\exp(\beta_j X_i)}{1 + \sum_{j-1}^{8} \exp(\beta_j X_i)} \forall_j = 1, 2, \ldots\ldots., 9 \tag{3}$$

where P_{ij} is the likelihood of being in each of the crop portfolio categories 1–9 of farm household, i

$$P_{i0} = \frac{1}{1 + \sum_{j-1}^{8} \exp(\beta_j X_i)} \forall_j = 0 \tag{4}$$

where P_{i0} is the likelihood of being in the reference crop portfolio category.

When estimating the MNL model, the coefficient of the reference group is normalised to zero. The reason is that the likelihood for all the choices must add to unity (Ojo et al. 2013). Thus, for nine options, only eight distinct sets of parameters can be identified and estimated.

The natural logarithm of the odds ratio of equation four gives the estimating equation as:

$$\ln \frac{P_{ij}}{P_{i0}} (\beta_j X_i) \tag{5}$$

Equation five denotes the relative probability of each of the 2-to-9 categories to the chance of the reference portfolio category. Therefore, the estimated coefficient for each choice reflects the effect of explanatory variables (X_i) on the likelihood of the farm household choosing that alternative crop portfolio over the reference group.

The parameter estimates of the MNL model provide only the direction of the effect of the independent variables on outcome variables. Therefore, differentiating equation two with respect to the explanatory variables gives marginal effects of the explanatory variables, as shown in equation 6.

$$\frac{\partial P_j}{\partial X_i} = P_j = (\beta_{ij} - \sum_{i-1}^{j-1} P_j \beta_{ji}) \tag{6}$$

The marginal effects values were estimated because the parameter estimates of the MNL model provide only the direction of the influence of the explanatory variables on the outcome variable. Moreover, parameter estimates do not represent the actual magnitude of chance or probability.

2.6 Limitation of the study

The study focused on the determinants of crop mix portfolio among smallholder farmers to improve the uptake and extent of crop diversification strategy as climate-smart agricultural (CSA) practise for enhanced resilience in the food system. However, the study did not cover the impact of crop choice on production risks, or on food security and poverty, which may affect the livelihood of smallholder farmers. The nature of the collected data limited the scope of this study.

3. Results and discussion

3.1 Descriptive statistics

The variables presented in Table 3 were chosen based on related literature (Sarr and Bezabih 2013; Khanal and Mishra 2017; Ojo et al. 2013; Oloo, Ngigi, and Mshenga 2013; Gbetibouo, Hassan, and Ringler 2010; Wanyama et al. 2010; Rahji and Fakayode 2009) and the particular variables of interest for this study.

The average age of the household head was 52.99 years (Table 3). This result confirms that most people engaging in farming activities are older people. The reason is that most youths migrate from rural areas to seek formal employment in urban areas. The average number of livestock owned per farmer – an indicator of wealth- measured in tropical livestock units (TLUs) was 4.98. Livestock ownership plays a vital role in providing labour and manure, thus potentially enhancing the practice of a crop diversification adaptation strategy. The survey results show that approximately 91.35% of the total respondents interviewed are practising crop diversification of some form.

Moreover, there was evidence in the survey that farm households are engaging in multiple activities to meet household needs. The survey revealed that the average monthly income from farm activities was Ksh. 8546. The suggestion is that the majority of the farm households were producing primarily for home consumption. However, Kom et al. (2020) found that on-farm income is a significant household economic resource as it plays a crucial role in improving crop varieties and purchasing hybrid seed varieties among smallholder farmers in South Africa. The average monthly off-farm earning was Ksh.14197. Wanyama et al. (2010) argued that income diversification from farming activities is increasingly becoming a vital component of poverty alleviation and food security improvement among rural farm households. Furthermore, Kumar et al. (2020) reported that off-farm income improves farmers' adaptive capacity during harsh climatic conditions. Therefore, those farmers who engage in off-farm activities such as business and formal employment are better positioned to diversify than those who rely only on on-farm income.

Table 3. Definition of variables used in econometric analysis and Descriptive statistics.

Variables Continuous variables	Definition of variables and its measurement	Mean
Household size	Household size in Adult Equivalent	4.66
Education	Household education level in years of schooling	45.68
Age	Age of household head in years	52.99
Farming experience	Years of farming of the household head	3.235
Off-farm income	Household off-farm income in KES	14197.22
On-farm income	Household on-farm income in KES	8546.28
Market distance	Distance to the nearest output market in Kilometres	1.73
Livestock ownership	Number of livestock owned by the household in TLUs	4.98
Farm size	Household s' farm size in acres	1.71
Categorical variables		Percentage
Gender	% of male respondent	57.68
Information access	% of respondent with access to information on climate variability	96.25
Credit access	% of households with access to credit services	32.75
Extension Access	% of households with access to extension services	16.48
Crop diversification	% of households practising crop diversity	91.35

On average, the respondents interviewed owned 1.71 acres of land, most of which was reported to be inherited from their grandfathers or fathers. The statistics also indicated that only 32.75% and 16.48% of the respondents interviewed had access to credit and extension services, respectively (Table 3). Access to credit allows farmers to buy farm inputs on time and diversify in producing labour-intensive crops as a response to climate variation (Kumar et al. 2020). Additionally, access to extension services provides information to farmers on awareness of changes in weather patterns and how to respond to or mitigate the possible effects of climate variability. To increase the probability of climate variability adaptation among smallholder farmers who mainly depend on rain-fed agriculture, Muzamhindo et al. (2015) emphasised the importance of improving access to extension services.

Descriptive results (Table 4) show that approximately 20.63% of the farm households have chosen a maize, cassava, sorghum, and sweet potato portfolio as a response strategy to climate risks, while about 19.44% of the farm household have chosen a maize, cassava, and sweet potato portfolio. Moreover, approximately 55% of the farm household have chosen either a maize and cassava or sorghum or sweet potato or other crops portfolio. Only 3.97% of the respondents reported cultivating maize only. The finding implies that a larger number of farm households interviewed are practising a crop diversification adaptation strategy to respond to climate change through the production of climate-smart crops such as sorghum, cassava, sweet potato, and drought-tolerant maize varieties.

Table 4. Distribution of the respondents according to the choice of crop mix portfolio in the study area.

Crop portfolio	Percent	Cumulative percent
Maize only	3.97	3.97
Maize and Cassava	9.13	13.10
Maize and Sorghum	7.94	21.–4
Maize and Sweet Potato	12.70	33.73
Maize, cassava, and Sorghum	7.94	41.67
Maize, Cassava and Sweet Potato	19.44	61.11
Maize, Sorghum and Sweet Potato	9.13	70.24
Maize, Cassava, Sorghum and Sweet Potato	20.63	90.87
Maize and other crops	9.13	100.00
Total	**100**	

We used a 5-point Likert scale to rank the impact of climate variability shocks on crop production, according to the respondents (Table 5). The respondents were required to indicate whether the impact is considered most serious, serious, not serious, neutral, or " do not know" on crop production. Table 5 results show that the majority of the farm households ranked drought, crop pest and diseases, and rainfall instability as the main shocks having severe impacts on crop production.

Table 5. Respondents' ranking on impact of climate variability shocks on crop production (5-point Likert scale measure).

Statements	MS	S	NS	N	DK	Weighted sum	Weighted Mean
Impact of Drought	67 (25.09)	68 (25.47)	56 (20.97)	21 (7.81)	55 (20.60)	872	3.27
Impact of Floods	16 (5.99)	35 (13.11)	89 (33.33)	110 (41.20)	17 (6.37)	724	2.71
Impact of Crop pest and Diseases	70 (26.22)	93 (34.83)	74 (27.72)	23 (8.61)	7 (2.62)	997	3.73
Impact of High Temperature	15 (5.62)	18 (6.74)	18 (6.74)	61 (22.85)	155 (58.03)	478	1.79
Impact of Rainfall Instability	100 (37.45)	53 (19.85)	30 (11.24)	52 (19.48)	32 (11.99)	938	3.51
Weighted mean sum							15.01
Weighted mean Average							3.00

MS = Most Serious, **S** = Serious, **NS** = Not Serious, **N** = Neutral, **DK** = don't know
Weights assigned: **MS** = 5, **S** = 4, **NS** = 3, **N** = 2, **DK** = 1

These results were also evident by the weighted mean of 3.27, 3.73 and 3.51, respectively, above the weighted mean average of 3.00 that climate variability affects crop production. The statistic implies that climate variability along other factors such as soil fertility also matters in the choice of crop portfolio in the diversification mix. The study results corroborate Kumar et al. (2020), who found that drought severely impacts crop productivity and crop yield in India.

3.2 Diagnostic tests

Multicollinearity between the explanatory variables was tested using the variance inflation factor (VIF). The results confirmed the absence of multicollinearity between any two or more explanatory variables. The mean VIF was found to be 1.48, and the values ranged from 1.04–3.24. Furthermore, all the variables were tested for heteroskedasticity using the Breuch-Pagan test. The *p*-value associated with the computed heteroskedasticity test statistics ($p < 0.1209$) is more significant than 0.05. The null hypothesis of homoskedasticity could not be rejected at a 5% significance level, and we concluded that the residuals are homogeneous. The validity of the IIA assumption was tested using the Hausman test. The *Chi-square* value of 0.00 and the high *Chi-square* probability value (Prob>$\chi 2 = 1.00$) of the Hausman test indicate insignificant results for IIA assumption; hence we fail to reject the null hypothesis that the crop combination categories are independent. The test implies that the coefficients of the variable from the full model with all the categories and estimated model when one of the categories excluded were similar, had the same signs, and shared a common statistical sign. Therefore, the results indicate that the model does not violate the IIA assumption of the multinomial logit model (MNL).

3.3 MNL model results

The model fits the data reasonably well since the likelihood ratio $\chi 2$-value was significant at a 1% significance level (LR $\chi 2$ (88) $= -357.83$, *P*-value = 0.00). This test confirms that all the slope coefficients are statistically significant, suggesting strong explanatory power of the model. Furthermore, the results imply that the explanatory variables included in the model significantly influence the choice of crop portfolio as a response to climate risks.

Table 6 shows the marginal effect coefficient results from the multinomial logit model that measures the actual magnitude of change in probability of a particular category of crop portfolio chosen for a unit change in an explanatory variable. As noted above, the marginal effects values are estimated because the parameter estimates of the MNL model provide only the direction of the influence of the explanatory variables on the outcome variable. In addition, they do not represent the actual magnitude of chance or probability. The parameter estimates of the determinants of crop choice portfolio were estimated, treating maize only (outcome 1) as the reference group. Therefore, the influence from the estimated marginal coefficient for each choice category was made relative to the maize only category.

The education level of the farm households was found to increase the probability of choosing the maize, sorghum, and sweet potato crop portfolio as a response to climate risks. The result implies that farm households with more years of schooling are more likely to make farm decisions based on the riskiness of a crop portfolio than farm households with a low number of years of schooling. A possible explanation for this could be that an increase in the farm household education stock increases the risk assessment of crop mix portfoilio among farm households. Similarly, Dembele et al. (2018) found that highly educated farm household heads were more likely to produce crop portfolios of cotton, maize, millet and cotton, and maize, sorghum and millet compared to other food crops in Southern Mali. This finding is also consistent with results reported by Ng'ombe, Kalinda, and Tembo (2017), Amare, Mavrotas, and Edeh (2018), Badjie et al. (2019) and Mihiretu, Okoyo, and Lemma (2019).

An increase in household size by one adult member increased the probability of choosing the maize, cassava, sorghum, and sweet potato portfolio (Table 6). On the other hand, household size

Table 6. Marginal coefficient results from the Multinomial logit regression (dy/dx).

Explanatory variables	Maize only Mfx & *P*-value	M & C Mfx & *P*-value	M &S Mfx & *P*-value	M & SWP Mfx & *P*-value	M, C&S Mfx & *P*-value	M, C,& SWP Mfx & *P*-value	M, S, & SWP Mfx & *P*-value	M, C, S & SWP Mfx & *P*-value	M & Other Crops Mfx & *P*-value
HHeducstock	0.0028 (0.084)	−0.0021 (0.252)	−0.0091 (0.566)	0.0004 (0.833)	−0.0003 (0.831)	−0.0006 (0.801)	0.0029 (0.088*)	−0.0034 (0.124)	0.0013 (0.397)
Hsize_Adult equiv	−0.0447 (0.085*)	0.0147 (0.466)	−0.0769 (0.389)	−0.0139 (0.552)	0.0191 (0.369)	0.0446 (0.144)	−0.0368 (0.**125)**	0.0567 (0.0**45**)**	−0.0228 (0.260)
AgeHHd	−0.0078 (0.387)	0.0097 (0.477)	−0.0019 (0.861)	0.0044 (0.749)	−0.0120 (0.377)	−0.0085 (0.630)	0.0096 (0.538)	0.0050 (0.768)	0.0114 (0.395)
Age_Squared	0.0001 (0.430)	−0.0001 (0.302)	−0.000(0.828)	−0.0001 (0.653)	0.0001 (0.404)	0.0001 (0.470)	−0.0001 (0.655)	0.0001 (0.631)	−0.0001 (0.386)
Farming Experience	0.0302 (0.256)	0.0563 (0.035**)	0.0053 (0.830)	0.0132 (0.641)	0.0549 (0.060*)	−0.0591 (0.073*)	−0.0134 (0.581)	−0.0504 (0.116)	−0.0368 (0.163)
Gender	0.0242 (0.394)	0.0331 (0.361)	−0.0455 (0.220)	−0.0224 (0.603)	−0.0129 (0.761)	−0.0367 (0.522)	0.0818 (0.051*)	−0.0975 (0.083*)	0.0024 (0.950)
FarmSize	−0.0731 (0.063*)	−0.0344 (0.158)	−0.0183 (0.401)	−0.0193 (0.495)	−0.0025 (0.897)	0.0640 (0.016**)	−0.0217 (0.321)	0.1006 (0.000***)	0.0049 (0.879)
HHTLUs	−0.0089 (0.235)	0.0042 (0.272)	0.0086 (0.006**)	−0.0066 (0.268)	0.0049 (0.180)	−0.0132 (0.059*)	0.0053 (0.152)	0.0090 (0.070*)	−0.0031 (0.430)
On-Income	−1.14e-6 (0.710)	3.75e-6 (0.004**)	−2.25e-6 (0.476)	1.42e-6 (0.472)	−2.66e-6 (0.394)	3.94e-6 (0.092*)	−3.55e-7 (0.330)	−1.54e-6 (0.584)	2.03e-6 (0.199)
Off_Income	6.45e-7 (0.382)	−2.21e-6 (0.**127)**	8.09e-7 (0.471)	1.46e-6 (0.159)	1.64e-6 (0.182)	−5.76e-7 (0.733)	1.28e-7 (0.929)	−5.76e-7 (0.727)	−1.32e-6 (0.250)
DstMrkt	−0.0083 (0.493)	0.0219 (0.014**)	−0.0087 (0.588)	0.0118 (0.418)	0.0104 (0.294)	0.0285 (0.126)	0.0033 (0.817)	0.0253 (0.100)	−0.0843 (0.005**)
Access to Information on climate variability	−0.0246 (0.719)	−0.0349 (0.735)	0.0194 (0.000***)	0.1035 (0.000***)	0.0982 (0.000***)	0.0440 (0.727)	−0.0075 (0.940)	−0.1450 (0.348)	−0.1131 (0.778)
CrdtAccess	0.0186 (0.579)	0.0077 (0.851)	−0.0061 (0.859)	0.0295 (0.525)	−0.0685 (0.077*)	−0.0219 (0.720)	−0.0772 (0.0**48**)**	−0.0243 (0.660)	0.1429 (0.005**)

M = Maize, C = Cassava, S = Sorghum, SWP = Sweet potato, Mfx = Marginal effect coefficient
Values in parenthesis are *P*-Values
*** = significance level at 1%, ** = significance level at 5%, * = significance level at 10%

negatively influenced the probability of choosing the maize only category. It could be that larger farm households are likely to choose a more diverse portfolio due to labour availability since producing a combination of these crops requires much more labour than single-crop production. This finding corroborates the finding of Uddin, Bokelmann, and Entsminger (2014).

The probability of choosing the maize, cassava, and sweet potato portfolio or the maize, sorghum, cassava and sweet potato combinations relative to maize only was positively influenced by farm size. This finding suggests that as farm size increases, farmers tend to diversify their crop production through the production of climate-smart crops. On the other hand, the probability of producing maize only was negatively influenced by farm size.

A possible explanation for this could be that as farm size decreases, smallholder farmers tend to specialise in their crop production due to inadequate land size to practice crop diversification. The implication is that most of the farm households in Kisumu County have acknowledged that climate variability is real, and they are responding through the production of climate-smart crops such as cassava, sorghum, and sweet potato as a response strategy to climate risks. Similarly, Rahman (2009a) in Bangladesh and Amare, Mavrotas, and Edeh (2018) in Nigeria and Uganda reported similar results. However, in Zambia, Ng'ombe, Kalinda, and Tembo (2017) found that farm size negatively affects the likelihood of smallholder farmers to practice more diversified farming.

The number of livestock owned by farm households was significant and positively influenced crop choice portfolio. The study result shows that an additional number of livestock (TLUs) owned by a farm household increases the probability of choosing maize, cassava, sorghum, and sweet potato portfolio relative to choosing maize only. A possible reason for this could be that farm households with a better resource endowment (i.e., livestock) tend to have a riskier crop portfolio in response to climate risks since livestock ownership acts as a measure of wealth, and provides draught power necessary for land preparation and a source of farmyard manure. Dembele et al. (2018) found similar results, where an increase in the number of oxen owned by farm households increased the probability of diversifying into cotton and maize, maize and two food crops, and maize and three opposed to the production of only food crops. Bezabih and Di Falco (2012) and Khonje et al. (2015) found similar results.

On the other hand, we found that the number of livestock owned by the farmer decreases the likelihood of choosing the maize, cassava, and sweet potato portfolio relative to choosing maize only. This implies that, the choice of maize, cassava and sweet potato portfoilio desreases with increase in livestock ownership. This is because most of the farm households were rearing mainly polultry, sheep and goats which reduces the availability of draught power for land preparation necessary for cassava, maize and sweet potato production. Consistent with this finding, Kunzekweguta, Rich, and Lyne (2017) found that livestock ownership negatively influences the uptake of a diversified and sustainable farming in Zimbabwe.

The monthly on-farm income of the farm households was significantly and positively associated with the likelihood of choosing maize, cassava and sweet potatoes portfolios. The suggestion is that farm households that earn more income from farming activities are more likely to choose crop a combination that generates on-farm income to improve household income. During the field survey, most farmers reported diversifying into the production of cassava and sweet potato for both consumption and commercial purposes. For instance, one farmer said, "He *used the money from cassava sales to buy fertiliser and certified maize seeds*. This study finding is in line with Amare, Mavrotas, and Edeh (2018), who found that wage income from farm activities increases the share of land allocated to tuber crops and cash crops but decreases the share of pulses in Nigeria.

Gender positively and negatively influenced the probability of choosing maize, sorghum and sweet potato, and maize, cassava, sorghum and sweet potato respectively. Male-headed farm households increases the chance of choosing maize, sorghum and sweet potato over maize, cassava, sorghum, and sweet potato relative to female-headed farm households. This impies that crop choice portfolio is preference gender based across the farm households interviewed. Similarly, Nordhagen, Pascual, and Drucker (2021) found that male farmers are motivated to practice agricultural diversity due to traditions and status.

Farming experience positively and negatively influenced the likelihood of choosing maize, cassava, and sorghum portfolios. The marginal effect results indicate that a one-year increase in years of farming increases the probability of choosing maize, cassava, and sorghum combinations while it decreases the likelihood of choosing maize, cassava, and sweet potato portfolio. A possible explanation could be that experienced farmers can more easily predict weather and climate variability and thus respond to climatic variabilty with smarter crop combinations to reduce production risk. For instance, this finding indicates that sorghum is more preferred to sweet potato because it is more droghout, pest and disease resistant, thus farm households prefer maize, cassava and sorghum to maize, cassva and sweet potato portfolio. Similarly, Mihiretu, Okoyo, and Lemma (2019) and Mulatu (2014) found that farming experience matters a lot in climate variability adaptation and mitigation.

Distance to the output market was found to have both positive and negative influences on the choice of crop portfolio. Though the distance to market increases the probability of farm households diversifying in producing maize and cassava, on the other hand, it decreases the likelihood of choosing maize and other crops combinations relative to maize only. This result suggests that due to the bulkiness of maize and cassava, nearness and better roads access to the output market is essential for ease of transportation for commercialising farmers. Similar findings are reported by previous studies (Mwaura and Adong 2016 and Amare, Mavrotas, and Edeh 2018), who found that land share allocated to different crops is influenced by the distance to the output market and its ease of accessibility.

Access to information on climate variability was positively associated with choosing the crop portfolio at a one per cent significance level. Farm households who received weather information were more likely to choose maize and sorghum, sweet potato, cassava, and sorghum combinations. The finding suggests that accessing climate change information positively influences farm households to make comparative decisions among crop portfolio choices to cope efficiently with climate risks. Abid et al. (2020) reported similar results in Malawi, where information on climate variability from the media regarding different coping strategies improved farmers' adaptive capacity. However, Ng'ombe, Kalinda, and Tembo (2017) results are at odds with this finding, who found that access to climate information negatively affects the probability of smallholder farmers practising climate-smart farming.

Access to credit negatively influenced the likelihood of choosing maize, cassava, sorghum, and sweet potatoes crop portfolios. The results of the field survey indicated most of the farmers who obtained financial credit from their groups or banks were using it to start a business rather than to invest in crop production. A possible explanation is that crop diversification involves an additional cost of production that requires a commitment of financial resources to purchase needed farm inputs. On the other hand, access to credit positively influences the choice of maize and other crops such as a vegetable portfolio relative to maize only, which implies that inadequate capital constrains farmers to choose climate-smart crops since some crops are labour and capital intensive in their production. This study finding confirms those of Chete (2019) and Mihiretu, Okoyo, and Lemma (2019) that access to affordable credit increases farm households' financial power, thus improving their capacity to meet additional transaction costs associated with crop diversification.

4. Conclusion and policy implications

We used cross-section survey data to evaluate the determinants of crop choice portfolio as an ex-ante risk management mechanism to combat climate risks, where crop insurance is limited or non-existent among smallholder farmers in Kisumu County, Kenya. We found that approximately 91.35% of the total farm households interviewed practised crop diversification of some sort as an adaptation strategy to climate variability. Furthermore, 20.63% of those practising crop diversification were found to produce maize, cassava, sorghum, and sweet potato combined in response to climate risks. Therefore, it follows that farm households in Kisumu County have acknowledged that climate variability is real and are responding by producing climate-smart crops such as drought-tolerant maize varieties, cassava, sorghum, and sweet potatoes within a crop diversification strategy.

The multinomial logit model regression results showed that the probability of choosing a specific crop portfolio category is positively and negatively influenced by education level, household size, gender, farming experience, farm size, livestock ownership, off-farm income, access to information as well as credit access. Farm size, distance to market, and access to climate variability information were found to be the most significant determinants of the choice of crop portfolio in the study area. For instance, most farmers reported that farm size remains the primary determinant of crop choice combination as a response strategy to climate risks. A possible explanation could be that most farmers found it challenging to intercrop maize with other crops such as cassava and sweet potato. Therefore, the significance of farm size in practising crop diversification suggests that an appropriate land distribution policy like the social land concession is essential among smallholder farmers. Furthermore, farmers reported that lack of credit access to rent additional land to produce other crops limits practice crop diversification. Therefore, the local government should provide credit services such as interest-free loans to smallholder farmers to promote diversification in the agricultural sector.

The results from this study have relevant policy implications regarding climate change adaptation, crop choice portfolio, and increasing crop diversity in the ever-changing climatic conditions for improved resilience in agri-food systems. Therefore, interventions that could promote climate variability awareness among smallholder farmers are highly recommended. The intervention can be accomplished by integrating awareness programmes on local radio stations and televisions to inform farmers about climate change and adaptation response strategies.

Finally, we conclude that as long as the availability of crop insurance remains limited in Kenya, crop portfolio choice remains an efficient way for farmers to protect themselves from climate-related risks. Therefore, development initiatives for improving climate change adaptation and increasing the production of climate-smart crops (cassava, sorghum, and sweet potato) need to pay more attention to enhancing climate variability awareness, and credit and information access. Moreover, given the effect of climate variability on smallholder farmers, integrating climate change policies and crop insurance policies should be considered. There is also a need for the government to consider undertaking policies to improve smallholder farmers' access to and control of land. This would enable farmers to grow crops such as cassava, sorghum, and sweet potato on separate plots rather than intercropping them with maize, thus improving crop yield per unit area. Furthermore, post-shock management actions that reduce the impact of climate variability shocks on crop yield are highly recommended to help in building resilience in agri-food systems.

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Availability of data

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

Disclosure statement

No potential conflict of interest was reported by the author(s).

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