Striving to be resilient: the role of crop-poultry integrated system as a climate change adaptation strategy in semiarid eastern Kenya

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ABSTRACT

Climate change continues to pose significant challenges to food security and livelihoods of smallholder farmers specifically in semi-arid regions. One approach that holds prospects for climate risk management is climate-smart agriculture (CSA). CSA has concentrated on crop practices with little attention to livestock especially indigenous (village) chickens as a potential practice that can be combined with crop agriculture. This study considers the adoption of three CSA practices: improved maize seeds (IS), soil management (SM), indigenous chicken (IC) enterprise and their various combinations. Using survey data collected from 300 farming households in semiarid Kenya, we estimate the impact of integrated crop-poultry system adoption on food security and farm income using multinomial endogenous treatment effect models. Robustness checks are conducted using alternative identification strategies. Results show that, generally, the adoption of IS, SM, IC and their combinations reduces the number of months without enough food and increases farm income. When we consider the magnitude of the impacts, interesting results emerge when a combination of the CSA practices are considered. The highest impact is observed with the joint adoption of SM & IC and IS &IC. Broadly, the empirical findings suggest that integrated systems (in our case crop-poultry integration), deserve both policy and research attention as they provide synergistic benefits that improve climate resilience and household welfare.

1. Introduction

Over 230 million people in sub-Saharan Africa are hungry and the numbers are likely to increase to 300 million in the next five years if not addressed (World-Bank, 2020). The increasing demand for food is a major concern because most of the sub-Saharan countries are adversely affected by climate change particularly the East Africa region (Ehui, 2020). The changes in rainfall patterns, flash floods, increased drought spells, and high temperatures affect agricultural production, increase food insecurity and affect the livelihood of most African smallholders (IPCC, 2014; Lipper et al., 2014). Climate change, therefore, might exacerbate poverty, food insecurity, and trap the poor, who are most vulnerable. Farming systems need to adapt and become more resilient to climate change. Climate change threat to agricultural production and food systems, thus, can be reduced by increasing the adaptive capacity of farmers as well as increasing resilience and resource use efficiency in agricultural production systems – a goal that climate-smart agriculture is meant to achieve (Lipper et al., 2014). Sustainable and resilient food systems that can protect the livelihoods of smallholder farmers are needed (Agovino et al., 2018; Zurek et al., 2022). Therefore, there is a need to promote the adoption of context-specific climate adaptation strategies that address the risk of climate change on livelihoods. In rural areas of developing countries, indigenous chickens (also called village chickens), which are mostly kept as free-range chicken, are a major part of the diversified livelihoods away from crop agriculture (Alemayehu et al., 2018). Indigenous chickens are valuable assets that have been found to be more resilient to the immediate effect of climate change as they do not depend on pasture, have low water, and feed needs (Gerbens-Leenes et al., 2013; Nyoni et al., 2021). Phiri et al. (2020) found that in Zimbabwe, poultry was a common climate change adaptation strategy. Because indigenous chickens are kept more by women, who are mostly in charge of food security, they are also effective at ensuring food security within the household (Bonis-Profumo et al., 2022; Nyoni et al., 2021). Phiri et al. (2020) found that in Zimbabwe, poultry was a common climate change adaptation strategy. Because indigenous chickens are kept more by women, who are mostly in charge of food security, they are also effective at ensuring food security within the household (Bonis-Profumo et al., 2022; Gitungwa et al., 2021). This means that the poultry-livestock farming system is among the most common among rural households and could be promoted as a potential climate change adaptation strategy. On the crop side, climate-smart agriculture (CSA) approach (Amadu et al.,

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2020; Ogada et al., 2020) has been promoted for climate adaptation. However, there is lack of evidence on the impact of indigenous chicken enterprises, and crop-poultry (indigenous chickens) on household welfare, with most studies focusing mostly on crop CSA (Fontes, 2020; Kassie et al., 2015; Khonje et al., 2018; Kpadonou et al., 2017; Martey et al., 2020; Wainaina et al., 2017). The aim of this study is therefore to determine the impact of integrated crop-poultry on food security and income, by focusing on indigenous chickens which have been found to be resilient to climate shocks. As an accompanying objectives or research questions, we also determine the factors that lead to the adoption of the integrated crop-poultry system and the impact of adopting one or two practices on food security and income, with the understanding that adopting two practices may present synergistic benefits. We demonstrate that indigenous chicken enterprises, when combined with crop-based CSA practices have larger impact on income and food security. Our study is consistent with the findings of Ponnusamy and Devi (2017) who show that the adoption of multiple farm enterprises like crop, dairy, poultry, and fish increased farm net profit by 660 USD per year compared to a less diversified crop in India. Similarly, Albers and Pym (2019) show that when small-scale poultry (SSP) production systems are integrated with human livelihoods, the household income, and food and nutrition security of the rural poor are enhanced.

CSA approach is the transformation and reorientation of agricultural systems to support food security taking into account climate change (Lipper et al., 2014). CSA is defined as a management strategy to address the challenges of climate change and food security by sustainably increasing productivity, bolstering resilience, reducing GHG emissions, and enhancing the achievement of national food security and development goals (FAO, 2010). Increasing agricultural productivity, feeding a growing population and reducing GHGs (mitigation) are some of the policy imperatives of CSA (Chandra et al., 2017). The Climate-smart Agriculture approach entails the adoption of resilient food production systems that have climate management potential through improving household food and nutrition security and increasing income under the ever-changing climate (Lipper et al., 2014). Some of the farm level CSA practices include agroforestry, soil and water conservation, drought-tolerant varieties, cropping patterns, and crop-livestock integration (McCarthy et al., 2011). A wide stream of literature from sub-Saharan Africa exists on the adoption and the impacts of CSA on various outcomes including income, food security and labour allocation (Fontes, 2020; Kassie et al., 2015; Khonje et al., 2018; Kpadonou et al., 2017; Martey et al., 2020; Wainaina et al., 2017). The findings of these studies show that the impacts of CSA adoption are mixed and generally the CSA adoption level remains low in Sub-Saharan Africa. However, crop-livestock integrated systems have received little attention even with the existing argument that system integration has the potential to increase household food and nutrition security and household income (Mulwa and Visser, 2020; Murendo et al., 2019; Parvathi, 2018) and crucially contribute to greenhouse gases reduction (Zervas and Tsipakou, 2012). Because there is universal uncertainty on some of the adaptation options such as crop-livestock systems, testing their effectiveness, learning and adaptive management should be part of the adaptation process to avoid maladaptation (Eriksen et al., 2021).

The crop-livestock integrated systems play two important roles that contribute to addressing climate management other than contributing to the synergistic benefits. First, livestock, specifically non-ruminants such as poultry have been shown to have lower greenhouse gas emission compared to cattle (Vergé et al., 2009). Specifically, chickens contribute less to GHGs compared to bigger ruminants such as pigs and cows (MacLeod et al., 2013). For example, in Japan Roy et al. (2012) found that the overall GHG emission of fresh chilled chicken, pork and beef are 6.0, 6.9 and 35.6 kg CO2 eq/kg-meat, respectively. Second, livestock manure and food waste can be used to produce biogas which in turn substitute for other fuels (Bhattacharya et al., 1997). Biogas is a clean and efficient energy source in rural areas that partly reduces the use of fossil fuels and firewood (Yu et al., 2008). Improved seeds have higher yields and more resistant to climate shocks as varieties are bred with the realities of climate change in mind (Cacho et al., 2020; Kansiime and Mastenbroek, 2016). Soil management such as reduced tillage reduces the negative effects of climate extremes such as droughts on crops by effectively managing water and moisture in the soil (Arslan et al., 2015, 2017; Malhi et al., 2021).

While there is science behind how these practices could help farmers adapt, the main concerns for rural households are income and food security, and agriculture is the primary source for both. Even with these benefits, the knowledge gap on the impact of crop-livestock farming systems on household welfare remains underexplored (Thornton and Herrero, 2014). This knowledge gap results partly from the limited availability of data on specific livestock enterprises (Garrett et al., 2017). Indeed, the few studies that have assessed the impact of crop-livestock integrated systems on household welfare do not focus on specific livestock category and majority employ crop-livestock simulation models (Rigolot et al., 2017; Thornton and Herrero, 2003).

In contributing to the literature on climate management options, this paper focuses on a specific form of crop-livestock integrated system, namely crop-poultry integrated systems and uses a causal econometric approach to estimate the impacts on household welfare. Explicitly, the study explores the adoption of multiple CSA practices, notably, the use of improved maize seeds (IS), soil management (SM), which is minimum tillage in this case, and indigenous chicken (IC) enterprise. We focus on maize as it is the most important crop in Kenya, accounting for nearly 40% of cultivated area, 2.4% of Kenya's GDP and 12.65% of agricultural GDP (FAOSTAT, 2019). We incorporate the indigenous chicken (IC) enterprise which is a specific livestock category to reflect the specificity in the crop-livestock integrated systems (hereafter referred to as crop-poultry integrated system) and estimate the causal impact of such integration on household welfare (farm income and food security) in semiarid eastern Kenya.Broadly, crop-livestock integrated systems are important climate change adaptation option in arid and semiarid regions because of the potential to increase environmental resilience through biological diversity which exploits synergies between the production systems (Devendra and Thomas, 2002; Lemaire et al., 2014; Thornton and Herrero, 2014). This synergy increases the efficiency in resource use which in turn may increase household incomes and food and nutrition security (Thornton and Herrero, 2015).

The focus of this study is on understanding the effectiveness of crop-poultry systems on food security and income. Results show that adoption is affected by household characteristics and that adopting a combination of technologies, especially those involving indigenous chickens, leads to better income and food security compared to adopting a single technology.

The rest of the paper is structured as follows: Section 2 provides an overview of the methods; section 3 explains the analytical methods. Section 4 presents the results and discussion and lastly, section 5 provides the conclusion and recommendations of the study.

2. Methods

2.1. The project

The “Innovating for Resilient Farming Systems” research project was implemented to catalyse the adoption of a range of climate-resilient farming practices in three semi-arid counties of Eastern Kenya: Machakos, Makueni and Tharaka-Nithi. The project focused on integrated assessment of social, economic, knowledge-based, institutional, and policy factors that impact farmers’ ability to adopt economic, social and ecological resilient farming practices and technologies. Specifically, the project promoted widespread diffusion and adoption of practices that drew on local resources including crop practices and poultry enterprises. The project setup demonstration sites in various villages where farmers could learn and evaluate the practices before applying them in individual farms.
2.2. Study area, data and sampling

The data used was collected in 2014 from a farm-level survey applied on smallholders in Machakos and Makueni counties of Kenya (Figure 1) to understand household uptake and the impact of the CSA practices promoted by the project. The average rainfall per annum in Machakos county is between 500mm and 1300mm with temperature between 18 °C and 29 °C on the other hand, Makueni county receives inadequate rainfall of about 600mm per annum with the average temperature being 23 °C.

A Multistage sampling procedure was used to draw the sample. In the first stage, three sub-locations were randomly selected in both Machakos and Makueni counties (Figure 1), and then, four villages from the six sub-locations were randomly selected. A total of 24 villages were randomly selected. Due to budget limitations, 300 farming households were interviewed. The sample was arrived at also based on literature that evaluates the uptake of technologies in sub-Sahara Africa (Mabuza et al., 2013; Mutuc et al., 2013; Yegbemey et al., 2013). Given this sample size, 9–12 farmers were randomly selected from each of the 24 villages using simple random sampling with replacement. The process of identifying the targeted households is as follows; a team of trained enumerators were tasked with visiting and interviewing the targeted households. First, enumerators were asked to visit a sampled village with coordination of the village elder. Once in the targeted villages, the enumerators randomly chose a household and conducted the interview. After interviewing the first household, the enumerators were asked to skip three households towards any direction and interview the fourth household, where the fourth household was not found, the household was replaced with the fifth household. The same process was repeated until the required number of households in the targeted villages was achieved. A pre-tested questionnaire was administered during the survey to collect information on household and farm characteristics. The questionnaire was administered using face-to-face interviews, and where possible, the respondent was the head of the household or the head of the household and their spouse. Questions collecting information on the household roster, land size, enterprises engaged in, crop management, access to services, and social capital were asked by trained enumerators. Questions specific to improved maize seeds asked what type of seed farmers used in their maize (i.e., local, hybrid, or open-pollinated varieties, with hybrid and OPVs taken as improved). Soil management referred to the use of minimum tillage. The questionnaires were checked by a supervisor every day in the field and a debriefing was held every morning the following day before starting a new set of interviews. After the collection, the data was entered in SPSS, cleaned, and exported to Stata for analysis.

2.3. Empirical strategy

The empirical approach employed estimates the determinants of adoption and the impact of the adoption of the CSA practices on food security and income. The authors begin with the determinants of adoption and outline the multinomial logit model that was used, excluding any potentially endogenous variables. To understand the impact of the adoption of CSA practices on farm income and food security, the multinomial endogenous treatment model was used to account for potential self-selection.
In this study, three different CSA practices that were promoted in the study area with the potential to make agriculture more resilient to climate change were considered. These are improved maize seeds (IS), soil management (SM), indigenous chicken (IC) enterprise and their various combinations. The total number of CSA practice profiles \( V_0 \) is given as \( J = 2^n \); where \( n = 3 \). This gives us a total of \( J = 8 \) possible CSA practice combinations. However, because the authors do not observe any household that has adopted all three practices and the number of households adopting IS & SM is too small, only \( J = 6 \) practices profiles remain, plus non-adoption. The goal of multiple practices evaluation is to be able to evaluate the combined practices as one and measure the impact on an outcome variable. The impact of the practices is measured on 2 outcomes: food security, and income.

This study uses the theory of random utility maximization as a theoretical framework that underpins the empirical analysis. To begin, applying random utility maximization to this study, we assume that (1) CSA practice choice is a discrete event and that, (2) the observed choice of practices arise from the random utility maximization process, where this maximization is, in part, conditioned by individual preferences (Kassie et al., 2013). With the theory of utility, what is deemed necessary about utility concerning choice/s being made is whether an option has a higher utility than another and not the measure of the difference between the available options. Therefore, farmers evaluate the potential benefits from the available practices and decide to adopt those that give them benefits. Smallholder farmers adopt CSA practices when the expected utility or net benefit is significantly higher than when they do not adopt. However, utility cannot be observed, but the resulting choices can be observed. We assume rational farmer whose aim is to maximize utility from production over a specific period and has a set of CSA practice \( J \) options to choose from. The farmer \( i \) decides to adopt CSA practice \( j \) if the utility from \( j \) is perceived to be more than that from other options, \( u(V_j) > u(V_{ij}) \) where \( j \neq k \).

In all the observed adopted profiles, farmers may be self-selecting themselves into adoption and this may result in problems of endogeneity because some of the unobserved factors that lead to the adoption of certain profiles may also be influencing the outcome variables (Kassie et al., 2013).

To correct for self-selection, a multinomial endogenous treatment effect model is used (Deb and Trivedi, 2006a,b). The model uses a latent factor structure to accommodate self-selection into treatment and a theoretical framework that underpins the empirical analysis. To begin, the probability of adopting CS practice \( j \) is replaced by \( \delta_j \) which means there is positive (negative) selection into adoption (Deb and Trivedi, 2006b; Manda et al., 2016). \( \gamma_j \) is the impact of CSA practice \( j \) on the outcome variable.

For the first stage estimation of the determinants of adoption of different practices, both the multinomial treatment model with ordinary multinomial logit to recover the marginal effects\(^2\) are combined. The marginal effects of the ordinary multinomial logit are interpreted and discussed to explain the determinants of CSA practices adoption.

The identification of treatment impact does not require instruments in the treatment equation; however, distance to the extension office and access to credit are included as instruments. These variables should not affect food security or farm income directly except by increasing the probability of adopting CSA practices (Gine and Yang, 2009; Manda et al., 2016). Following Di Falco et al. (2011) a test for the admissibility of these instruments is conducted. The admissibility test asserts that if these are valid instruments, they should affect the decision to adopt a CSA practice but not the outcome variable for those who did not adopt.

However, rather than relying on these instruments to robustly identify the impact, the authors instead do a robustness check using a Poisson endogenous treatment effect model for food security and a linear endogenous treatment effect model for farm income. An endogenous-treatment (both Poisson and linear) model allows for estimation of treatment impact when the treatment variable is binary (Terza, 1998). However, we modify the model to allow for estimation under a case of multiple practices. Formally, the model would be stated as:

\[
E\left[ t_j|\alpha, \beta, \delta, \mu \right] = \exp(\alpha \beta + \delta \mu + \epsilon)
\]

where \( \alpha, \beta, \delta, \) and \( \mu \) are the exogenous variables in the model with the associated parameters \( \alpha, \beta, \delta, \mu \). The endogenous multinomial latent choice variable is represented by \( m_0 \) with the associated parameters as \( \delta \) while \( \epsilon \) are the stochastic errors. An assumption that \( m_0 \) and \( \epsilon \) are not correlated is made. Letting \( j = 0 \) represent a household that does not adopt any of the practices' profiles, then it is fair to assume that they get zero utility from any of the practices such that \( u(V_i) = 0 \).

The researchers can only observe the adopted practice profiles \( d_i = d_j \) that correspond with the latent variable \( m_i = m_j \). The probability of adopting any of the practice profiles is then represented as:

\[
Pr(d_i|z_i, m_i) = g(z_i; \alpha_1 + \delta_1 m_1, ..., z_i; \alpha_j + \delta_j m_j)
\]

where \( g \) is assumed to have a mixed multinomial logit structure such that:

\[
Pr(d_i|z_i, m_i) = \frac{\exp(z_i; \alpha_j + \delta_j m_j)}{1 + \sum_{j=1}^n \exp(z_i; \alpha_j + \delta_j m_j)}
\]

For food security, a count variable (i.e., the number of months without enough food) is used. This is a measure that indicates the number of months in the year the household did not have enough food to meet the household food needs (Wineman, 2016). Income is a continuous variable; hence a linear model is used. Outcomes \( y_i \), depending on exogenous, endogenous, and latent variables as:

\[
E(y_i|d_i, x_i, m_i) = X_i \beta + \sum_j y_j d_j + \sum_j y_j m_j
\]

where \( X_i \) is a set of exogenous covariates associated with parameter vectors \( \beta \) and \( \gamma_j \) is the impact of adopting CSA practice profile \( j \) relative to non-adoption. The dependent variable for food security is specified as a negative binomial distribution with an over-dispersion parameter while that for income is specified as a Gaussian distribution. Model (4) corrects for self-selection by including the factor loading parameter \( \gamma_j \) that accounts for the unobserved factors correlated with both the adoption decision and the outcome variables. The relationship between treatment and the outcome variable is indicated by the sign of \( \gamma_j \). If the sign of \( \gamma_j \) is positive (negative), it means treatment is positively (negatively) correlated with the outcome variable – which means there is positive (negative) selection into adoption (Deb and Trivedi, 2006b; Manda et al., 2016). \( \gamma_j \) is the impact of CSA practice \( j \) on the outcome variable.
and indigenous chickens (IC). About 3% had adopted a combination of improved maize seeds (IS) and indigenous chicken (IC) and about 7% adopted a combination of soil management practices (SM) and indigenous chickens (IC). About 3% had adopted a combination of improved maize seeds only, about 6% soil management practices only, and about 21% had adopted indigenous chickens only. About 20% adopted a combination of improved maize seeds and indigenous chicken (IS & IC) and about 17% adopted a combination of improved maize seeds and soil management (ISSM) practices. Inversely, this means that about 6 members. Institutional factors such as access to services were also included. Households on average had markets and extension services within their vicinity, while about 48% had access to credit.

3. Results and discussion

3.1. Descriptive statistics

Table 1 presents the definition and descriptive statistics of the variables used in the empirical analysis. On average, households experienced about 6.8 months without enough food, measured as the total sales by price for all farm products sold. In terms of practice profiles that were adopted, 18% of the households had adopted improved seeds only, about 6% soil management practices only, and about 21% had adopted indigenous chickens only. About 20% adopted a combination of improved maize seeds (IS) and indigenous chicken (IC) and about 7% adopted a combination of soil management practices (SM) and indigenous chickens (IC). About 3% had adopted a combination of improved maize seed (IS) and Soil Management practices (SM), hence this profile was dropped from the analysis due to insufficient observations. No household had adopted all three practices.

The average age of a household head in the sampled household was 53 years, with an average of 65% of the households headed by a male. Of the remaining 35% of female-headed households, 20% were de jure female household heads (i.e., women live without a male partner such as those who are single or widowed) and the average family size was about 6 members. Institutional factors such as access to services were also included. Households on average had markets and extension services within their vicinity, while about 48% had access to credit.

3.2. Adoption of CSA practices

Table 2 presents the results of the first-stage multinomial selection model. Only the marginal effects are presented for brevity. Table 3 presents the multinomial results that show the likelihood of adopting one or two CSA practices. This shows the factors associated with the adoption of CSA integrated crop-poultry farming systems.

Household-level variables that measure both endowments (e.g., family size, land size), accessibility (e.g., distance to market, distance to extension office), experience (primary occupation) and household head characteristics like age, gender and education level were included as control variables. Results show that de jure female-headed households are less likely to adopt most of the practices while an increase in the education level of the household head increases the likelihood of adopting soil management practices. Inversely, this means that de factor female-headed households are more likely to adopt these practices compared to the de jure female-headed households. This could be explained by the lack of resources that is common among de jure female-headed households as they are divorced or widowed.

Surprisingly and inconsistent with previous studies (Amsalu and de Graaff, 2007; Fontes, 2020), results show land size to be negatively

\[ y_i = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_p x_p + \epsilon_i \]

where \( y_i \) is a dummy variable that takes the value 1 if the combination is practised, 0 otherwise.

\[ \delta_{ij} = \gamma_0 + \gamma_1 x_1 + \gamma_2 x_2 + \cdots + \gamma_p x_p + \epsilon_{ij} \]

where \( \delta_{ij} \) is a dummy variable that takes the value 1 if the combination is practised, 0 otherwise.

In 2014, $1 = Ksh88.
correlated with the adoption of soil and water management practices implying that an increase in land size is associated with a reduced likelihood to adopt soil management practices. It is possible that with large land sizes, households are more likely to practice extensive farming methods. Soil management practices are considered intensive farming meant to reduce the impact of climate change (Pender and Gebremedhin, 2007). In explaining the negative effects of farm size on the adoption of soil management practices, Gebremedhin and Swinton (2003) show that a bigger farm size reduces the incentive to conserve the land through soil management practices.

Livestock ownership (measured in tropical livestock units – TLU, which is a weighted average of all livestock excluding chicken) is positively correlated with an increased likelihood of adopting CSA practices. Livestock ownership represents household assets that are relatively easy to liquidate to invest in the adoption of CSA practices (Bekele and Drake, 2003). Distance to the extension office negatively affects the likelihood of CSA adoption, especially the combined practices. Results also show that off-farm income is negatively correlated with the adoption of improved seed and soil management practices. This implies that farmers are not willing to invest their off-farm income into farming probably given climate change risks.

To further understand the differences between non-adopters, households adopting one practice or two practices, we estimate a multinomial logit model. Results are shown in Table 3. In the multinomial regression results, farmers that did not adopt any of the practices are the base category. De jure female-headed households are less likely to adopt both one and two practices compared to de facto female-headed households (inversely, de facto are more likely to adopt). An increase in farm size is also associated with a reduced probability of adopting one practice compared to none. With large farm sizes, farmers tend to practice extensive farming with limited adoption of new farming technologies. As expected, an increase in TLU is positively correlated with a higher likelihood of adopting both single and two practices. Further, distance to extension services is negatively correlated with the adoption of two practices, meaning that households with limited access to extension services are less likely to adopt any CSA practice. Overall, we find that for most variables that were significant in the individual technologies are not significant in the single or double technologies adoption compared to one. Adoption of multiple technologies requires more resources as has been shown in literature (Kanyenji et al., 2020; Musafiri et al., 2022). For example, Kassie et al. (2013) found that key factors included government effectiveness in the provision of extension services.
3.3. Impact of CSA practices on farm income and household food security

Because of the resources required, the adoption of individual CSA practices may be much lower than the adoption of synergies when adopted together (as we show in the impact results). This presents the results that determine the impact of integrated crop-poultry CSA practices on household welfare. First, results related to the impact of determinants (i.e., the control variables) included in the outcome equation are interpreted. The preferred specification is the one that includes household characteristics to control for any further confounding after correcting for self-selection.

Table 4 presents the results of the multinomial endogenous treatment effect model. This presents the results that determine the impact of integrated crop-poultry CSA practices on household welfare. First, results related to the impact of determinants (i.e., the control variables) included in the outcome equation are interpreted. The preferred specification is the one that includes household characteristics to control for any further confounding after correcting for self-selection.

### Table 3. Determinants of adoption of one or two CSA practices—multinomial logit results.

| Variables                          | Coefficients  | Marginal Effects                  |
|-----------------------------------|---------------|-----------------------------------|
|                                   | One practice  | Two practices                     |
| Age of HH head                    | 0.009         | -0.000                            |
|                                   | (0.018)       | (0.009)                           |
| Male headed household             | -0.320        | -0.217                            |
|                                   | (0.476)       | (0.538)                           |
| De jure female head               | -1.205**      | -1.063*                           |
|                                   | (0.583)       | (0.640)                           |
| Household size                    | -0.004        | 0.004                             |
|                                   | (0.069)       | (0.074)                           |
| Education of HH head              | 0.007         | -0.009                            |
|                                   | (0.052)       | (0.054)                           |
| Log of farm size                  | -0.418*       | 0.008                             |
|                                   | (0.218)       | (0.252)                           |
| Livestock ownership               | 0.252***      | 0.319***                          |
|                                   | (0.093)       | (0.096)                           |
| Agriculture primary occupation    | 0.238         | 0.374                             |
|                                   | (0.375)       | (0.415)                           |
| Access to credit                  | 0.448         | 0.460                             |
|                                   | (0.326)       | (0.354)                           |
| Log of distance to extension office | -0.165      | -0.557**                          |
|                                   | (0.221)       | (0.235)                           |
| Log of off farm income            | 0.028         | -0.020                            |
|                                   | (0.048)       | (0.049)                           |
| Remittances                       | -0.473        | -0.522                            |
|                                   | (0.376)       | (0.405)                           |
| Log of distance to market         | 0.149         | 0.452**                           |
|                                   | (0.155)       | (0.188)                           |
| County dummy                      | 0.011         | 0.057                             |
|                                   | (0.355)       | (0.379)                           |
| Constant                          | 0.372         | 0.206                             |
|                                   | (1.543)       | (1.635)                           |
| Observations                      | 300           | 300                               |
| LR statistic                      | 44.38         | 44.38                             |
| Prob > chi2                       | 0.0255        | 0.0255                            |
| Log-likelihood                    | -293.1        | -293.1                            |

Robust standard errors in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1.

### Table 4. Impact of different CSA practices on food insecurity and farm income—multinomial endogenous treatment effect results.

| Variables         | Impact on food insecurity | Impact on farm income |
|-------------------|----------------------------|-----------------------|
|                   | With controls | Without controls | With controls | Without controls |
| IS                | -0.121        | -0.070             | 0.942***      | 0.859***         |
|                   | (0.149)       | (0.180)            | (0.097)       | (0.092)          |
| SM                | 0.009         | -0.130             | 1.604***      | 0.828***         |
|                   | (0.174)       | (0.175)            | (0.071)       | (0.110)          |
| IC                | -0.468***     | -0.472*            | 1.559***      | 0.103            |
|                   | (0.146)       | (0.267)            | (0.071)       | (0.113)          |
| IS and IC (IS&IC) | -0.492***     | -0.747***          | 1.535***      | 1.651***         |
|                   | (0.134)       | (0.151)            | (0.079)       | (0.074)          |
| SM and IC (SM&IC) | -0.253        | -0.311             | 1.268***      | 1.324***         |
|                   | (0.177)       | (0.202)            | (0.049)       | (0.115)          |
| Age of HH head    | -0.003        | 0.013***            | (0.004)       | (0.004)          |
| Male headed household | 0.126      | -0.104*            | (0.092)       | (0.054)          |
| Household size    | 0.043***      | 0.100***            | (0.016)       | (0.015)          |
| Education of HH head | 0.062***     | 0.135***            | (0.015)       | (0.017)          |
| Log of off-farm income | 0.003       | 0.002              | (0.012)       | (0.007)          |
| Remittances       | -0.127        | -0.093             | (0.108)       | (0.063)          |
| Log of distance to market | -0.205*** | -0.192***          | (0.041)       | (0.059)          |
| Constant          | 2.550***      | 2.966***            | 6.500***      | 9.359***         |
|                   | (0.299)       | (0.094)            | (0.223)       | (0.067)          |

Robust standard errors in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1.

The variable is not included due to the potential endogeneity of de-facto female-headship and male headship.

Because there is self-selection into adoption, an instrumental variable approach to strengthen the identification strategy in the multinomial endogenous treatment effect model is used. The admissibility of the instruments as they affect food security and income only through CSA adoption (see Table A1 in the appendix). To unravel the effects of multiple CSA practice adoption, a categorical variable that differentiates between non-adopters is further constructed, and analysis done by these groups.

Table 3 presents the results of the multinomial endogenous treatment effect model. This presents the results that determine the impact of integrated crop-poultry CSA practices on household welfare. First, results related to the impact of determinants (i.e., the control variables) included in the outcome equation are interpreted. The preferred specification is the one that includes household characteristics to control for any further confounding after correcting for self-selection.

**3.3. Impact of CSA practices on farm income and household food security**

Tenure status of plot, social capital, plot size, and household assets—which are all assets that indicate the level of resources—were significant in influencing the adoption of multiple agricultural practices. This means that overall, even though those technologies may have advantages and synergies when adopted together (as we show in the impact results), their adoption may be much lower than individual technologies because of the resources required.

Table 4 presents the results of the multinomial endogenous treatment effect model. This presents the results that determine the impact of integrated crop-poultry CSA practices on household welfare. First, results related to the impact of determinants (i.e., the control variables) included in the outcome equation are interpreted. The preferred specification is the one that includes household characteristics to control for any further confounding after correcting for self-selection. **de jure** female-headed...
An increase in the age of the household head by one year increases farm income by about 1.3% while having no significant impact on food security. This is in line with the life income hypothesis that older people tend to have more income from previous savings. An increase in household size is associated with an increase in both food security and income. This suggests that an increase in household size represents an increase in the number of mouths to feed within the household. This is shown by an increase in the number of months without enough food by 4.3% for an increase in household size by one member. On the other hand, an increase in household size increases farm income by 10%. As household size increases, income increases in absolute terms but not necessarily per capita. Bigger household sizes could have more labour and desire to generate higher income. An increase in the education of the household head leads to an increase in farm income and a reduction in the number of months a household goes without enough food.

The other significant variable is the distance to the market, indicating, unexpectedly, that an increase in distance to the market has a positive impact on both food security and income. Even though others have found this relationship (for example Ahmed and Mesfin, 2017), the authors believe in this case it is because the project targeted communities who are in remote areas and living far away from the market. This is also confirmed by the positive coefficient in the CSA practices adoption model, showing that those who live far from the market were more likely to adopt one and two practices compared to not adopting any practice. Among the CSA practices, only IC and IS&IC have a significant effect on food security, showing that the adoption of IC reduces the number of

![Figure 2. Impact of CSA practices on household food security and farm income. The light blue diamond is the mean effect and the black lines the 95% confidence intervals. IS = improved seeds, SM = soil management, IC = indigenous chickens.](image)
months without enough food by about 46% while the adoption IS&IC reduces the number of months without enough food by about 49.2% compared to those who do not adopt any CSA practice. Without accounting for household characteristics that may be confounding the impact, higher impact for both IC, and IS&IC on food security is found. Specifically, the number of months without enough food reduces by 47.2% and 74.7% respectively for IC, and IS&IC compared to non-adopters.

Results further indicate that all CSA practices significantly increase farm income compared to non-adopter. Focusing on the magnitude of impact, SM has the largest impact on income followed by IC, and IS&IC. However, if household characteristics are not controlled for, the impact of IC is not statistically significant, the impact of SM reduces while that of IS&IC and SM&IC increases. This shows that ignoring household characteristics confounds the impact of adoption on food security and income, albeit in different ways.

Figure 2 shows, visually, the levels of predicted food insecurity (in the number of months without enough food) and income associated with each of the CSA practice profiles. The impact, in this case, is simply the level of the outcome variable observed for households adopting any of the CSA practice profiles, less the level of the outcome for non-adopters and not the marginal effect or coefficient. As can be seen in part (a) of Figure 2, only IC and its combinations significantly reduce the number of months without enough food compared to not adopting any practice. The biggest impacts are observed in IS&IC profiles.

The adoption of any of the CSA practices significantly increases income compared to non-adopters; however, IS adoption has the lowest impact on income compared to other practices. Again, IC and IS&IC have the largest impact on farm income. The factor-loading parameters ($\lambda_j$) or selection terms show that there is negative selection into the adoption of any of the CSA practices except for IC with farm income (Table 5). This means that selection into adoption and outcome (food insecurity, and farm income) are negatively correlated. There is negative self-selection into adoption.

When the adopters are put into two categories, that is examining those who adopt one versus two practices, results indicate that adopting only one practice has no impact on food security while two practices have a significant impact on food security. However, adopting either one or two practices significantly increases farm income compared to not adopting any practice. These results corroborate previous studies that find that adopting multiple technologies is much more beneficial as there are synergies gained from different technologies (Bagheri and Teymouri, 2022; Lemaire et al., 2014; Wainaina et al., 2017). Further, by adopting multiple technologies, households are able to insure their welfare against different types of risk (Khoza et al., 2020). For example, in our case, IC enterprise, which is much more resilient to climate shocks (Gheyas et al., 2021), is possibly shielding households from crop failure that could result from climate shocks. Further, crop and livestock prices are different, offering households a diversified portfolio.

### 3.4. Robustness checks

To test the robustness of the results, two separate models are estimated, one on food security and another on farm income. Results in Table 6 are robust to different estimation strategies. For the food security model, the Poisson model with endogenous treatment effects is used while for the impact on farm income a linear regression model with endogenous treatment effects is used. In both cases, results hold. Again, regarding food security, results show that the greatest impact comes from IC while for farm income it comes from a combination of SM&IC.

### 4. Conclusion and implications

This study examined the adoption of CSA practices as a potential pathway for building farm resilience to climate change. The main objective of this paper was to estimate the impact of CSA practices on household food insecurity (measured by the number of months without enough food) and farm income. Overall, climate management through CSA adoption significantly reduces the number of months without enough food and increases farm income. Specifically, differences in the impacts of CSA adoption on food insecurity and farm income are observed. For food security, significant impacts are realized with the adoption of IC alone and the highest impact with the joint adoption of IC and crop management practices. This highlights the importance of IC as a climate risk management practice that improves household welfare. This is mainly because chicken enterprises provide both meat and eggs which

### Table 5. Impact of one or two CSA practices on food security and farm income—multinomial endogenous treatment effect model results.

| Variable | Impact on food insecurity | Impact on farm income |
|----------|---------------------------|-----------------------|
|          | With controls | Without controls | With controls | Without controls |
| One practice | -0.306 | -0.131 | 1.458*** | 0.612*** |
|           | (0.355) | (0.195) | (0.046) | (0.242) |
| Two practices | -0.462** | -0.744*** | 0.840*** | 2.132*** |
|           | (0.206) | (0.125) | (0.072) | (0.178) |
| Constant | 2.718*** | 2.074*** | 4.765*** | -1.294*** |
|           | (0.324) | (0.119) | (0.055) | (0.085) |
| Household controls | Yes | No | Yes | No |
| Factor-loading parameters ($\lambda_j$) | 0.117 | 0.156 |
|          | (0.405) | (0.149) |
| Two practices | 0.226 | 0.475*** |
|           | (0.243) | (0.048) |
| Observations | 300 | 300 | 295 | 295 |
| LR statistic | 173.9 | 199.30 | 4317 | 216.3 |
| Prob > chi2 | 0.000 | 0.000 | 0.000 | 0.000 |
| Log-likelihood | -1125 | -1157 | -723.5 | -766.9 |

Robust standard errors in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1.

Household controls are similar to those included in Table 4, excluded from this table for brevity.

### Table 6. Robustness checks on the impact of CSA adoption on household food security and farm income.

| Practices | Impact on Food Insecurity – Poisson model with endogenous treatment effects | Impact on Income – OLS with endogenous treatment effects |
|-----------|-------------------------------------------------------------------------------------------------|--------------------------------------------------------|
| IS        | -1.210*** (0.218)                                                                             | 4.098*** (0.648)                                       |
| SM        | -0.061 (0.174)                                                                                  | 0.789** (0.367)                                       |
| IC        | -1.412*** (0.248)                                                                               | 3.936*** (0.658)                                      |
| IS & IC   | -1.357*** (0.222)                                                                               | 4.403*** (0.639)                                      |
| SM & IC   | -1.403*** (0.241)                                                                               | 4.764*** (0.710)                                      |
| Constant  | 2.633*** (0.360)                                                                                | 5.538*** (0.828)                                      |
| Observations | 292                                                                                       | 83.68                                                 |
| LR statistic | 981.4                                                                                      | 0.000                                                 |
| Prob > chi2  | 981.4                                                                                       | 0.000                                                 |
| Log-likelihood | -981.4                                                                                   | -981.4                                                 |

***p < 0.01, **p < 0.05, *p < 0.1. OLS: ordinary least squares.
can be used as food within the household or easily liquidated to buy other food needs. The paper demonstrates that integrated crop-poultry systems can act as a resilient pathway to minimize the climatic challenges faced by smallholder farmers especially in semiarid areas. Specifically, by focusing on indigenous chickens, this study hopes to bring indigenous chickens into the climate-smart literature and discussions that have often focused on crop-related practices and large ruminant livestock.

When estimating the impact of combined and single CSA practice(s), results show that the adoption of single practices do not have any significant impact on food security, however, with the adoption of two practices a significant impact on household food security is observed. This highlights the importance of promoting CSA interventions as bundles of practices given that a single practice may not provide all the benefits contemplated in the CSA approach.

Regarding the impacts of CSA practices on farm income, we found that the adoption of both combined and single CSA practice(s) has significant impact on farm income. Larger impacts were observed from the adoption of all practices except the adoption of only IS. Improved seed is a low-return technology, with most studies finding that on its own, it does not improve crop yields. Again, IC and its combinations with crop enterprises (IS and SM) have a higher impact on farm income compared to other practices – suggesting that integrated systems such as crop-poultry integrated systems have the potential to improve household welfare under climate change and are potentially better climate management options.

The results have important implications for research, policy and development practitioners involved in efforts to build climate change resilience in semiarid areas. Our findings suggest that there is a need to implement interventions that support crop-poultry system integration as this has shown higher impacts on household food security and farm income. The findings indicate that the often neglected small-livestock such as poultry have positive benefits on welfare, and when combined with crops as a technology bundle they contribute to achieving the triple-win objectives of CSA. Policies will need to invest further into poultry in terms of encouraging adoption, breeding resilient breeds, and understanding how smallholder farmers manage IC to improve practices related to rearing IC.

One of the impediments to adoption is the distance to the extension offices. There is thus a need to expand the network of extension services this may also include the use of telephone services and radio programs to reach the most remote parts of a farming community. This will ensure that farmers increase the contacts with extension agents and access extension services which will in turn influence investment in CSA adoption. There is also a need to integrate crop extension, which is the dominant approach in most countries, with the livestock or veterinary services to promote integrated crop-poultry adoption.

Finally, the findings of this study are based on cross-section data. These estimates, therefore, may not fully control for unobserved differences in the factors of adoption even though a strong attempt at causal estimation was made. The use of number of months the household was food insecure has further challenges as households’ recall may not be very accurate. Future studies need to make use of panel data to control for unobserved heterogeneity, unravel salient adoption dynamics and provide more robust results on the impacts of CSA adoption on household welfare and test whether the impacts are consistent over time. Further studies are needed to understand if there is impact heterogeneity depending on who is owns the indigenous chickens, as there could be potential implications on food security. Studies that understand the management of indigenous chickens to improve on the stocks and reduce mortality, which has been reported to be common in other studies could also help increase the adoption of IC. There could also be a focus on measuring food security using such as focusing on children’s nutrition like stunting, underweight, which reflect diversified food consumption over time and not reported food insecurity.

Declarations

Author contribution statement

Kelvin Mulungu: Conceived and designed the experiments; Analyzed and interpreted the data; Wrote the paper.

Daniel Kangogo: Conceived and designed the experiments; Performed the experiments; Contributed reagents, materials, analysis tools or data; Wrote the paper.

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Data availability statement

Data will be made available on request.

Declaration of interests statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

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### Table A1. Falsification test for the instruments

| Variable                  | Food insecurity | Income  |
|---------------------------|-----------------|---------|
| Credit                    | -0.098 (0.122)  | 0.533 (0.283) |
| Log of distance to extension | -0.114 (0.078)  | 0.071 (0.187) |
| Constant                  | 1.592 (0.179)  | 8.795 (0.435) |
| Chi2, F stat              | 3.11            | 1.99    |
| Prob > F                  | 0.211           | 0.144   |

The falsification test that includes access to credit and log of distance to extension office as independent variables in the regression for non-adopters is not significant both as individual variables and the model as a whole. This means these are good instruments as they affect food security and income only through the decision to adopt and not directly.
Terza, J.V., 1998. Estimating count data models with endogenous switching: sample selection and endogenous treatment effects. J. Econom. 84 (1), 129–154.

Thornton, P.K., Herrero, M., 2001. Integrated crop-livestock simulation models for scenario analysis and impact assessment. Agric. Syst. 70 (2-3), 581–602.

Thornton, P.K., Herrero, M., 2014. Climate change adaptation in mixed crop-livestock systems in developing countries. Global Food Secur. 3 (2), 99–107.

Thornton, P.K., Herrero, M., 2015. Adapting to climate change in the mixed crop and livestock farming systems in sub-Saharan Africa. Nat. Clim. Change 5 (9), 830–836.

Verge, X.P.C., Dyer, J.A., Desjardins, R.L., Worth, D., 2009. Long-term trends in greenhouse gas emissions from the Canadian poultry industry. J. Appl. Poultry Res. 18 (2), 210–222.

Wainaina, P., Tongruksawattana, S., Qaim, M., 2017. Synergies between different types of agricultural technologies in the Kenyan small farm sector. J. Dev. Stud. 54 (11), 1974–1995.

Wineman, A., 2016. Multidimensional household food security measurement in rural Zambia. Agrekon 55 (3), 278–301.

World Bank, 2020. The World Bank Annual Report 2020. The World Bank.

Yegbemey, R.N., Yabi, J.A., Tovignan, S.D., Gantoli, G., Haroll Kokoye, S.E., 2013. Farmers' decisions to adapt to climate change under various property rights: a case study of maize farming in northern Benin (West Africa). Land Use Pol. 34, 168–175.

Yu, L., Yaoqiu, K., Ningsheng, H., Zhifeng, W., Lianzhong, X., 2008. Popularizing household-scale biogas digesters for rural sustainable energy development and greenhouse gas mitigation. Renew. Energy 33 (9), 2027–2035.

Zervas, G., Tsipalakou, E., 2012. An assessment of GHG emissions from small ruminants in comparison with GHG emissions from large ruminants and monogastric livestock. Atmos. Environ. 49, 13–23.

Zurek, M., Ingram, J., Bellamy, A.S., Goold, C., Lyon, C., Alexander, P., Bruce, A., 2022. Food system resilience: concepts, issues, and challenges. Annu. Rev. Environ. Resour. 47.