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# Climate adaptation, perceived resilience, and food security

## Comparative Evidence from Kenya and Zambia

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Food and Agriculture Organization of the United Nations
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# Abstract

Keywords: Climate Adaptation; Climate Change; Farm-Household Production; Resilience; sub-Saharan Africa.

This study uses comparable data collected in a pastoralist setting in Kenya and a rain-fed crop production context in Zambia to examine the relationship between climate-adaptive practices, food security, and households' perceived resilience against climatic shocks. We sort climate-adaptive practices based on their relative factor intensities or diversification decisions, which allows us to draw comparisons regarding these relationships across diverse production systems. Using the doubly robust inverse probability weighted regression adjustment (IPWRA) approach to account for potential selection issues, we find that capital-intensive adaptive strategies are consistently and positively associated with resilience, food security, and income in both contexts. Labour-intensive and diversification strategies have generally positive but heterogeneous impacts across the two production systems, likely governed by contextual differences. Results also highlight the complementarity of adaptive practices in improving household welfare in both contexts. The findings suggest that alleviating the barriers to adoption of climate-adaptive practices and promoting adaptation in several dimensions of rural livelihoods simultaneously can enhance resilience to climate shocks and reduce poverty.

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# Abbreviations and acronyms

| | |
|---|---|
| ATT | average treatment effect on the treated |
| CBO | community-based organization |
| CWAC | community welfare assistance committee |
| FAO | Food and Agriculture Organization of the United Nations |
| FIES | Food Insecurity Experience Scale |
| FSP | food security package |
| IPWRA | inverse probability weighted regression adjustment |
| IPW | inverse probability weights |
| KIHBS | Kenya integrated household budget survey |
| KES | Kenyan shillings |
| RA | regression adjustment |
| SSA | sub-Saharan Africa |
| TLU | tropical livestock unit |
| WFP | World Food Programme |
| ZMW | Zambian Kwacha |

# Introduction

Climate change continues to adversely affect agricultural production and food security in sub-Saharan Africa (SSA) (Calzadilla *et al.*, 2013; Stuch *et al.,* 2021). These negative effects are particularly significant for resource-poor farmers of SSA (Azzarri and Signorelli, 2020). To alleviate the burdens that arise from climate volatility, many governments have included climate adaptation into their national development plans. Climate adaptation measures are seen as complementary to climate change mitigation and are expected to build resilience of farmers and farming systems, reduce sensitivity of agricultural systems to climate risks, and increase food security (Govt. of Kenya, 2016; 2018). Thus, to accelerate climate adaptation and foster resilience and wellbeing, there is a need to understand the adoption of climate-adaptive practices and their relationship with resilience and food security across varied rural contexts.

This study aims to contribute to two strands of literature: (a) conceptualization and measurement of farmers' resilience to climatic change (e.g. Jones and Tanner, 2017; Spiegel *et al.*, 2021; Wouterse *et al.*, 2022); and (b) the role of climate-adaptive practices in improving resilience and broader farm and household welfare (Di Falco and Chavas, 2009; Di Falco and Veronesi, 2014; Abdulai and Huffman, 2014; Khanal *et al.*, 2018; Issahaku and Abdulai, 2020b; Issahaku and Abdulai, 2020c; Mulwa and Visser, 2020; Scognamillo *et al.*, 2022). Specifically, the paper asks the following questions: (1) how can we measure farm-households' perceived resilience to climate shocks across diverse rural contexts, and (2) what is the impact of climate-adaptive practices on perceived resilience, food security, and income.

To answer these questions, we pilot a novel survey-based scale that measures the self-assessed or perceived resilience of farm-households to climatic stressors in Kenya and Zambia. Perceived resilience measures elicit farmers' cognitive valuation of their capacity to navigate production

processes in presence of shocks and allow for comparisons across a variety of farming systems (Lockwood *et al.*, 2015; Clare *et al.*, 2017; Jones and Tanner, 2017). Our definition of perceived resilience is based on the conceptual framework of adaptive cycles in socioecological or agricultural systems (e.g. Darnhofer, 2014; Meuwissen *et al.*, 2019; Spiegel *et al.*, 2021) and is operationalized in the context of a farm-household as its ability to ensure key functions (i.e. food and income security) in face of climatic stressors through absorptive, adaptive, and transformative capacities. Several objective and subjective measures of resilience have been developed, each having its own strengths and limitations (Barrett *et al.*, 2021). However, subjective measures can be elicited without requiring a significant amount of socioeconomic data and can consider the wealth of knowledge and contextual information that respondents have about the state of their wellbeing (Marshall, 2010; Maxwell *et al.*, 2015; Clare *et al.*, 2017; Jones and Tanner, 2017; Jones and d'Errico, 2019).

We then estimate the impact of climate-adaptive practices on cost of production, income, food security, and resilience among pastoralists and smallholder crop producers in Kenya and Zambia, respectively. Given that farmers tend to adopt practices only when they are profitable (e.g. Piñeiro *et al.*, 2020), estimating the costs, benefits, and trade-offs associated with adoption of adaptive practices will highlight the economic viability of these practices. To explore these relationships and draw comparisons across diverse production systems, we develop a simple typology of climate-adaptive practices being promoted in each context based on their relative factor intensity. In our analysis, analogous climate-adaptive practices across the Kenyan and Zambian contexts include herd and crop diversification strategies, system-specific capital-intensive strategies such as adoption of feed storage and use of improved/hybrid seeds, and off-farm diversification strategies, respectively. Collective production within the community-based organization or self-help group in pastoral production systems of Kenya and conservation agriculture practices in crop production system of Zambia are included as system-specific labour-intensive climate-adaptive strategies. The

differing factor intensities of the climate-adaptive practices may constrain their adoption (Amadu *et al.*, 2020; Sertse *et al.*, 2021).

From an econometric perspective, impact estimates of climate-adaptive practices are prone to misspecification due to selectivity bias. We use "doubly robust" inverse probability weighted regression adjustment (IPWRA) method to control for this selectivity bias (Woolridge, 2010). Binary (logit) treatment effect models are employed to assess the impact of adaptive practices individually, while multivalued treatment effect models are used to empirically test the complementarity in the effects of these practices.

The paper contributes to the existing literature in several ways. First, we adapt the resilience framework based on adaptive cycles in socioecological systems for the case of farm-households under the risk of climate shocks and postulate that farm-households need to build both on- and off-farm resilience capacities to successfully navigate risks posed by climatic change (Folke *et al.*, 2010; Darnhofer *et al.*, 2014; Bullock *et al.*, 2017). Therefore, we elicit information on households' perceived capacity to bounce-back (*robustness*), adapt at the farm-level (*farm adaptability*), transform production (*transformability*), and adapt their livelihoods (*livelihood adaptability*) to measure their resilience to droughts (in Kenya and Zambia) and floods (in Zambia).

Second, by sorting climate-adaptive practices based on either context-specific diversification strategies or their relative factor intensities, we generate novel comparative evidence regarding the drivers and impacts of climate-adaptive practices across crop and livestock-based production systems. Third, there is scarcity of impact assessment of climate-adaptive practices in the context of pastoralists of eastern Africa. We currently only know of Ndiritu and Muricho (2021) that estimate the impact of feed storage, better watering practices, and destocking on food security of pastoralist households. We extend their work by not only assessing impacts of on-farm adaptive practices but also examine impacts of off-farm and collective action strategies on a wider array of farm and

household wellbeing variables. This allows us to document the trade-offs between on-farm and off-farm strategies as well as provide insights related to impacts on experiential as well as psychological dimensions of wellbeing. Finally, we provide evidence that the simultaneous adoption of climate-adaptive practices offers greater benefits to households. While most papers model impacts of adaptive practices individually (e.g. Asfaw *et al.*, 2019; Mulwa and Visser, 2020), we only know of Issahaku and Abdulai (2020b) and Tabe-Ojong *et al.* (2023) that document the joint effects of climate smart practices in crop production systems.

# Conceptualizing resilience and the role of climate-adaptive practices

Our subjective resilience measure is based on the conceptual foundations of adaptive cycles in socioecological literature and goes beyond the narrow definitions of resilience that focus on maintaining an equilibrium (Folke *et al.*, 2010; Bullock *et al.*, 2017). This stream of literature posits that a system's resilience is based on its ability to (a) bounce-back from a shock (*robustness*), (b) adapt to the shock (*adaptability*), and (c) transform production processes under pressure from external shocks (*transformability*) (Darnhofer, 2014; Meuwissen *et al.*, 2019; Roy *et al.,* 2019; Tittonell, 2020).

We build on this conceptual framework and operationalize it for the case of smallholder farm-households (*resilience of what*) that increasingly bear the brunt of climate shocks (*resilience to what*). We postulate that there are four key resilience capacities that determine the overall resilience of farm-households in SSA. *Robustness* (or absorptive capacity) is the ability to withstand (un)anticipated climate shocks. (b) *Farm Adaptability* is the capacity to change the composition of inputs, production, and risk management strategies without changing the structure of the farm. (c) *Transformability* is the capacity to significantly change the farming structure in response to consistent stressors; and (d) *Livelihood Adaptability* is the capacity to engage in off-farm labour to supplement household income.

This framework allows us to elicit households' perceived resilience and assess its relationship with climate-adaptive practices, which may play a central role in defining rural households' resilience. Furthermore, climate change poses multi-dimensional risks to rural people, and therefore are likely to require multiple and complementary adaptive actions. Indeed, several studies show that adoption of sustainable or climate-adaptive agricultural practices are associated positively with households' resilience to climatic events (e.g. Hasan and Kumar, 2019; Ahmed and Afzal, 2021;

Wouterse *et al.*, 2022; Maja *et al.*, 2023). The relationships between resilience and adaptation action of a household are represented in Figure 1 (adapted from Wouterse *et al.*, 2022). On-farm adaptive production practices (e.g. adoption of inputs and diversification strategies), adaptive livelihood practices (e.g. strategies that reduce climate risk to overall livelihoods), and transformative strategies (e.g. radical changes or transitions to a new production system or process) may have differential impacts on the resilience capacities outlined above and may enhance household resilience through preservation or improvement of farm and household welfare (e.g. Asfaw *et al.*, 2018; Alfani *et al.*, 2021; Maggio *et al.*, 2022).

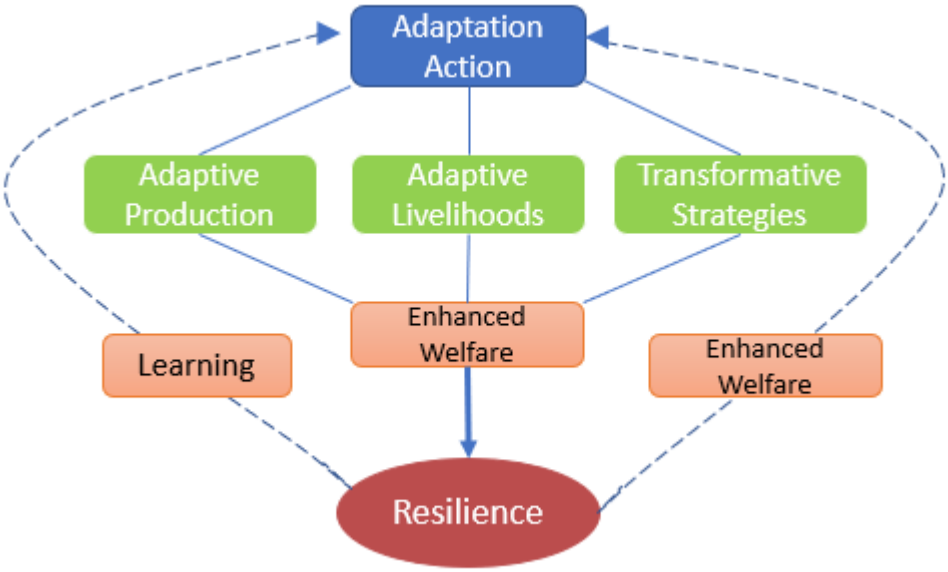
In the pastoralist setting of Kenya, adaptive production practices include herd diversification, adoption of feed storage (capital-intensive adaptive production strategy), and collective kitchen gardening with self-help groups or community organization (labour-intensive adaptive production strategy).[1] In Zambia, adaptive production practices include crop diversification, adoption of improved seeds (capital-intensive adaptive production strategy), and conservation agriculture (labour-intensive adaptive production strategy). The latter has the potential to reduce labour requirements during specific periods of the cropping season, but it can also result in increased labour demand during other stages, such as weeding and harvesting (Pannell *et al.*, 2014; Farnworth *et al.*, 2016). Furthermore, studies indicate that the impact of conservation agriculture on labour demand in sub-Saharan Africa varies depending on the combination of practices employed, with some cases showing no changes while others demonstrating an overall increase in labour demand (Teklewold *et al.*, 2012; Montt and Luu, 2020). Adaptive livelihood strategies include off-farm diversification in both contexts.

While adaptation action is expected to affect resilience, the opposite may be true as well. A 'resilient' household, benefiting from improved economic conditions, reduced sensitivity and

[1] Feed storage can be an effective strategy to ensure animal health and nutrition during lean seasons. However, procuring and storing feed requires capital, which may be constrained in this context (Ndiritu & Muricho, 2021; Berhe *et al.*, 2017). Similarly, collective production with the community-based organization provides an additional avenue of producing food for the household. However, in the presence of labour constraints faced by the households, not all households may be able to practice it (Fischer & Qaim, 2012).

vulnerability to climatic events, and accumulated experience, is likely to invest more in adaptation actions. This creates feedback loops between the adaptive and resilience capacities of the farm-household (Abid *et al.,* 2016; Bartelet *et al.*, 2022; Wouterse *et al.*, 2022). Furthermore, enhancing resilience may not always be an end in itself, but perhaps a means to achieve some ultimate end such as food security (Ansah *et al.*, 2019; Ansah *et al.*, 2023). This conceptual framework provides a basis for thinking about and developing the empirical strategy to estimate the relationship between climate-adaptive practices and resilience and identify potential limitations in estimation of this relationship.

Figure 1. Conceptual Framework of Adaptation and Resilience




***Source**:* Authors' own elaboration

# Econometric framework

Our focus is to estimate the relationships between climate-adaptive practices and household wellbeing. Adoption of climate-adaptive practices is a choice variable and is influenced by various observed and unobserved characteristics that are likely to differ systematically between adopters and non-adopters and correlate with welfare outcomes, characterizing the self-selection problem in the estimation. Therefore, to assess the relationship between adoption of climate-adaptive practices and various farm and household welfare outcomes, we need a suitable counterfactual against which to compare the group of adopters.

In order to reduce problems of self-selection and generate a suitable counterfactual against which adopters can be compared, we apply the doubly robust inverse probability weighted regression adjustment (IPWRA) method proposed by Wooldridge (2010). The IPWRA estimator is obtained by combining inverse probability weighting (IPW) in the treatment stage with regression adjustment (RA) in the outcome stage of the empirical model. The IPW in the treatment stage and the RA in the outcome stage allow controlling for selection bias and confounding factors at both stages. This property is referred to as 'doubly robust', since only one of the two models needs to be correctly specified to obtain consistent estimates (Wooldridge, 2010). To empirically validate this approach, we test the overlap assumption and check whether balance is achieved. Both requirements are satisfied.

In the IPW stage, the inverse probability weights are calculated based on the estimated probability of being an adopter. For this purpose, we estimate propensity scores as defined by Rosenbaum and Rubin (1983), using a range of observable covariates. Then in the RA stage, the regression adjustment method fits separate linear regression models for adopters and non-adopters, and then predicts the covariate-specific outcomes for each subject under each adoption status. Together, we obtain the average differences between predicted outcomes for adopters under adoption and hypothetical non-adoption, which is the Average Treatment Effect on Treated ($ATT^{A}_{IPWRA}$). The

equation for the IPWRA model can be expressed as follows (Hörner and Wollni 2021; Manda *et al.*, 2018, Wooldridge, 2010):

$$ATT^{A}_{IPWRA} = n_A^{-1} \sum_{i=1}^{n} T_i [r_A(X, \delta_A) - r_N(X, \delta_N)] \quad (1)$$

where $n_A$ is the number of adopters, while $r_i(X)$ describes the regression model for adopters $(A)$ and non-adopters $(N)$ with covariates $X$ and estimated parameters $\delta_i$, where $\delta_i$ are obtained from weighted regression procedures. The standard errors are clustered at the village- and community welfare assistance committee (CWAC)-level for Kenya and Zambia, respectively, to account for intergroup correlation in errors.

To estimate robust parameters of the impact of adoption on outcomes using IPWRA method, the balance and overlap assumptions need to hold. To ascertain whether the balance assumption holds after the IPW procedure, we run an overidentification test, and calculate normalized differences for each covariate as Imbens and Wooldridge (2009) propose. To ensure the overlap assumption holds (i.e. conditional on covariates, each observation has a positive probability of being an adopter), we run our models with the tolerance level set between $\hat{p} = 0.001$ and $\hat{p} = 0.999$ for being an adopter, ensuring imprecision in the estimates is minimized.

Furthermore, we want to estimate the combined impacts of these strategies on household wellbeing to assess if combinations of these practices are complementary in improving wellbeing. To do this, we rely on the IPWRA multivalued treatment effects model to measure the impacts of different levels of adoption of practices on household wellbeing (Woolridge, 2010; Cattaneo, 2010; Cattaneo *et al.*, 2013). The multivalued treatment effects approach is simply an extension of the binary approach to the multivalued case, where the inverse probability weighting is done using a multinomial logit regression instead of logit or probit regressions. Some recent examples of the multivalued treatment effects models used for impact evaluation in agricultural settings include Esposti (2017), Smale *et al.* (2018), and Issahaku and Abdulai (2020a).

One limitation of the IPWRA method is that it relies on observable covariates to reduce selection bias and confounding and is, therefore, vulnerable to heterogeneity due to unobservables. In the context of climate-adaptive practices in smallholders of Zambia and Kenya, unobservable heterogeneity (e.g. farmer ability, knowledge, quality of local institutions, etc.) is likely to play a role. Although conditioning on a rich set of observable covariates may help to reduce selection bias due to unobservables (Imbens and Wooldridge, 2009), the potential threat from unobserved heterogeneity remains. Therefore, our results should be interpreted as associations with strong controls that are suggestive but are not conclusive of causal effects.[2]

[2] This literature has made use of binary and multinomial endogeneous switching regressions (e.g. Abdulai & Huffman, 2014; Issahaku & Abdulai, 2020b etc.) to overcome selection issues that arise from observable and unobservable heterogeneity. However, in the absence of strong and valid exclusion restrictions, estimates from endogenous switching models can suffer from non-robustness and collinearity problems (Moffitt, 1999).

# Data

## Context and sampling

The target region for data collection in Isiolo, Kenya was chosen in collaboration with officials from Ministry of Agriculture, Livestock, and Fisheries and National Disaster Management Authority (NDMA). We collected this data from October to November 2022 in collaboration with FAO Kenya from four wards of Isiolo, namely: Chari, Cherab, Sericho, and Oldonyiro. Rural households in these arid and semi-arid areas of Isiolo are pastoral and agropastoral smallholders who rely substantially on their livestock for income and food security. Isiolo is an ethnically diverse county and rural households in these areas face considerable risks from droughts and drought-induced conflicts (Quandt, 2021).

The collected data in Kenya forms the baseline for a clustered randomized impact evaluation where the intervention will go through rural community-based or self-help groups.[3] Therefore, as a first step, 75 groups were randomly selected from the four wards. In the second step, about 11 households were randomly selected within each group for data collected. We ended up with a total of 788 observations with an average of 16 observations per village. However, we had to drop 120 observations and ended up with 668 observations for this analysis since these households do not own any livestock and our climate adaptation practices in Kenya are primarily associated with adaptation within the livestock sector.[4] For the households that own livestock, the average herd

[3] Rural community-based or self-help groups are formal organizations registered with the Department of Social Development in Kenya. These groups act as forums for citizens in the region to come together and address common issues facing their communities. Therefore, these organizations can be helpful in planning, implementing, and monitoring rural development programmes.

[4] Table A1 provides the pairwise comparisons across livestock owners and non-owners across our sample. We find that non-owners of livestock have lower gross incomes. However, this is not a concern for our estimation because our climate-adaptive practices concern mainly with livestock owners. For the climate-adaptive practices that are shared between livestock owners and non-owners, we provide results for these practices for livestock owners as well as the whole sample to illustrate robustness of our estimates.

size is 5.85 in tropical livestock unit (TLUs) with 61 percent own cattle, 82 percent own goats, and 81 percent own sheep, respectively.

In Zambia, data was collected from villages belonging to 68 CWACs[5] (community welfare assistance committee) from 26 different wards and within three districts (Chipangali, Katete, and Sinda) of Eastern Province. The data was collected as part of a quasi-experimental evaluation clustered at the CWAC level of the food security package (FSP), which provides seeds and fertilizer to eligible farmers. This area was selected for an expansion of the wetland's subprogram of the FSP in 2022, which targets households with access to wetland areas, known locally as *dambos.* Data collection was completed between October and December 2022. The districts belong to the same agroecological zone, characterized by a rainy season that generally occurs from November to April, with peak rainfall between December and February. Farmers engage in rainfed agriculture, utilizing the rainfall pattern to determine planting and harvesting seasons, making them highly vulnerable to climatic shocks (Arslan *et al.*, 2015). We obtained a total of 2996 valid surveys with an average of 44 observations per CWAC. Farmers in the sample have access to 2.23 hectares of land for agricultural activities. The principal crops cultivated include maize (90 percent of households), soybeans (58 percent of households), and sunflower (25 percent of households). Agriculture accounts for 73 percent of the total income, with production being entirely reliant on family labour for 75 percent of households.

# Variables

## Adoption variables

Climate adaptation is a comprehensive concept that does not comprise a clearly defined, fixed set of practices. It can include a wide range of site-specific, improved technologies depending on local conditions, resource levels and the production system in question. The definitions of the adoption

[5] These committees consist of volunteer members elected from the community/communities they cover that help identify potential beneficiaries. The committees were initially part of the structure of the Public Welfare Assistance Scheme (PWAS), which aimed at supporting the most disadvantaged members of the population to enable them to fulfill their essential requirements and fostering community resilience in tackling poverty and vulnerability.

variables included in this analysis are summarized in Table 1. In the pastoral setting of eastern Africa, feed storage, herd-diversification, livelihood diversification, and collective production are 'treatment' variables in the IPWRA models and are important climate-adaptive practices (Ndiritu and Muricho, 2021; Ng'ang'a *et al.*, 2016). In our sample, 29 percent, 57 percent, 37 percent, and 16 percent of the households adopt feed storage, herd-diversification, off-farm work, and collective production, respectively (Table 1). Overall, 41 percent of the households practice at least one of these strategies followed by 29 percent adopting two, 10.3 percent adopting three, and 2.1 percent adopting all four of these strategies. In the crop production setting of Zambia, adoption of improved/hybrid seeds, crop-diversification, off-farm diversification, and conservation agriculture are considered important adaptation practices and 55 percent, 53 percent, 20 percent, and 40 percent of the households in Zambian sample adopt these practices, respectively (Table 1).

To conduct a comparative study in these diverse production systems, we develop a simple typology of climate-adaptive practices based on their relative factor intensities. In particular, feed storage and adoption of improved seeds are considered analogous given the capital-intensive nature of these practices. Herd and crop-diversification are comparable on-farm diversification strategies for the livestock and crop production systems studied in this paper, respectively. Off-farm wage or enterprise work are again comparable livelihood diversification strategies in the two contexts. Finally, collective production and conservation agriculture are system-specific labour-intensive climate-adaptive strategies.

Table 1. Summary statistics (adoption variables)

| Country | Variable | Description | Mean |
|---|---|---|---|
| **Kenya** | Feed storage | Indicator variable = 1 if household has access to individual or communal livestock feed storage, 0 otherwise. | 0.29 |
| | Herd diversification | Indicator variable = 1 if household owns more than one type of livestock, 0 otherwise. | 0.57 |
| | Off-farm diversification | Indicator variable = 1 if any member of the household works or runs an enterprise outside the farm, 0 otherwise. | 0.37 |

| Country | Variable | Description | Mean |
|---|---|---|---|
| | Collective production | Indicator variable = 1 if the household engages in collective production (of crops, poultry etc.) with the community-based organization or self-help group, 0 otherwise. | 0.16 |
| **Zambia** | Improved seed | Indicator variable = 1 if household has used improved and/or hybrid seeds in the previous year, 0 otherwise. | 0.55 |
| | Crop diversification | Indicator variable = 1 if household has a summary crop diversification index a la Anderson (2008) larger than the median. The summary crop diversification index is a standardized weighted average of the number of cultivated crops and of both a Simpson and Shannon index of crop diversity. | 0.53 |
| | Off-farm diversification | Indicator variable = 1 if any member of the household operates an enterprise outside the farm, 0 otherwise. | 0.20 |
| | Conservation agriculture | Indicator variable =1 if household has adopted at least 3 out of 4 conservation agriculture practices (crop residue are spread over plot, zero tillage, crop rotation, intercropping), 0 otherwise. | 0.40 |

***Note:*** *N* = 668 for Kenya and 2 996 for Zambia.
***Source****:* Authors' own elaboration.

## Outcome variables

As a proxy for household wellbeing, we consider two food security variables (the food consumption index based on food consumption scale and the food security index based on food insecurity experience scale) and the subjective resilience measure described above to elicit the self-assessed resilience of farm-households to droughts (in Kenya and Zambia) and floods (in Zambia). Furthermore, to understand the channels through which household wellbeing is affected by adoption of climate-adaptive practices, we examine impacts on annual farm-related expenditures, farm income, and total income of the household in Zambia and Kenya. Table 2 provides details on the definitions, means, and standard deviations of these outcome variables.

The food consumption index uses the Food Consumption Score (FCS) (WFP, 2008) and is a standardized weighted average (a lá Anderson (2008)) of the number of times each of the food groups were consumed within the last 7 days. The food security index is estimated using the weighted average approach and is based on the Food Insecurity Experience Scale (FIES) (Smith *et al.*, 2017). The two indices, combined, provide a holistic view of households' food security through more objective (FCS) as well as experiential measures (FIES). Both these measures have been regularly used in the literature as indicator of household food security and consumption (e.g. Smith *et al.*, 2017), while Anderson (2008) has been used in several papers for creation of composite indices (e.g. Haushofer and Shapiro, 2016).

The subjective resilience measure elicits the self-assessed resilience of farm-households against climatic shocks. The measurement scale is presented in Appendix Table A2. Like food security measures, the subjective resilience measure is also estimated using the standardized weighted average approach of Anderson (2008). We find a scale reliability coefficient (Cronbach's $\alpha$) of 0.77 for resilience against droughts in Kenya, while in Zambia, this was 0.81 for resilience against droughts and 0.84 for resilience against floods. We also test the predictive validity of the scale by plotting the relationship between subjective resilience with variables that should be theoretically correlated with it. A robust measure of resilience should therefore be positively correlated with food security measures especially in this setting (d'Errico *et al.,* 2018). Figure 2 shows that indeed food consumption and food security indices are positively related to subjective resilience index, providing evidence that our measure of farm-households' perceived resilience to climatic stressors is robust.
In Kenya, the mean annual livestock expenditure is KES 9 447 (~USD 80), while mean livestock and total income are KES 76 127 (~USD 650) and KES 130,428 (~USD 1 100), respectively. This total income (~USD 92 per month) is slightly less than the representative rural incomes in Kenya, which are reported to be USD 105 per month likely because Isiolo is far away from wealthier urban locations, faces ethnic conflict, and faces higher drought risk than western or southern Kenya (KIHBS, 2018; Quandt ,2021). In Zambia, the mean annual agricultural expenditure is ZMW 1 689 (~USD 90), while mean agricultural and total income are ZMW 13 260 (~USD 700) and ZMW 22 302

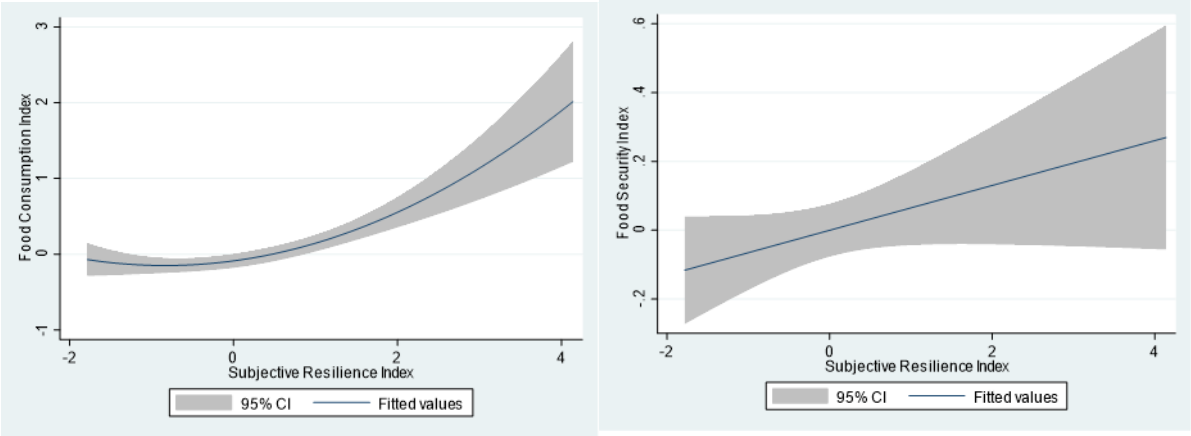
(~USD 1 200), respectively (Table 2). Agricultural and non-agricultural incomes are similar across the two samples and, on average, income from agricultural activities makes about 60 percent and 75 percent of the total income in Kenya and Zambia, respectively. While average incomes are similar across the two contexts, cross-country comparisons for food security and subjective resilience, presented in Table A3, indicate that pastoralist households in Kenya are more food insecure and less resilient to droughts likely due to the prolonged drought they faced preceding the data collection period.

Table 2. Summary statistics (outcome variables)

| Variable | Description | Kenya | Zambia |
|---|---|---|---|
| **Food consumption index** | Standardized weighted average of the number of times a certain food group was consumed by the household in the last 7 days. | 0 (1) | 0 (1) |
| **Food security index** | Standardized (negatively) weighted average of 8 Likert-scale statements regarding experiencing food insecurity at various levels of intensity by the household in the last month. | 0 (1) | 0 (1) |
| **Subjective resilience index** | Standardized weighted average of 11 Likert scale items eliciting subjective resilience of farm-household. | 0 (1) | 0 (1) |
| **Livestock expenditure** | Inverse hyperbolic sine of total livestock expenditure in the last 12 months (Kenya). | KES 9 447 [20 867] | - |
| **Agricultural expenditure** | Inverse hyperbolic sine of the total agricultural input expenditure from May 2021 to April 2022. | - | ZMW 1 689 [2 579] |
| **Livestock income** | Inverse hyperbolic sine of the total livestock income in the last 12 months. | KES 76 127. [109 531] | - |
| **Agricultural income** | Inverse hyperbolic sine of the total agricultural income from May 2021 to April 2022. | - | ZMW 13 260 [43 582] |
| **Gross income** | Inverse hyperbolic sine of the total household income in the last 12 months. | KES 130 428. [175 458] | ZMW 22 302 [55 010] |

***Note:*** *N* = 668 for Kenya and 2 996 for Zambia. Standard deviation in brackets.
***Source****:* Authors' own elaboration.

Figure 3. Relationships between Food Security Measures and Subjective Resilience




***Source:*** Authors' own elaboration.

## Control variables

The selection of household- and farm-level control variables is based on the literature on adaptation and resilience in rural Africa (e.g. Issahaku and Abdulai, 2020b; Maggio and Sitko, 2019; Maja *et al.*, 2023). These variables include age, gender, and education of the household head (in case of Kenya) and main respondent (in case of Zambia), total number of household members, total herd size (in TLUs), whether the household received any climate information services, and whether the household was visited by an extension officer. Table 3 provides the summary statistics related to these variables. The average household size is 6.59 in Kenya and 5.47 in Zambia. The average age of the household heads in Kenya is 45, while the average age of a respondent in Zambia is 40. In Kenya, 41 percent of the household heads have received some formal schooling and 71 percent of them are males. In Zambia, respondents, on average, have received about 5 years of schooling and 65 percent of them are male. 42 and 37 percent of the households receive information on seasonal forecast on rainfall or drought in Zambia and on short- and near-term weather forecast (two to three days) or forecasts for the next two to three months in Kenya, respectively. Finally, 32 percent

of the household report extension contact in the last six months in Kenya, while 45 percent of the households in Zambia report receiving extension services.

Table 3. Summary statistics (control variables)

| Variable | Description | Kenya | Zambia |
|---|---|---|---|
| **Herd size (TLUs)** | Number of tropical livestock units (TLUs) owned by the household. | 5.85<br>(8.56) | 2.24<br>(4.40) |
| **Household size** | Total number of household members. | 6.59<br>(2.33) | 5.47<br>(2.11) |
| **Age** | Age of the household head in years (Kenya).<br>Age of main respondent in years (Zambia). | 45.38<br>(13.70) | 39.8<br>(13.8) |
| **Gender** | Indicator variable = 1 if household head is male, 0 otherwise (Kenya).<br>Indicator variable = 1 if main respondent is male, 0 otherwise (Zambia). | 0.71 | 0.65 |
| **Schooling** | Indicator variable = 1 if household head received any level of formal schooling, 0 otherwise (Kenya).<br>Number of years of formal schooling attended by the main respondent (Zambia). | 0.41 | 5.33<br>(3.81) |
| **Market distance** | Number of minutes it takes to walk to the nearest market (Kenya). | 40.55<br>(46.74) | - |
| **Climate information services** | Indicator variable = 1 if the household received information regarding weather, 0 otherwise. | 0.42 | 0.37 |
| **Extension contact** | Indicator variable = 1 if the household was visited by an extension officer in the last six months, 0 otherwise (Kenya).<br>Indicator variable = 1 if household received information about agricultural practices, soil conservation, and agro-forestry practices, (Zambia) | 0.32 | 0.45 |
| **Saving group** | Indicator variable = 1 if any member of the household is a member of any savings group, 0 otherwise. | 0.65 | 0.17 |
| **Labour constraint** | Indicator variable = 1 if household does not have an able-bodied adult or the dependency ratio (household members not fit to work / household members fit to work) is greater than 3. | 0.26 | 0.23 |
| **Drought shock** | Indicator variable = 1 if household has experienced a drought shock in the past 8 years (self-reported) | - | 0.78 |
| **Flood shock** | Indicator variable = 1 if household has experienced a flood shock in the past 8 years (self-reported) | - | 0.39 |

***Note:*** *N* = 668 for Kenya and 2 996 for Zambia. Standard deviations in parenthesis.
***Source****:* Authors' own elaboration.

# Results & discussion

## Correlates of climate-adaptive practices

Table 4 presents the correlates of climate-adaptive practices from Poisson regressions. The adoption model within the IPWRA approach is a logit model that serves as a method to estimate propensity scores and achieve balance between the observed covariates across adopters and non-adopters (Table A5 and Table A6). However, the Poisson regressions included in the main text allow us to provide summary results of these adoption regressions in a concise manner (Table 4).

While no causal interpretation can be inferred from the results in Table 4, some of the covariates stand out in terms of explaining the adoption of climate-adaptive practices. In line with previous literature, access to extension services has a positive relationship with adoption of climate-adaptive practices in Kenya and Zambia, likely through transfer of necessary knowledge that make adoption of climate-adaptive practices and technologies possible in both contexts (e.g. Hasan and Kumar, 2019; Issahaku and Abdulai, 2020b). Labour constraints (which capture high dependency ratio and/or disability in the household) are negatively correlated with adoption of climate-adaptive practices in Kenya (as in Scognamillo *et al.*, 2022), but do not have significant correlates in Zambia. These results highlight that some dimensions of adaptation in the Kenyan context may be more labour intensive and may not be adopted due to labour constraints.

Among other correlates, being part of a savings group, household size, formal education and herd sizes are associated positively with adoption of practices in both contexts. Indeed, feed storage and hybrid seeds are capital-intensive technologies, and participation in savings groups can help farm-households adopt these technologies as well as adapt in other dimensions when faced with negative shocks (e.g. Carter *et al.*, 2016). Higher household size, perhaps due to availability of necessary labour resources for labour-intensive practices, is positively associated with adoption in both

contexts (Teklewold *et al.*, 2013; Shikuku *et al.*, 2017). For example, off-farm diversification in both contexts is positively associated with household size (Table A5 and Table A6), highlighting that a households' ability to engage in off-farm labour may depend on the availability of labour within the household. Similarly, schooling is positively associated with adoption, perhaps through improving the learning component of adaptive capacity of households (see e.g. Walker *et al.,* 2022), illustrating that access to formal education may play a significant role in promoting climate adaptation in rural communities. Lastly, herd size, a measure of wealth as well as savings in these contexts, correlates significantly with adoption of climate-adaptive practices.

In Table A4, we also provide correlates of resilience. We observe that some of the covariates associated with climate-adaptive practices, such as labour constraints and access to extension services, are also correlated with households' perceived resilience. These results, in line with previous literature (Mutabazi *et al.*, 2015; Hasan and Kumar, 2019), are important from the perspective of designing development interventions and highlight that strengthening factors, such as rural extension networks, financial inclusion, and access to education, can potentially enhance adoption of climate-adaptive practices as well as resilience capacities of rural households in diverse rural contexts.

Table 4. Correlates of climate-adaptive practices in Kenya and Zambia

| | **Kenya** | **Zambia** |
|---|---|---|
| | Climate adaptive practices | Climate adaptive practices |
| **Household size** | 0.052*** | 0.010** |
| | (0.009) | (0.004) |
| **Gender (male = 1)** | 0.007 | 0.072** |
| | (0.044) | (0.029) |
| **Age** | 0.001 | 0.001 |
| | (0.002) | (0.001) |
| **Schooling** | 0.188*** | 0.015*** |
| | (0.049) | (0.003) |
| **Labour constrained** | -0.178*** | 0.009 |
| | (0.048) | (0.022) |
| **Extension contact** | 0.263*** | 0.114*** |
| | (0.073) | (0.022) |

| | Kenya | Zambia |
|---|---|---|
| **Climate information services** | 0.074 | 0.079*** |
| | (0.077) | (0.025) |
| **Savings group** | 0.289*** | 0.108*** |
| | (0.069) | (0.025) |
| **Herd size** | 0.008*** | 0.010*** |
| | (0.003) | (0.003) |
| **Observations** | 664 | 2996 |

***Note***: ***, **, * indicate statistical significance at 1, 5 and 10%, respectively.
Both regressions are Poisson regressions with ward-level fixed effects.
Standard errors in parenthesis are clustered at the village-level for Kenya and CWAC-level for Zambia.
***Source****:* Authors' own elaboration.

## Relationships between climate-adaptive practices and household wellbeing

Table 5 and Table 6 present the relationships between climate-adaptive practices and household and farm outcomes in Kenya and Zambia, respectively. These tables show the predicted outcomes for adopters under hypothetical non-adoption (the counterfactual) and the average differences between predicted outcomes for adopters under adoption and hypothetical non-adoption $(ATT^{A}_{IPWRA})$. The $ATT^{A}_{IPWRA}$ can be interpreted as a measure of the association between the adoption of climate-adaptive practices and the respective outcome variables.

We start by comparing the effects of adoption of capital-intensive climate-adaptive practices, such as feed storage and hybrid seeds in Kenya (Table 5) and Zambia (Table 6), respectively. Feed storage in Kenya is associated with an increase of food consumption, food security, and subjective resilience by 0.350, 0.346, and 0.256 standard deviations (SD), over the counterfactual mean, respectively (Table 5). In terms of expenditures and incomes, adoption of feed storage is associated with a 20.1 percent and 6.4 percent increase in livestock expenditures and gross income over the counterfactual

mean, respectively (estimates statistically significant at 1 percent and 5 percent level of significance).[6] In comparison, adoption of improved/hybrid seeds in Zambia is associated with an increase of food consumption, food security, and subjective resilience against droughts by 0.27, 0.31, and 0.14 SD, over the counterfactual mean, respectively (Table 6). In terms of expenditures and incomes, adoption of hybrid seeds is associated with an increase of 29.8 percent, 7.4 percent, and 7.0 percent in agricultural expenditures, agricultural income, and gross income over the counterfactual mean, respectively (estimates statistically significant at 1 percent level of significance).[7] We observe that the impacts of capital-intensive climate-adaptive practices are similar across the two production systems. While feed storage and hybrid seeds can be effective in improving overall household wellbeing, capital requirement can be a major barrier to adoption of these technologies (e.g. Pauline *et al.,* 2017; Amadu *et al.*, 2020).

Herd and crop-diversification strategies are analogous on-farm diversification strategies in the two production systems. In Kenya, herd-diversification has no significant impacts on household wellbeing or farm-related outcomes (Table 5). While we do not find any impacts of herd diversification on farm or household-level measures, this strategy may be of importance in terms of managing the risk of disease and drought, rebuilding cattle herd sizes through investment and growth in small stock or improving longevity and productivity of animals (Ahmed *et al.,* 2022). These dimensions are not captured by our outcome measures. In comparison, crop-diversification has small, positive associations with food security as well as subjective resilience outcomes (Table 6). Furthermore, crop-diversification is associated with increases of 2.6 percent and 2.2 percent in agricultural and gross income, respectively.[8] While statistically significant, these impacts are small and unlikely to be economically significant. Taken together, the results suggest that farm production diversification generates marginal, if any, benefits in the two contexts.

[6] 20.1% = 100*1.54/7.63. Similarly, 6.4% = 100*0.668/10.33.
[7] 29.8% = 100*1.731/5.801), 7.4% = 100*0.677/9.186, and 7.0% = 100*0.683/9.640.
[8] 2.6% = $100 * \frac{0.243}{9.38}$ and $2.2\% = 100 * \frac{0.214}{9.846}$.

In Kenya, off-farm diversification (typically includes casual labour, *boda-boda* taxi service, and small businesses mostly related to charcoal burning and sales (Quandt, 2021)) is associated with an increase of 0.40, 0.30, and 0.32 SD in food consumption, food security and subjective resilience against droughts over the counterfactual mean, respectively (Table 5). Furthermore, off-farm diversification is associated with a decrease in livestock income by 15.2 percent, and an increase in total income by 23.3 percent over the counterfactual mean.[9] Generating off-farm income has an overall positive impact on total income and household wellbeing. However, households in Kenya encounter a trade-off between adopting off-farm and farm adaptation strategies, and off-farm work may not complement income generation from farming and could potentially impede capital and labour investment in on-farm activities. In comparison, off-farm diversification does not have statistically significant impacts on food security in Zambia. However, it is associated with an increase of 0.22 SD in subjective resilience against drought. Furthermore, off-farm diversification in Zambia is associated with increase in agricultural (by 3.4 percent) and total income (by 9.4 percent).[10] In contrast to Kenya, off-farm diversification in Zambia, which typically consists in the operation of agricultural retail and trading businesses, complements agricultural income. The heterogeneity in impacts in the two contexts likely arises because of the difference in nature of available off-farm diversification options in the two contexts and their relationship with farm production.

Lastly, participation in collective production with community organization and conservation agriculture practices are system specific labour-intensive practices in Kenya and Zambia, respectively. Collective production is associated with an increase in food consumption, food security, and subjective resilience of 0.57 SD, 0.2 SD, and 0.56 SD over the counterfactual mean, respectively (Table 5). As expected, we find no impacts of collective production on farm-level economic outcomes since collective production generally occurs on communal lands. However, it is associated with an increase of 7 percent in total income over the counterfactual mean.[11] Collective

[9] 15.2% = $100 * \frac{1.53}{10.06}$ and 23.3% $= 100 * \frac{2.366}{10.14}$

[10] 3.4% = $100 * \frac{0.318}{9.416}$ and 9.4% $= 100 * \frac{0.905}{9.638}$

[11] 7% $= 100 * \frac{0.705}{10.02}$

production may provide an additional avenue of livelihood diversification in terms of providing the households with supplementary agricultural goods (mostly vegetables from collective kitchen gardens) that can be sold in the nearby market for extra income. Indeed, the ability to act collectively has been considered an important aspect in building adaptive capacity in varied contexts (Adger, 2003; Villamayor-Tomas and García-López, 2017).[12]

Conservation agriculture practices in Zambia are not significantly associated with food security outcomes and the impacts on farm income are not economically significant. Furthermore, these practices are negatively associated with subjective resilience to droughts and floods. This is likely because conservation agriculture benefits, if any, take time to be observed (Thierfelder *et al.*, 2015; Thierfelder *et al.,* 2017). Both the improvement of soil quality and the acquisition of proper knowledge by farmers regarding the implementation of these practices require multiple agricultural seasons. While our survey does not provide information on the duration of farmers' adoption of conservation agriculture practices, it is evident from the data that their implementation is not yet prevalent in the study area. Despite a nearly eight-fold increase in the number of hectares dedicated to conservation agriculture between 2009 and 2016 in Zambia, the set of practices were utilized on less than 1 percent of the country's arable land in 2016 (Kassam *et al.*, 2019), suggesting adoption is probably recent. Additionally, the potential for increased yields frequently relies on a range of factors and the integrated adoption of diverse practices and use of inputs (Giller *et al.*, 2009). The lack of short-term welfare effects of adoption of conservation practices may break the feedback loop between increased resilience and climate adaptation practices.

For our IPWRA impact estimates to be valid, we must ensure that firstly, the overlap assumption is fulfilled. To do so, we only include observations with a probability of being an adopter between $p = 0.001$ and $p = 0.999$, which ensures sufficient overlap. Secondly, the inverse-probability-weighted sample should be balanced between adopters and non-adopters. Therefore, we run an

[12] Collective production as well as off-farm diversification can be effective climate-adaptive strategies for owners as well as non-owners of livestock. Table A7 shows that the treatment effects for full sample are similar to that of the livestock owners in the sample, illustrating robustness of our impact estimates.

overidentification test for each of the climate-adaptive practices with the null hypothesis that covariates are balanced. All the p-values associated with overidentification tests in Kenya and Zambia are above 0.1, failing to reject the hypothesis that covariates are balanced. In addition, we calculate the normalized differences after weighting for each control variable in Kenya (Table A8) and Zambia (Table A9). As suggested by Imbens and Wooldridge (2009), these normalized differences should be as small as possible, and not exceed 0.25. We find that none of the covariates in Zambia exceed 0.25 (Table A9). In Kenya, we find that in each regression, at most only two control variables have a normalized difference greater than 0.25 (Table A8), which does not pose a significant threat to the assumption of covariate imbalance (Manda *et al.*, 2018). Taken together with the overidentification tests, results indicate that our covariates are well balanced.

Table 5. Relationship between climate adaptive practices and household welfare outcomes in Kenya: ATT from IPWRA model

| | Food consumption index | Food security index | Subjective resilience | Livestock expenditure | Livestock income | Gross income |
|---|---|---|---|---|---|---|
| **Feed storage** | | | | | | |
| Predicted outcome under non-adoption | -0.059 | 0.101 | -0.094 | 7.63 | 9.49 | 10.98 |
| ATT | 0.350*** | 0.346*** | 0.256*** | 1.536*** | 0.591* | 0.680** |
| | (0.088) | (0.088) | (0.095) | (0.254) | (0.337) | (0.281) |
| Over identification test for covariate balance (p – value) | 0.578 | | | | | |
| **Herd-diversification** | | | | | | |
| Predicted outcome under non-adoption | 0.119 | -0.189 | 0.052 | 9.36 | 11.16 | 11.18 |
| ATT | -0.100 | 0.220 | -0.062 | -0.823** | -1.185 | -0.190 |
| | (0.145) | (0.138) | (0.236) | (0.357) | (0.725) | (0.669) |
| Over identification test for covariate balance (p – value) | 0.566 | | | | | |
| **Off-farm diversification** | | | | | | |
| Predicted outcome under non-adoption | -0.118 | 0.113 | -0.144 | 7.97 | 10.06 | 10.14 |
| ATT | 0.401*** | 0.299*** | 0.318*** | 0.566** | -1.532*** | 2.366*** |
| | (0.091) | (0.111) | (0.103) | (0.227) | (0.307) | (0.308) |

| | Food consumption index | Food security index | Subjective resilience | Livestock expenditure | Livestock income | Gross income |
|---|---|---|---|---|---|---|
| Over identification test for covariate balance (p – value) | 0.481 | | | | | |
| **Collective Production** | | | | | | |
| Predicted outcome under non-adoption | -0.018 | 0.040 | -0.191 | 8.10 | 9.05 | 10.63 |
| ATT | 0.568*** (0.121) | 0.196* (0.108) | 0.565*** (0.112) | 0.107 (0.429) | -0.014 (0.615) | 0.736* (0.411) |
| Over identification test for covariate balance (p – value) | 0.968 | | | | | |

***Note:*** *N* = 664
***, **, * indicate statistical significance at 1, 5 and 10%, respectively.
Standard errors in parenthesis are clustered at the village-level.
***Source:*** Authors' own elaboration.

Table 6. Relationship between climate adaptive practices and household welfare outcomes in Zambia: ATT from IPWRA model

| | Food security index | Food consumption index | Subjective resilience Drought | Subjective resilience flood | Agricultural expenditure | Gross income | Agricultural income |
|---|---|---|---|---|---|---|---|
| **Crop diversification** | | | | | | | |
| Predicted outcome under non-adoption | -0.105 | -0.047 | -0.051 | -0.042 | 6.526 | 9.846 | 9.380 |
| ATT | 0.099* (0.039) | 0.114* (0.044) | 0.096** (0.037) | 0.076* (0.034) | 0.188 (0.104) | 0.214*** (0.041) | 0.243*** (0.037) |
| Over identification test for covariate balance (p – value) | 0.9679 | | | | | | |
| **Conservation agriculture** | | | | | | | |
| Predicted outcome under non-adoption | -0.016 | 0.014 | 0.131 | 0.092 | 6.842 | 9.962 | 9.485 |
| ATT | -0.045 (0.047) | 0.011 (0.044) | -0.271*** (0.053) | -0.210*** (0.060) | -0.390** (0.130) | 0.085 (0.047) | 0.152** (0.048) |
| Over identification test for covariate balance (p – value) | 0.5528 | | | | | | |
| **Hybrid or improved seed** | | | | | | | |

| | Food security index | Food consumption index | Subjective resilience Drought | Subjective resilience flood | Agricultural expenditure | Gross income | Agricultural income |
|---|---|---|---|---|---|---|---|
| Predicted outcome under non-adoption | -0.215 | -0.120 | -0.065 | -0.060 | 5.801 | 9.640 | 9.186 |
| ATT | 0.309*** | 0.273*** | 0.138** | 0.116* | 1.731*** | 0.683*** | 0.677*** |
| | (0.040) | (0.043) | (0.049) | (0.049) | (0.093) | (0.043) | (0.043) |
| Over identification test for covariate balance (p – value) | 0.4453 | | | | | | |
| **Off-farm diversification** | | | | | | | |
| Predicted outcome under non-adoption | -0.060 | 0.041 | -0.059 | -0.015 | 6.294 | 9.638 | 9.416 |
| ATT | 0.048 | -0.027 | 0.220*** | 0.085 | 1.123*** | 0.905*** | 0.318*** |
| | (0.036) | (0.048) | (0.043) | (0.046) | (0.114) | (0.047) | (0.041) |
| Over identification test for covariate balance (p – value) | 0.3590 | | | | | | |
| # of observations | 2,996 | 2,996 | 2,996 | 2,996 | 2,996 | 2,996 | 2,996 |

***Note:*** ***, **, * indicate statistical significance at 1, 5 and 10%, respectively.
Standard errors in parenthesis are clustered at the CWAC-level.
***Source:*** Authors' own elaboration.

## Multivalued treatment effects of climate adaptive practices

Given that climate adaptive practices may be adopted in combination as part of a broader farm or livelihood adaptation strategy, it is important to understand how the impact estimates change at different intensities of adoption. Table 7 and Table 8 provide the $ATT$ for different adoption intensities in Kenya and Zambia, respectively. In both countries, adoption of one strategy has no statistically significant impact on food security and resilience, although income increases in both contexts relative to non-adoption. Most of the complementarity in effects of adopting bundles of climate-adaptive practices is observed in terms of food consumption, food security, and income in both countries. However, the magnitude of these effects differs across Kenya and Zambia. In Kenya, we also observe this complementarity in effects for subjective resilience. However, we do not observe this for Zambia, likely due to the negative association between one of the climate-adaptive practices (conservation agriculture) and subjective resilience measures, which may cancel out the positive impacts of other strategies.

Results from multivalued treatment effect models in Table 7 and Table 8 show that increase in adoption intensity by combining several climate-adaptive practices is associated with increases in household wellbeing and income for most outcomes. These results, in line with Tabe-Ojong *et al.* (2023), highlight the increasing returns to additional adoption of climate-adaptive practices. Thus, programs that bundle several climate-adaptive interventions together are most likely to have the highest returns for rural households in SSA. Though they still need to account for the potential trade-offs between farm and off-farm activities. A key limitation of multivalued treatment effect models is that while they allow us to estimate the differential impacts of additional adoption, they do not provide information on what combination of strategies is the most effective in improving household wellbeing.

Table 7. Combined effects of climate adaptive practices on household wellbeing in Kenya: ATT from IPWRA multivalued treatment effects model

| | Food consumption index | Food security index | Subjective resilience | Gross income |
|---|---|---|---|---|
| **Predicted outcome under non-adoption** | -0.234 | 0.085 | -0.164 | 9.42 |
| $ATT_{1vs0}$ | 0.121 | 0.018 | 0.069 | 0.985** |
| | (0.108) | (0.120) | (0.165) | (0.503) |
| $ATT_{2vs0}$ | 0.269** | 0.118 | 0.227 | 2.090*** |
| | (0.118) | (0.136) | (0.171) | (0.503) |
| $ATT_{3vs0}$ | 0.745*** | 0.327** | 0.554* | 2.587*** |
| | (0.181) | (0.162) | (0.298) | (0.601) |
| $ATT_{4vs0}$ | 1.551*** | 0.010 | 1.982*** | 3.112*** |
| | (0.205) | (0.195) | (0.240) | (0.469) |
| **# of Observations** | 664 | 664 | 659 | 662 |

***Note:*** ***, **, * indicate statistical significance at 1, 5 and 10%, respectively.
Standard errors in parenthesis are clustered at the village-level.
***Source**:* Authors' own elaboration.

Table 8. Combined effects of climate adaptive practices on household wellbeing in Zambia: ATT from IPWRA multivalued treatment effects model

| | Food security index | Food consumption index | Subjective resilience index, drought | Subjective resilience index, flood | Gross income | Agricultural Income |
|---|---|---|---|---|---|---|
| **Predicted outcome under non-adoption** | -0.244 | -0.137 | -0.120 | -0.111 | 9.055 | 8.781 |
| $ATT_{1vs0}$ | 0.072 | 0.003 | 0.040 | 0.083 | 0.383*** | 0.318*** |
| | (0.074) | (0.077) | (0.093) | (0.116) | (0.070) | (0.095) |
| $ATT_{2vs0}$ | 0.184* | 0.102 | 0.113 | 0.094 | 0.942*** | 0.776*** |
| | (0.075) | (0.089) | (0.083) | (0.104) | (0.076) | (0.099) |
| $ATT_{3vs0}$ | 0.229** | 0.177 | 0.142 | 0.167 | 1.209*** | 0.930*** |
| | (0.076) | (0.094) | (0.086) | (0.120) | (0.081) | (0.101) |
| $ATT_{4vs0}$ | 0.406*** | 0.446*** | 0.084 | 0.020 | 1.795*** | 1.419*** |
| | (0.101) | (0.100) | (0.102) | (0.122) | (0.129) | (0.144) |
| **# of Observations** | 2,996 | 2,996 | 2,996 | 2,996 | 2,996 | 2,996 |

***Notes:*** ***, **, * indicate statistical significance at 1, 5 and 10%, respectively.
Standard errors in parenthesis are clustered at the CWAC-level.
***Source**:* Authors' own elaboration

# Conclusions

In this paper, we used comparable farm-level data from pastoralists of Kenya and smallholder rain-fed crop producers of Zambia to (i) measure farm-households' resilience to climatic stressors using the conceptual framework of adaptive cycles in socio-ecological systems, (ii) assess the correlates of climate-adaptive practices, and (iii) examine the relationship between climate-adaptive practices and household wellbeing.

We show that our resilience measure performs well and can be successfully replicated in diverse rural contexts. While there are drawbacks to our subjective measure, such as being a 'snapshot' and not necessarily a dynamic measure of resilience, it has the potential to measure household resilience for different rural development projects without requiring copious amounts of data. Furthermore, this measurement allows us to examine the relationship between climate-adaptive practices and household resilience in diverse production systems. Such comparative analysis can help in the design of broad-based development interventions that aim to enhance adoption of climate-adaptive practices and resilience of rural households in multiple contexts.

Impact assessments related to climate-adaptive practices indicate that capital-intensive adaptive strategies, such as feed storage in Kenya and hybrid seeds in Zambia, have positive associations with food security, resilience, and income in both countries, highlighting the importance of promoting such capital-intensive on-farm strategies in diverse production systems. Similarly, off-farm diversification strategies have a robust positive association with household income and resilience in both contexts, though impacts on food security outcomes are different across the two production systems, likely due to differences in the nature of off-farm opportunities in these contexts. System-specific labour-intensive strategies, such as conservation agriculture in Zambia and collective production in Kenya, also show heterogeneous impacts. Additionally, we find that combining these strategies can have greater positive impacts on household food security and resilience across both contexts, indicating the complementarity of climate-adaptive strategies in generating benefits.

Overall, these results imply that interventions that support the adoption of climate-adaptive practices in rural areas of SSA can benefit the economic, experiential, and psychological dimensions of farm-households' wellbeing. Furthermore, bundling and promoting capital and labour-intensive off- and on-farm adaptive strategies together can achieve greater benefits for rural communities as these strategies are complementary in nature. However, supporting their uptake requires addressing some of the key adoption barriers, which include expanding access to information and extension, improving education systems, and providing adequate adaptation finance.

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# Appendices

Table A 1. Differences in means of outcome variables for livestock owners and non-owners in Kenya data

| | Owners | Non-owners | P-value |
|---|---|---|---|
| **Food consumption index** | -0.016<br>(0.038) | 0.094<br>(0.100) | 0.269 |
| **Food security index** | -0.004<br>(0.049) | 0.022<br>(0.052) | 0.787 |
| **Gross income** | 130,429<br>(175 450) | 59,149<br>(12 190) | 0.000 |

**Notes:** P-values for two-tailed pairwise t-tests are provided in the third column.
N for owners = 668
N for non-owners = 120.
***Source**:* Authors' own elaboration.

Table A 2. Subjective resilience measurement scale

Please rank the following statements on a 5-degree-Likert scale (1 = strongly disagree, 2 = disagree, 3 = neither agree nor disagree, 4 = agree, and 5 = strongly agree).

| ***Robustness*** | |
|---|---|
| After a drought/flood, it is easy for my farm to recover to its previous profitability within a year | + |
| It is hard to manage my farm in a way that it recovers quickly from the drought/flood | - |
| I consider myself well-prepared to protect my farm production in case there is a drought/flood. | + |
| ***Farm Adaptability*** | |
| If needed, my farm can adopt new activities, varieties, or technologies in response to a drought/flood within a year | + |
| I can adopt alternative management techniques and technologies to adapt quickly and successfully to a drought/flood | + |
| It is difficult for my farm to adopt new practices and techniques in the short-term to minimize damages from a drought/flood | - |
| ***Transformability*** | |
| My farm can easily transform to produce an alternative primary product and access different value chains when faced with a drought/flood in the short-term | + |
| Due to circumstances not in my power (water availability, soil composition, markets, etc.), it is hard to quickly rearrange my farm especially when faced with a drought/flood. | - |
| ***Livelihood Adaptability*** | |
| It is possible for me to get a job or start a business outside of farming when own-farm production declines due to a drought/flood | + |
| It is possible for me to travel outside my village and earn money to support my family when a drought/flood occurs | + |
| It is it very difficult for me to find a job or start a business outside my farm when a drought/flood occurs | - |

Table A 3. Comparisons for food security and subjective resilience against droughts in Kenya and Zambia

| | Kenya | Zambia | P-values |
|---|---|---|---|
| **Food security index** | -0.288 | 0.076 | 0.000 |
| | (0.732) | (1.046) | |
| **Subjective resilience** | -0.686 | 0.177 | 0.000 |
| **index, droughts** | (0.867) | (0.954) | |
| **# of obs** | 788 | 3002 | |

***Source**:* Authors' own elaboration.

Table A 4. Correlates of perceived resilience in Kenya and Zambia

| | Kenya | Zambia | | | |
|---|---|---|---|---|---|
| | Subjective resilience index, drought | Subjective resilience index, drought | Subjective resilience index, flood | Subjective resilience index, drought | Subjective resilience index, flood |
| **Household size** | -0.005 | 0.008 | 0.015* | 0.009 | 0.017* |
| | (0.017) | (0.008) | (0.009) | (0.008) | (0.009) |
| **Gender (male = 1)** | -0.076 | 0.102** | 0.115*** | 0.099** | 0.109*** |
| | (0.083) | (0.042) | (0.041) | (0.042) | (0.041) |
| **Age** | -0.006** | -0.005*** | -0.008*** | -0.005*** | -0.008*** |
| | (0.002) | (0.001) | (0.001) | (0.001) | (0.001) |
| **Schooling** | -0.013 | 0.004 | -0.003 | 0.004 | -0.004 |
| | (0.071) | (0.005) | (0.005) | (0.005) | (0.005) |
| **Labour constrained** | -0.173** | -0.027 | -0.035 | -0.031 | -0.035 |
| | (0.084) | (0.050) | (0.046) | (0.049) | (0.045) |
| **Extension contact** | 0.170** | 0.147*** | 0.064 | 0.147*** | 0.069 |
| | (0.082) | (0.049) | (0.044) | (0.048) | (0.044) |
| **Climate information services** | 0.152 | -0.060 | 0.008 | -0.045 | 0.029 |
| | (0.122) | (0.055) | (0.051) | (0.055) | (0.050) |
| **Savings group** | -0.089 | 0.011 | 0.115** | 0.013 | 0.116** |
| | (0.095) | (0.053) | (0.051) | (0.054) | (0.051) |
| **Herd size** | 0.0006 | 0.013** | 0.007 | 0.013** | 0.007 |
| | (0.003) | (0.005) | (0.005) | (0.005) | (0.005) |
| **Drought shock** | - | - | - | -0.124*** | |
| | | | | (0.046) | |
| **Flood shock** | - | - | - | | -0.142*** |
| | | | | | (0.050) |
| **Observations** | 668 | 2996 | 2996 | 2996 | 2996 |

***Note**:* ***, **, * indicate statistical significance at 1, 5 and 10%, respectively.
Standard errors in parenthesis are clustered at the CWAC-level for Zambia and village-level for Kenya.

All regressions are OLS regressions with ward-level fixed effects to account for unobserved heterogeneity at the ward-level.
***Source**:* Authors' own elaboration.

Table A 5. Adoption of climate adaptive practices: marginal effects from treatment model (logit regressions)

| | Feed storage | Herd diversification | Off-farm work | Collective production |
|---|---|---|---|---|
| **Herd size** | -0.017 | 0.071*** | 0.002 | -0.007* |
| | (0.012) | (0.009) | (0.002) | (0.004) |
| **Age of household head** | 0.001 | -0.005 | -0.003* | 0.002** |
| | (0.008) | (0.001) | (0.001) | (0.0009) |
| **Household size** | 0.016*** | 0.007 | 0.029*** | 0.003 |
| | (0.005) | (0.006) | (0.007) | (0.005) |
| **Male headed household** | 0.084* | 0.030 | -0.115*** | 0.032 |
| | (0.044) | (0.029) | (0.038) | (0.030) |
| **Market distance** | 0.002 | 0.007*** | -0.009 | -0.005 |
| | (0.019) | (0.001) | (0.018) | (0.003) |
| **Saving group** | 0.171*** | 0.027 | 0.136*** | 0.073* |
| | (0.047) | (0.036) | (0.041) | (0.042) |
| **Formal schooling** | 0.006 | -0.018 | 0.230*** | 0.041 |
| | (0.003) | (0.039) | (0.034) | (0.031) |
| **Climate information services** | 0.248*** | -0.063 | 0.099* | 0.039 |
| | (0.041) | (0.053) | (0.057) | (0.044) |
| **Extension contact** | 0.070 | 0.052* | 0.068** | 0.014 |
| | (0.054) | (0.031) | (0.031) | (0.048) |
| **Chari** | -0.053 | -0.159* | 0.146** | 0.081 |
| | (0.065) | (0.088) | (0.059) | (0.124) |
| **Oldonyiro** | 0.053 | -0.094 | 0.188*** | 0.022 |
| | (0.054) | (0.070) | (0.058) | (0.091) |
| **Sericho** | -0.091 | 0.021 | -0.035 | -0.152** |
| | (0.061) | (0.063) | (0.054) | (0.060) |

***Note**: N* = 664
***, **, * indicate statistical significance at 1, 5 and 10%, respectively.
Standard errors in parenthesis are clustered at the village-level.
***Source**:* Authors' own elaboration.

Table A 6. Adoption of climate adaptive practices in Zambia: marginal effects from treatment model (logit regressions)

| | Crop Diversification | Conservation agriculture | Hybrid or improved seed | Off-farm Diversification |
|---|---|---|---|---|
| **Household size** | -0.002 | -0.008* | 0.021*** | 0.012*** |
| | (0.005) | (0.004) | (0.005) | (0.004) |
| **Gender** | 0.026 | 0.069*** | 0.055** | 0.005 |
| | (0.024) | (0.019) | (0.025) | (0.024) |
| **Age** | 0.002*** | 0.001 | 0.001 | -0.001* |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| **Years of education** | 0.004 | -0.000 | 0.018*** | 0.005** |
| | (0.003) | (0.002) | (0.003) | (0.003) |
| **Labour constraint** | -0.018 | -0.015 | -0.004 | 0.023 |
| | (0.025) | (0.022) | (0.028) | (0.024) |
| **Extension contact** | 0.008 | 0.018 | 0.059*** | 0.143*** |
| | (0.019) | (0.021) | (0.021) | (0.021) |
| **Climate information services** | -0.005 | 0.083*** | 0.021 | 0.048* |
| | (0.025) | (0.024) | (0.021) | (0.026) |
| **Saving group** | 0.005 | 0.004 | 0.108*** | 0.085*** |
| | (0.025) | (0.026) | (0.029) | (0.030) |
| **Observations** | 2996 | 2996 | 2996 | 2996 |

***Note:*** ***, **, * indicate statistical significance at 1, 5 and 10%, respectively.
Standard errors in parenthesis are clustered at the CWAC-level.
***Source:*** Authors' own elaboration.

Table A 7. Relationship between collective production, off-farm diversification, and household welfare outcomes for full sample in Kenya: ATT from IPWRA model

| | Food consumption index | Food security index | Subjective resilience | Livestock expenditure | Livestock income | Gross income |
|---|---|---|---|---|---|---|
| **Off-farm Diversification** | | | | | | |
| Predicted outcome under non-adoption | -0.162 | -0.088 | -0.128 | 7.179 | 8.260 | 8.411 |
| ATT | 0.471*** (0.090) | 0.247*** (0.053) | 0.239*** (0.060) | 0.297 (0.305) | -1.236*** (0.328) | 3.358*** (0.363) |
| **Herd-Diversification** | | | | | | |
| Predicted outcome under non-adoption | -0.044 | -0.021 | -0.290 | 7.369 | 7.596 | 9.572 |
| ATT | 0.575*** (0.114) | 0.117 (0.153) | 0.522*** (0.100) | 0.018 (0.365) | 0.058 (0.529) | 0.715* (0.394) |

**Notes:** N = 771
***, **, * indicate statistical significance at 1, 5 and 10%, respectively.
Standard errors in parenthesis are clustered at the village-level.
***Source:*** Authors' own elaboration.

Table A 8. Normalized differences of covariates between adopters and non-adopters after IPW in Kenya

| | Feed storage | Herd diversification | Off-farm work | Collective production |
|---|---|---|---|---|
| **Herd size** | -0.17 | 0.11 | 0.12 | -0.23 |
| **Age of household head** | -0.07 | 0.12 | -0.23 | **0.27** |
| **Household size** | 0.24 | 0.24 | **0.26** | 0.08 |
| **Male-headed household** | 0.24 | 0.12 | -0.10 | 0.14 |
| **Market distance** | 0.19 | 0.12 | -0.17 | -0.09 |
| **Saving group** | 0.22 | -0.14 | 0.25 | 0.20 |
| **Formal schooling** | 0.03 | -0.14 | **0.44** | 0.10 |
| **Climate information services** | **0.45** | -0.06 | 0.13 | 0.18 |
| **Extension contact** | -0.22 | **0.33** | 0.16 | 0.09 |

***Source:*** Authors' own elaboration.

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