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Technical Report

Climate Risk Perception and Adoption of Sustainable Agricultural Practices: Insights from Kenya's Central Highlands

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About the CGIAR Sustainable Farming Program

The science program addresses key challenges in agri-food systems by fostering efficient production of nutritious foods and safeguarding the environment to create fair employment opportunities, as we simultaneously tackle climate change, soil degradation, pests, diseases, and desertification in Bangladesh, Benin, Burundi, Cambodia, Colombia, Côte d'Ivoire, Democratic Republic of Congo, Egypt, Ethiopia, Ghana, Guatemala, India, Kenya, Laos, Madagascar, Malawi, Mali, Mexico, Morocco, Mozambique, Nepal, Niger, Nigeria, Pakistan, Peru, Philippines, Rwanda, Senegal, Tanzania, Uganda, Uzbekistan, Vietnam, Zambia and Zimbabwe.

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Summary

Smallholder farmers are increasingly exposed to climate variability that threatens agricultural productivity and household livelihoods. Sustainable agricultural practices (SAPs) are widely recognized as a key pathway for sustaining yields, conserving resources, and enhancing resilience. Identifying the factors that drive adoption is therefore essential for designing effective adaptation strategies. While much of the literature has focused on socio-economic determinants of technology adoption, the role of behavioral factors remains less examined. Using survey data from the Kenya Central Highlands and a Poisson regression framework, we find a non-linear, U-shaped relationship between climate concerns and adoption, with higher adoption at low and high levels of concern and lower adoption at moderate levels. The results show that subjective climate risk perceptions exert a stronger influence on adoption decisions than beliefs about climate exposure. This suggests that the way farmers interpret and internalize climate risks matter more for their behavior than whether they believe they have personally experienced climate events, underscoring the importance of addressing risk awareness and interpretation in adaptation strategies. We also find notable heterogeneity: in female-managed plots, education strongly predict adoption, while in male-managed plots, training frequency and climate concerns play important role. Additionally, certain practices such as organic inputs and soil and water conservation are more sensitive to climate concerns, while input and resource intensive practices like irrigation, intercropping, and no-tillage appear to be less influenced by climate perceptions. The findings highlight the need to integrate behavioral dimensions, particularly climate risk perceptions, into adaptation policies and contextualize interventions by gender and farm size. We emphasize that the analysis relies on cross-sectional data and therefore unobserved behavioral traits, and social-contextual factors may be correlated with climate risk perception, as well as with adoption decisions, potentially biasing our estimates. To mitigate this, we include a comprehensive set of covariates to account for socio-economic and behavioral factors that prior literature identifies as influencing technology adoption. Nonetheless, we acknowledge that some unobserved confounders may remain, and therefore we interpret our results as associations rather than causal effects. Even so, insights into how perceptions shape adoption decisions provide valuable guidance for grassroots implementers, allowing them to design awareness campaigns, training programs, and extension strategies that align with farmers' experiences and address the thresholds or barriers that may impede timely adoption of sustainable practices.

1.Introduction

Smallholder farmers are increasingly exposed to extreme weather events, including recurring droughts, occasional floods, and unpredictable rainfall patterns, which threaten both food production and livelihood security. To address these challenges, climate-smart agriculture (CSA) and sustainable agricultural practices (SAPs) have been promoted as strategies to enhance productivity and resilience (FAO, 2022). SAPs encompass practices such as crop rotation, cover cropping, reduced tillage, organic fertilization, agroforestry, and soil and water conservation (Piñeiro et al. 2020). These measures aim to safeguard natural resources while maintaining or improving crop yields. Recent evidence from Africa indicates that agroecological practices can significantly increase land productivity (Romero Antonio et al., 2025). Accordingly, there is growing emphasis on sustainable production approaches that maximize yields on limited land while preserving biodiversity and ecosystem functions (Giller, Delaune, Silva, Descheemaeker, et al. 2021; Giller, Delaune, Silva, van Wijk, et al. 2021; Pretty and Bharucha 2014).

The adoption of SAPs can be understood within the broader literature on technology adoption, as it requires farmers to modify established production methods and resource-use patterns (Alhassan and Haruna 2024). Seminal work by Feder, (1980) emphasized that technology adoption is often constrained by limited credit access, inadequate information, risk aversion, and small farm size. Subsequent research highlights farmers' aversion to uncertainty as a central barrier to adoption (Binswanger 1980). Agriculture is inherently risky, with production, marketing, and climate-related shocks lying largely beyond farmers' control. The growing frequency and intensity of climate events have further amplified these uncertainties, which can hinder the uptake of both conventional technologies (Ward and Singh 2015) and SAPs.

While existing studies largely examine socioeconomic, institutional, and environmental determinants of climate-smart technology adoption (Amadu et al. 2020; Feder et al. 1985; Teklewold et al. 2019; Yegbemey et al. 2013), the role of farmers' cognitive traits remains underexplored (Dessart et al. 2019). Most research on cognitive traits focuses on risk preferences—the propensity to engage in activities involving varying levels of risk—as a determinant of technology adoption (Isik and Khanna 2003; Kangogo et al. 2021; Liu 2013; Ward and Singh 2015). However, risk preferences alone do not capture the full spectrum of behavioral influences. Other traits, including perceptions of innovation benefits, aspirations, intentions, and attitudes, also shape adoption decisions (Dessart et al. 2019; Kangogo et al. 2021).

Building on this literature, we propose a behaviorally informed framework that integrates insights from behavioral economics to analyze how farmers' climate risk perceptions (CRP), both beliefs about exposure and subjective concerns influence adaptive choices. Farmers' CRP warrants particular attention given the increasing frequency and severity of extreme climate events (Intergovernmental Panel on Climate Change (IPCC) 2022). Climate risk is closely linked to vulnerability, as impacts arise from the interaction between hazards and the social and ecological systems exposed to them (Selvaraju 2012). Understanding farmers' perceptions of weather and climate changes is therefore crucial for scientists, policymakers, and civil society organizations engaged in climate adaptation initiatives (Simelton et al. 2013).

Here we examine the factors that influence adoption of sustainable agricultural practice with a focus on how farmers perceive and respond to climate risk. While CRP has been widely studied in agricultural contexts, most empirical analyses explain variation primarily through socio-demographic characteristics or access to information, extension services, and social networks (Ricart et al. 2023; van der Linden 2015). The psychological mechanisms by which risk perceptions translate into adaptive behaviors remain critically understudied (van der Linden 2015; Waldman et al. 2020). Few studies have analyzed how farmers in rural areas of low and middle income countries were able to perceive the risks from climate change and adapt to the impacts of climate change on agriculture (Abid et al. 2019; Chikosi et al. 2018; Debela et al. 2015; Deressa et al. 2009; Joshi et al. 2017; Thomas et al. 2007; Twecan et al. 2022). Prior studies have often treated perceived climate exposure and subjective concern as interchangeable, without distinguishing their distinct roles. In this study, climate exposure reflects respondents' beliefs about whether they have experienced climate events, while climate concern captures their perceptions of climate-related risks. Examining both is important because individuals may believe they have experienced climate events, yet do not interpret them as indicators of climate change, particularly when knowledge of changing climate risks is limited. Differentiating these dimensions provides deeper insight into how farmers perceive and respond to climate variability and helps design adaptation policies that address both experiential and perceptual behavior. Adaptation decisions ultimately depend on how risks are interpreted and weighed psychologically. Extending this literature, our study contributes by jointly examining perceived climate exposure and subjective risk perceptions to understand adoption decisions in Kenya's Central Highlands. Unlike prior work, we explicitly account for behavioral factors—including finite worry, risk attitudes, optimism bias, and consensus heuristics—alongside household, decision-maker, and plot characteristics, while also controlling for geographical fixed effects. This approach allows us to understand ways in which psychological and contextual factors interact to influence adaptation decisions. We also conduct heterogenous analysis across two sub-groups. First, we test if the relationship varies by the gender of the plot-manager. In many agricultural contexts, different household members (men and women) act as the primary decision-makers for specific plots. While resources may be pooled at the household level, the individual responsible for a plot typically determines input use, labor allocation, and the adoption of agricultural practices. A large body of evidence shows that plots managed by women often have lower yields than those managed by men, largely due to differential access to and use of inputs rather than intrinsic differences in productivity (FAO 2011; Goldstein and Udry 2004; Hill and Vigneri 2014; Peterman et al. 2011; Quisumbing 1996). Moreover, reallocating inputs toward women-managed plots has been shown to increase overall household production (Udry 1996). Focusing only on the gender of the household head would therefore obscure important intra-household heterogeneity. For example, in male-headed households, women may still manage specific plots and exercise considerable autonomy over production choices. Linking plot-level data to the identified manager enables us to capture these differences and analyze how male- and female-managed plots vary in their adoption of sustainable practices and perceptions of climate risk. This approach follows a growing literature that highlights households as non-unitary decision-making entities, where intra-household gender dynamics are central to agricultural outcomes (Doss 2015; 2002).The second sub-group analysis we undertake is by disaggregating the data by size of plot. While all plots are part of the same household farm, plot size is a critical dimension of heterogeneity in agricultural decision-making. Farmers often allocate resources and practices differently depending on the scale of the plot. For instance, larger plots may attract greater investment in technologies such as irrigation or conservation structures, while smaller plots may be used for subsistence crops, experimentation, or crops requiring intensive management. Analyzing adoption by plot size thus helps capture the variation in opportunity costs, risk exposure, and labor requirements associated with different scales of cultivation. Such an analysis allows us to design more context-specific, behaviorally informed interventions that promote the adoption of sustainable practices. We address the following research questions:

1. What factors influence farmers' adoption of sustainable agricultural practices?
2. What is the nature of the relationship between climate risk perception and adoption decisions?
3. Does the relationship between climate risk perception and adoption differ by gender of decision-maker and plot size?

Using survey data from the Kenya Central Highlands and a Poisson regression framework, we find a non-linear, U-shaped relationship between climate concerns and adoption, with higher adoption at low and high levels of concern and lower adoption at moderate levels. The results show that subjective climate risk perceptions exert a stronger influence on adoption decisions than beliefs about climate exposure. This suggests that the way farmers interpret and internalize climate risks matter more for their behavior than whether they believe they have personally experienced climate events, underscoring the importance of addressing risk awareness and interpretation in adaptation strategies. We also find notable heterogeneity: in female-managed plots, education strongly predict adoption, while in male-managed plots, training frequency and climate concerns play important role. Additionally, certain practices such as organic inputs and soil and water conservation are more sensitive to climate concerns, while input and resource intensive practices like irrigation, intercropping, and no-tillage appear to be less influenced by climate perceptions. The findings highlight the need to integrate behavioral dimensions, particularly climate risk perceptions, into adaptation policies and contextualize interventions by gender and farm size. We emphasize that the analysis relies on cross-sectional data and therefore unobserved behavioral traits, and social-contextual factors may be correlated with climate risk perception, as well as with adoption decisions, potentially biasing our estimates. To mitigate this, we include a comprehensive set of covariates to account for socio-economic and behavioral factors that prior literature identifies as influencing technology adoption. Nonetheless, we acknowledge that some unobserved confounders may remain, and therefore we interpret our results as associations rather than causal effects. Even so, insights into how perceptions shape adoption decisions provide valuable guidance for grassroots implementers, allowing them to design awareness campaigns, training programs, and extension strategies that align with farmers' experiences and address the thresholds or barriers that may impede timely adoption of sustainable practices.

This report is organized as follows. Section 2 presents the conceptual framework that underpins the analysis of farmers' adoption of sustainable agricultural practices. Section 3 outlines the empirical strategy, while Section 4 details the measurement of key variables. Section 5 describes the data, including the study context, the study area, and the sampling strategy. Section 6 presents the results, beginning with descriptive statistics and followed by econometric analyses, which examine the key determinants of SAP adoption, the role of climate risk perception, and heterogeneous effects across gender of plot manager and plot sizes, and conduct robustness checks. Section 7 discusses the recommendations from the study while Section 8 presents the limitations of the study and finally, Section 9 concludes with a discussion of the main findings and their implications for policy and climate adaptation interventions.

2. Conceptual Framework

Understanding the factors that influence farmers' technology adoption requires attention to both structural and behavioral dimensions. Traditional economic explanations highlight market imperfections, rationing, and uncertainty as key constraints on technology adoption (de Janvry et al. 1991; Just and Zilberman 1988; Key et al. 2000; Sadoulet et al. 1998; Smale et al. 1994). While these factors remain important, behavioral economics has expanded this perspective by showing that farmers' decisions are also shaped by perceptions, heuristics, and cognitive biases (Dessart et al. 2019; Wuepper et al. 2023).

The concept of bounded rationality suggests that individuals do not necessarily maximize utility when information and cognitive capacity are limited; instead, they aim for outcomes that are "good enough" (Simon 1955). Prospect Theory further refines our understanding of decision-making under risk, highlighting four key propositions: outcomes are evaluated relative to reference points; losses loom larger than equivalent gains; individuals are risk-seeking in losses but risk-averse in gains; and small probabilities are overweighted when stakes are high (Kahneman and Tversky, 1979). Other behavioral insights, such as hyperbolic discounting, show that people disproportionately value immediate benefits over future gains, which can contribute to underinvestment in long-term strategies (Herrnstein 1997; Laibson 1998). Theories of social preferences also demonstrate that decision-making is shaped not only by self-interest but also by altruism and fairness (Charness and Rabin 2002; Fehr and Camerer 2007; Levitt and List 2007). Collectively, these insights suggest that conventional rational-choice models are insufficient for explaining behavior in contexts characterized by uncertainty and complexity (Waldman et al. 2020). Empirical evidence shows that, under such conditions, individuals often rely on heuristics—simple rules of thumb—to guide decisions (Gigerenzer et al. 2000; Kahneman and Tversky 1979; Simon 1955; Wuepper et al. 2023).

In the context of climate change, farmers in developing countries generally acknowledge increasing weather variability but this awareness does not always translate into adaptive action (Mertz et al. 2009; Osbahr et al. 2011; Simelton et al. 2013). Cognitive biases play a key role in shaping risk appraisal. While biases are not inherently detrimental, they can lead to misperceptions of climate risk, with individuals often underestimating threats compared to expert assessments (Botzen 2022; Siegrist and Árvai 2020; Siegrist and Gutscher 2006). Even farmers with direct exposure to climate variability are not immune to this mismatch (Ricart et al. 2023). Most prior studies have treated climate exposure and subjective concern as interchangeable, failing to differentiate between the effects of farmer's belief on experience and perceived risk associated with climate hazards. Examining both is crucial because individuals may not interpret climate events as indicators of climate change, particularly when their knowledge of climate risks is limited. Exposure to climate change captures whether a respondent actually believes they have experienced specific climate-related events, while climate change worry reflects the respondent's subjective concerns about climate risks farmers are most worried about, regardless of prior experience. These measures are different because "experience" reflects past occurrences, whereas "worry" captures perceptions and anticipatory concerns. Analyzing both is important, as belief about actual exposure and perceived risk can influence adaptation decisions in distinct ways. To capture the behavioral dimensions of adaptation, we therefore distinguish between two interconnected constructs of climate risk perception: farmers' belief about exposure (CEXP) to climate change and subjective concerns of climate-related threats (CWORRY). We test whether both respondent's belief about climate exposure and subjective climate concerns influence the adoption of adaptive practices in a potentially non-linear manner. Moderate exposure or concern can encourage adoption, as farmers recognize risks and invest in resilience. However, very high exposure or concern may discourage adoption, as farmers revert to familiar strategies—such as intensifying the use of chemical fertilizers and pesticides—to reduce potential yield losses. In some cases, high exposure combined with strong concern may instead accelerate adoption, highlighting the complex, non-linear relationship between climate experience, perceptions, and adaptive behavior. Therefore, the relationship must be examined empirically. Recognizing these non-linear effects is critical for designing effective interventions. To our knowledge, no study has empirically examined these non-linear relationships between climate exposure, perceptions, and adaptation in low- and middle-income country contexts. The formal econometric specification is presented in Section 3.

3.Empirical Strategy

In this section we present the empirical framework that enables us to determine whether climate risk awareness leads to action and where added support is needed to foster sustainable adoption in the Use Case target area. To examine how climate change risk perception influences the adoption of sustainable agricultural practices (SAPs), we estimate the following model.

$$Adapt_{iph} = \beta_0 + \beta_1' Cworry_{ih} + \beta_2' Cexp_{ih} + \beta_3' \boldsymbol{X}_h + \beta_4' \boldsymbol{DM}_{ih} + \beta_5' \boldsymbol{TRP}_{ih} + \beta_6' \boldsymbol{P_{ph}} + \beta_7' \boldsymbol{BF_{ih}} + \Phi_c + \varepsilon_{iph} \quad (1)$$

The dependent variable $Adapt_{iph}$ denotes the number of sustainable agricultural practices adopted by decision-maker i on plot p in household h. Our main variables of interest are $Cexp_{ih}$ which measures climate change experience and $Cworry_{ih}$which measures subjective climate change worry (Details of how these variables are constructed is mentioned in Section 4.2). To account for potential non-linearities, we also include a quadratic term for both these indices. By estimating Equation (1), our objective is not limited to assessing the linear coefficients of $Cworry_{ih}$ and $Cexp_{ih}$, but also to examining their quadratic forms to capture possible non-linearities in these relationships. The linear term provides information about the overall direction of the relationship, while the quadratic term indicates whether the effect of climate change experience or worry accelerates or decelerates as the level of perception increases. Including both terms allows us to test whether adoption behavior may initially decline with increasing perception but subsequently rise once a certain level of concern or experience is reached, or vice versa. This specification allows us to uncover more complex behavioral responses that a purely linear framework would fail to identify. A detailed explanation of the construction of this variable is provided in Section 4.1.

In the specification, the vector $\boldsymbol{X}_h$ captures household specific characteristics such as household size and attributes of the household head, including gender, age, and main occupation. $\boldsymbol{DM}_{ih}$ represents decision-maker of the plots' characteristics, including age, gender, ethnicity, education, and occupation. $\boldsymbol{P_{ph}}$ is a vector of variables that account for plot specific characteristics such as area of plot, crops grown and terrain of plots. We also control technology-related risk perceptions using a vector $\boldsymbol{TRP}_{ih}$,which includes variables such as participation in training programs, ownership of mobile phones, familiarity with digital agricultural applications, and access to extension services. These factors are expected to enhance the availability of information and reduce the perceived technological risks associated with adopting SAPs. High TRP, resulting from limited training, weak extension services, or social isolation, can make adaptive technologies appear risky, costly, or unfamiliar, thereby reducing uptake. Conversely, access to training, digital agricultural tools, and participation in farmer groups can lower TRP, increase confidence, reduce uncertainty, and promote peer learning. By accounting for determinants of TRP, our empirical analysis enables us to isolate the independent effect of climate experience and perceptions on SAP adoption. Furthermore, we include a vector of behavioral controls, $\boldsymbol{BF_{ih}}$ to address concerns of endogeneity. In cross-sectional data, unobserved behavioral traits and social-context factors may be correlated with both CRP and adoption decisions, which could bias our estimates of the coefficients of interest (β_1 and β_2). To mitigate this risk, we control general (non-climate) worry, optimism bias, group membership (as a proxy for social norms and consensus heuristics), and risk preferences. Including these behavioral variables helps isolate the association between climate risk perception and adoption of SAPs, thereby improving the internal validity of our estimates. However, it is important to emphasize that including $\boldsymbol{BF_{ih}}$ does not fully eliminate endogeneity concerns in cross-sectional data. Reverse causality (adopters updating their perceptions) and remaining unobserved confounders may persist, so we interpret the coefficient β_1 and β_2 as a conditional association rather than a causal effect. In our specification, we also include county fixed effects Φ_c to control unobserved, time-invariant geographical heterogeneity. The error term ε_{iph} captures all unobserved factors. Standard errors are clustered at the household level to account for potential intra-household correlation and heteroskedasticity. Since the outcome variable is a count variable, we use a Poisson Model to estimate Equation (1). To assess whether overdispersion is present in the Poisson regression model, we conduct the Pearson goodness-of-fit test. The test yields a p-value greater than 0.05, indicating no significant evidence of overdispersion; thus, the Poisson model provides an adequate fit for the data.

We also do a heterogeneity analysis by estimating Equation (1) separately by gender of the decision-maker and by plot size. This analysis helps us understand whether climate induced adoption decisions differ between male and female farmers as well as are induced by key farm attributes such as field size. Although our estimates are not causal, examining these associations remains highly relevant from a policy and implementation perspective. Understanding how perceptions shape adoption decisions provide valuable insights for grassroots implementers, who can leverage this knowledge to design more effective awareness campaigns, training programs, and extension strategies that resonate with farmers' realities and address the thresholds or barriers that may prevent timely adoption of sustainable practices. Further, in addition to examining how climate risk perception is associated with the aggregate index of sustainable practices, we also analyze the relationship with the adoption of individual practices. This allows us to assess whether the observed patterns are broad-based across multiple practices or driven primarily by specific ones.

Further, to ensure that our results are robust, we undertake two additional checks. First, including both objective and subjective measures of climate concerns in the same framework may raise concerns of multicollinearity, as individuals who have directly experienced climate events are also plausibly more likely to report higher subjective perceptions of climate risk. To address this, we estimate Equation (1) using $Cexp_{ih}$ and $Cworry_{ih}$ in separate models, allowing us to test whether the interpretations remain consistent when the two measures are analyzed individually. Second, to further mitigate multicollinearity concerns and to provide a more comprehensive assessment of how overall climate risk perception influences adoption of sustainable agricultural practices, we construct a composite Climate Risk Perception (CRP) index that combines both dimensions. This enables us to evaluate whether the relationship exhibits similar patterns when perceptions are aggregated into a single measure. These results are presented in the Appendix.

4.Measurement of Key Variables

Table 1 provides an overview of the variables included in the analysis along with their descriptions. Section 4.1 details the construction of the outcome variable, Section 4.2 describes the climate risk perception variables, and Section 4.3 outlines the behavioral variables.

Table 1: Overview of Measurement of Variables

Category	Variable	Definition	Description
Sustainable Agricultural Practices	Intercropping	Whether multiple crops were cultivated simultaneously on the same plot.	Enhances biodiversity, improves soil fertility, and reduces pest/disease risks.
	Use of Organic Fertilizer	Whether compost, manure, or other organic inputs were applied.	Improves soil health, reduces reliance on chemicals, and promotes long-term fertility.
	Irrigation	Whether the plot had access to irrigation.	Reduces vulnerability to rainfall variability and supports stable yields.
	No Tillage	Whether the plot was cultivated without tilling.	Preserves soil structure, reduces erosion, and enhances carbon sequestration.
	Crop Diversification	Growing more than one crop in a plot	Reduces risks of monocropping, increases resilience to climate shocks.
	Water Conservation Practices	Household implements ≥1 water conservation method (e.g., bunds, check dams, terraces, harvesting ponds, contour ploughing, afforestation).	Improves water retention, reduces runoff, and enhances resilience to drought.
Climate Risk Perception	Climate Change Experience Index (Cexp)	Count of self-reported experiences with climate risks (rainfall shortage, drought, heat stress, floods, soil erosion, soil fertility).	Captures farmers lived exposure to climate change and its role in shaping adoption.
	Climate Change Worries (Cworry)	Count of subjective concerns about climate risks (late/insufficient rainfall, flooding, soil erosion, frost).	Highlights perceived vulnerability beyond actual experience.
Other Behavioral Factors	Finite Worry Index	Count of top five non-climatic risks (e.g., seed/fertilizer issues, health shocks, pests).	Distinguishes competing operational challenges from climate-related concerns.
	Risk Attitudes	Self-reported risk attitudes.	Determines openness to innovation and resilience strategies.

Category	Variable	Definition	Description
	Optimism Bias	Divergence between farmer versus enumerator assessments of farm conditions.	Shows perceptual bias that can distort risk evaluation and decisions.
	Consensus Heuristic Proxy	Number of group memberships (welfare, credit, producer, marketing, water, cooperatives).	Captures peer and social influence in shaping adoption behavior.
Technology Risk Perception	Exposure to Information	Access to extension, mobile, apps, or ag-technology knowledge.	Increases awareness, reduces perceived risk of adopting practices.
	Training	Participation in short- or long-term agricultural training.	Builds skills and confidence, lowering uncertainty in adoption.
	Access to Credit	Whether respondent has access to financial credit.	Enhances capacity to invest in or try sustainable practices.

4.1 Outcome variable

Plot-level data for the last cropping season was collected on agronomic practices for the largest plot where use-case crops were grown (see Table A1 in the Appendix for the list of crops). The outcome variable is created by counting the number of sustainable agricultural practices adopted at the plot level. This score ranges from 0 to 6 and is constructed by summing six binary indicators, each representing the use of a specific sustainable practice. A value of 1 indicates the practice was adopted, and 0 otherwise. The count reflects the total number of sustainable practices used, providing a simple yet informative measure to the extent to which households engage in environmentally sustainable farming.

The six components of the index are:

i. **Intercropping:** Indicates whether multiple crops were cultivated simultaneously on the same plot. This practice aims to increase biodiversity, improve soil fertility, and reduce pest and disease risk.
ii. **Use of organic fertilizer:** Captures whether organic inputs such as compost or manure were applied to the plot. Organic fertilizers are known to improve soil structure and fertility while reducing reliance on chemical inputs, thereby promoting long-term soil health.
iii. **Irrigation:** Identifies whether the plot had access to irrigation. Reliable water access can improve yields and reduce vulnerability to climate variability.
iv. **No tillage:** Reflects whether the plot was cultivated without tilling. No-till farming helps preserve soil structure, reduces erosion, and enhances carbon sequestration, all of which are core components of conservation agriculture.
v. **Crop diversification:** Crop diversification is defined as growing more than one crop in each plot. Diversification reduces risk associated with monocropping, by improving resilience to climate shocks.
vi. **Water conservation practices:** Water conservation is assessed at the household level. A household is considered to practice water conservation if it implements at least one of the following techniques in at least one plot: Soil or stone bunds, check dams (wooden, stone, gabion), percolation pits, micro basins (half-moon/eyebrow), cut-off drains, water harvesting ponds, ridge and furrow drainage systems, contour ploughing, stone terraces, strip planting (grasses, trees) and hill-side afforestation. These techniques are known to contribute to improved water retention, reduced runoff, and better moisture availability, making them essential for sustainable water management in agriculture.

4.2 Climate Risk Perception

a. Climate Change Experience Index ($Cexp$)[1]: We develop a composite index to capture farmers' self-reported experiences with climate-related problems. The index is based on five types of climate risks: limited rainfall, drought, heat stress, floods, soil erosion, and soil fertility. For each risk, respondents are assigned a value of 1 if they reported having experienced and 0 if they had never encountered it. The Climate Experience Index is calculated by summing these binary responses, resulting in a score ranging from 0 to 5. We then construct an ordinal variable to reflect respondents' overall perception of their climate change experience. This variable captures the intensity of perceived exposure and is coded as follows: 0 for "None," 1 for "Little," 2 for "Some," 3 for "Moderate," 4 for "High," and 5 for "Very High." This ordinal scale allows us to account for both the number and the perceived severity of climate-related challenges faced by farmers.

b. Climate Change Worries ($Cworry$)[2]: In addition to the Climate Experience Index, we also construct a separate score to reflect the respondent's subjective concerns about climate-related risks. These include late rainfall, insufficient rainfall, flooding, soil erosion, and frost. For each risk, a binary indicator is coded as 1 if the respondent identifies it as a source of personal concern, and 0 otherwise. We sum these indicators to create a worry score and further categorize it into an ordinal variable to reflect the intensity of climate concern: 0 for "None," 1 for "Little," 2 for "Some," 3 for "Moderate," 4 for "High," and 5 for "Very High." This measure captures the subjective perception of climate vulnerability, distinguishing it from the experience-based index and highlighting the risks that households view as most pressing.

4.3 Other Behavioral Factors

a. Finite worry index: To capture the most pressing non-climate-related agricultural concerns of farmers, we construct a "Finite Worry Index" based on respondents' selection of their top five concerns from a predefined list of risks. These risks relate to common, non-climatic challenges such as input quality and availability, health constraints, and pest or disease damage. Specifically, farmers were asked to identify up to five risks they were most concerned about from the following: poor quality of seeds, poor quality of fertilizers, seeds not available on time, fertilizers not available on time, poor crop response to fertilizers, sickness of household members working on the farm, sickness of livestock, and crop loss due to pests or plant diseases. Each selected concern is coded as 1, and the total number of selected risks is summed up to create the index, which ranges from 0 to 5. This measure helps distinguish households facing minimal operational challenges from those dealing with multiple agricultural concerns not directly related to climate change.

b. Risk attitudes: To approximate farmers' underlying risk preferences, we create a categorical variable based on their self-reported attitudes toward risk: those who do not like taking risks, those who accept or tolerate some level of risk, and those who are comfortable taking risks. Risk attitudes can significantly influence agricultural decision-making—shaping choices around technology adoption, investment in sustainable practices, and responses to external shocks. Including this measure allows us to examine how variations in risk tolerance may impact household behavior and decisions under uncertainty.

c. Optimism bias: To measure optimism bias—the tendency to overestimate favorable outcomes—we construct a proxy based on the divergence between farmers' self-assessments and enumerators' expert evaluations of specific plot-level characteristics, such as soil erosion. When a farmer's evaluation was more favorable than the enumerator's, they were classified as having an optimism bias. Conversely, if their assessment was more negative than the enumerator's, they were labeled cautious. If the farmer and enumerator assessments aligned, the classification was same. This categorization captures perceptual bias in evaluating farm conditions, which can influence farm decisions and risk perception.

[1] TableA3:1 in Appendix A3 presents the list of questions
[2] TableA3:2 in Appendix A3 presents the list of questions

d. Consensus heuristic proxy: We use the number of groups a respondent is affiliated with as a proxy for reliance on the consensus heuristic. This is based on the notion that stronger social embeddedness increases exposure to shared norms, peer actions, and group decisions, which can encourage decision-making based on what others do rather than personal evaluation. Our assumption is that individuals with more exposure to others' choices and participation in collective decision-making processes are more likely to adopt certain practices. The variable is constructed by counting the number of the following groups a respondent is part of: Social welfare; Savings and credit; Agricultural producers; Livestock producers; Agricultural marketing; Livestock marketing; Water Use (or Watershed Committee); and Multi-Purpose Cooperatives.

4.4 Technology Risk Perception variables

We use a set of proxy variables to capture technology risk perception, focusing on three key dimensions: exposure to information, participation in training programs, and access to credit. These factors are expected to reduce perceived risks associated with adopting new technologies by enhancing knowledge, building familiarity, and easing financial constraints—thereby facilitating uptake of sustainable practices.

a. Exposure to information: Exposure to information captures the respondent’s access to and engagement with agricultural knowledge sources and communication tools. This includes the number of extension sources consulted, ownership of a personal mobile phone, knowledge about ag-related applications, and familiarity with use-case-specific agricultural technologies. These factors indicate how well-informed an individual is about agricultural innovations, which can influence how they perceive and assess risks associated with new technologies.

b. Training: Training reflects direct learning experiences, distinguishing between short-term training (received within the past year) and long-term training (undertaken within the past five years) in agriculture or related fields. Training equips individuals with knowledge and skills that can reduce uncertainty around new practices.

c. Access to credit: Access to credit is included as a third dimension, recognizing that financial capacity plays a critical role in risk perception. Individuals with access to credit are more likely to experiment with or adopt new technologies, as they are better able to absorb potential losses or make necessary investments.

5. Data

5.1 Context of the Study

The CGIAR initiative on Sustainable Farming is working to support sustainable agriculture by promoting science-based solutions that improve farm productivity and resilience to climate change. As part of its efforts, CGIAR is working with local partner on the initiative Central Highlands Eco-Region Foodscape (CHEF) in Kenya. CHEF aims to transform food production in the Central Highlands of Kenya by promoting practices that restore and protect natural ecosystems. Through sustainable land management, improved soil and water conservation, and biodiversity protection, local partners are working to build a more resilient and productive landscape. As part of this effort, farmers participating in pilot innovations are being monitored, and their agronomic practices are being evaluated. This process is generating evidence to inform the potential for scaling up successful interventions more broadly across the landscape. A key component of this evidence-generation approach involves incorporating insights from behavioral economics into the design of Minimum Viable Products (MVPs). These MVPs are intended to support farmers in managing climate-related risks more effectively by aligning interventions with actual decision-making behaviors and constraints. The aim of this exercise is to support grassroot organizations in designing agronomic solutions at the local level that reflect actual behavioral patterns observed among farmers.

5.2 Study area and Sampling Strategy

A household survey was carried out in three geographically adjacent counties in the central highlands of Kenya — Laikipia, Meru, and Nyandarua — with the aim of generating insights into existing farming practices, the diversity of smallholder farmers, their strategies for managing climate-related challenges, the influence of gender on agricultural decision-making, and the extent of adoption of sustainable farming practices (Figure 1 Panel A). A cluster-based sampling approach was employed, identifying similar clusters based on elevation, crop diversity, forestry, urbanization, water bodies, rainfall (total, frequency, and mean), temperature (maximum, minimum, and average), and soil nutrient characteristics (zinc). To delineate agroecologically comparable zones, we used the Sustainable Farming Sampling Framing Application[3]. This tool first drew on land cover data—including crop masks, forested areas, urban settlements, and water bodies—to exclude urban and peri-urban wards, resulting in 23 eligible wards across the three counties. These wards were then classified into five distinct agroecological zones, defined by a combination of biophysical and environmental variables. The five different colors in Figure 1 Panel B depicts the different clusters. Wards with shared characteristics were grouped together, as illustrated in Figure 1.

Within each agro-ecological zone, the estimated number of smallholder farmers was extrapolated using arable land area and county-level population data. In the absence of official records, it was assumed that 75% of all farming households in the three counties were smallholder farmers. This stratification framework guided the allocation of sample sizes across counties and ecological zones. Based on a 95% confidence level, a 5% margin of error, an assumed population proportion of 0.5 for maximum variability, and a finite population correction, the minimum required sample size was calculated to be 370 households. To account for the design effect, the study oversampled and surveyed 622 farm households. Household selection across the three counties was undertaken through randomization of farmer lists obtained from Ward Agricultural and Extension Officers (WAOs) at the village level. To ensure equitable representation, a proportionate-to-population-size sampling strategy was employed, thereby facilitating the inclusion of men, women, and youth in accordance with their demographic distribution within each ward. Furthermore, WAOs were responsible for scheduling interviews and monitoring participation, with absent farmers replaced by their immediate neighbors to maintain sample consistency. Table A2 in the Appendix gives the distribution of the sample.

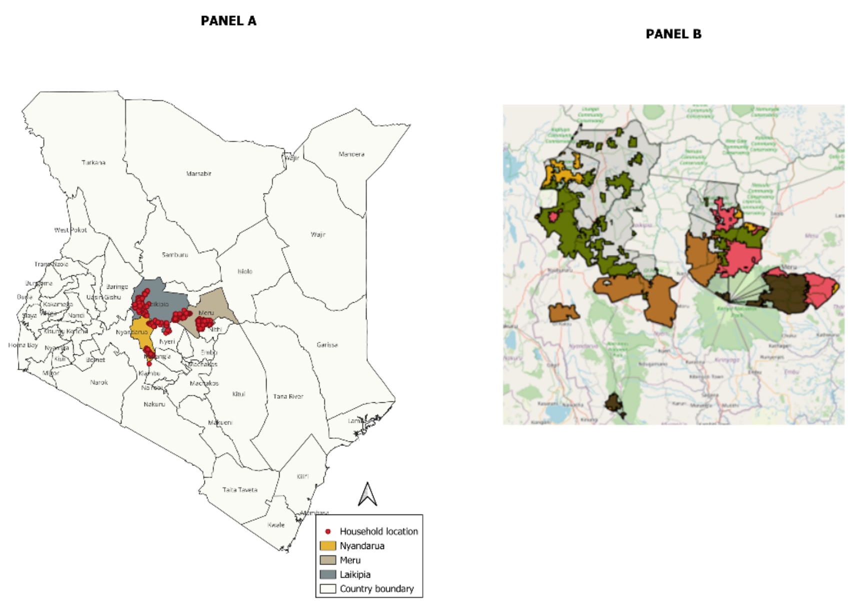


Figure 1: Study Region (Panel A) and Classification of Ward based on Biophysical and Environmental Characteristics (Panel B).
Source: Created by authors

The survey was structured into three parts: the first involved interviews with the household head or their representative to gather information on household characteristics and farm assets. The second part collected gender-disaggregated data from the primary male and female decision-makers within the household capturing gender-specific roles, risk preferences, and decision-making patterns in farming. In cases where households do not include an adult (18 years old) male household member, only the female primary decision maker was interviewed. Likewise, if there were no adult

[3] Sampling Framework Application

female household member in the household then only the male primary decision maker was interviewed for this section. The third section of the survey gathered plot-level data on agronomic practices for the use-case crops (see Table A1 for the list of use-case crops) targeted by our local partners' interventions. This information was gathered from the largest plot on which a use-case crop had been grown during the most recent cropping season.

6.Results

6.1 Descriptive Statistics

6.1.1 Climate Risk Perception

The climate risk perception profiles of the full sample reveal several notable patterns. Figure 2 Panel A shows the distribution of the experience with climate hazard score, while Panel B depicts the subjective climate change concern score. Nearly 60% of respondents reported high to very high exposure to climate-related events, such as limited rainfall, drought, heat stress, floods, soil erosion, and declining soil fertility, indicating widespread recognition of the tangible impacts of climate variability. However, Panel B presents a contrasting picture: despite frequent exposure to these events, the majority of households do not report a high level of concern about climate risks. This highlights a gap between experienced exposure and perceived worry. This gap may suggest that repeated exposure does not necessarily translate into heightened concern, possibly due to adaptation, normalization, or other contextual factors.

Figure 3 further illustrates this relationship using a Sankey diagram showing respondents' self-reported Climate Change Experience (CCEXP) and corresponding levels of Climate Change Concern (CCWORRY) in percentages. The left side shows the distribution by experience level, and the right side by concern level. The flows connecting the two sides represent how respondents with a particular experience level correspond to a level of concern, with the width of each band proportional to the percentage of respondents. It is evident that those reporting "very high" experience mostly fall into the "some," "little," or "none" concern categories, with only a small fraction expressing very high concern. Similarly, respondents with "high" experience predominantly report "some," "little," or no concern. These patterns indicate that experience alone may not drive concern. We, therefore, use a simple test to identify the relationship between the two variables in Figure 4. We observe a positive and significant correlation between the two variables. Despite observing that there is a gap between experienced exposure and perceived worry in Figure 2 and Figure 3, the positive correlation suggests that, on average, households who report greater exposure tend to exhibit slightly higher levels of climate worry, highlighting that individual concern varies even among those who have experienced climate hazards. However, these results should not be overinterpreted since there could multiple unobserved factors that could be correlated with climate concerns and also could influence beliefs about climate exposure.

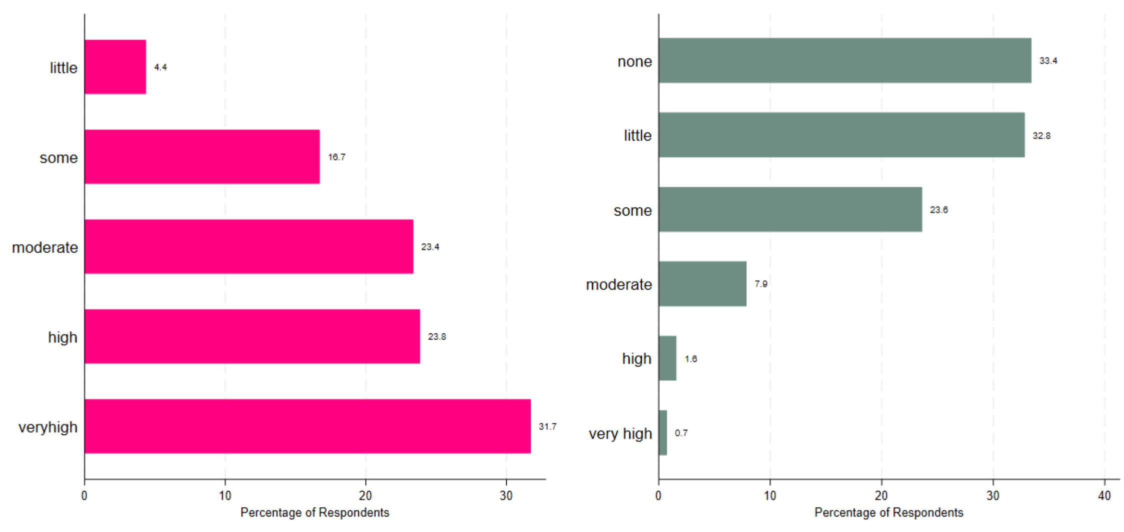


Figure 2: Percent distribution of Climate Change Experience (left) and Climate Change Worry Index (right).

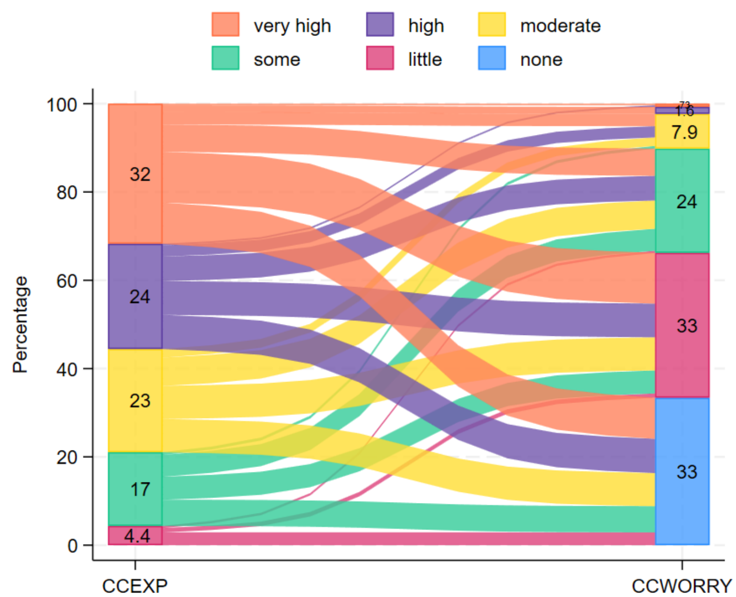


Figure 3: Flow of Responses Between Climate Change Experience (CCEXP) and Climate Change Concerns (CCWORRY).

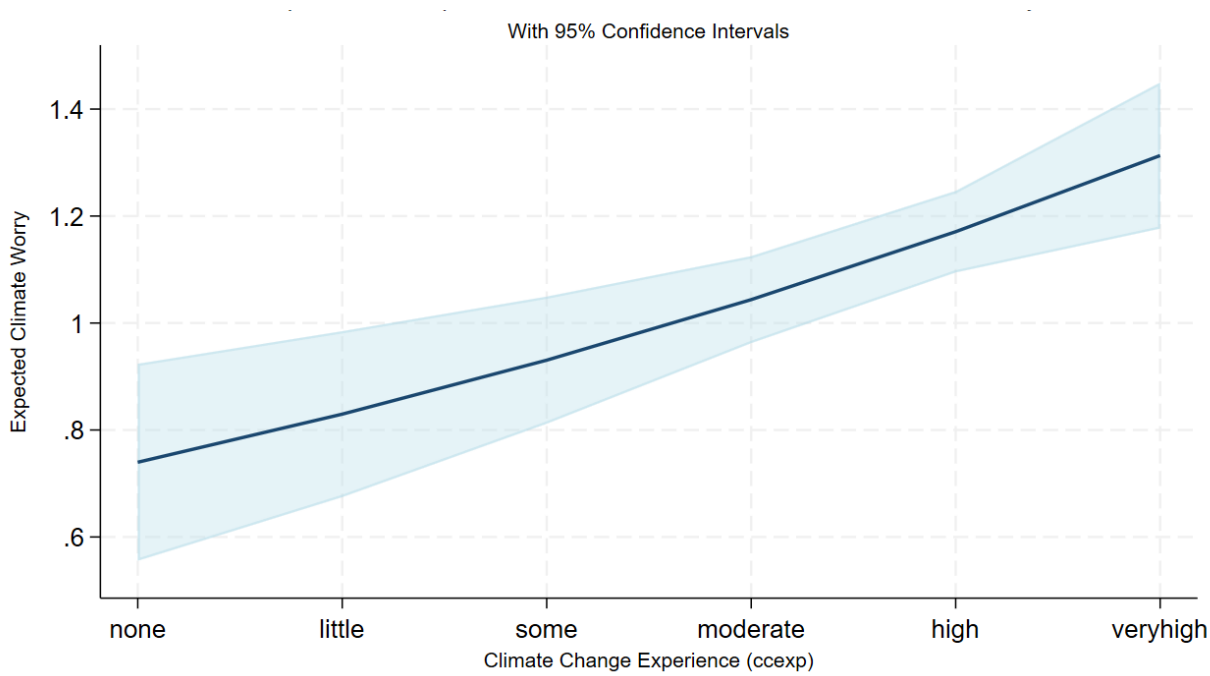


Figure 4: Relationship between Exposure to Climate Hazard and Climate Hazard Concerns

Note: We run a simple Poisson regression controlling household characteristics, decision-maker characteristics, behavioral factors and account for county fixed effects.

In Figure 5, Panel A, we present the main climate-related challenges reported by farmers in the CHEF region. A majority of respondents indicated that floods pose the greatest problem, followed closely by limited rainfall, declining soil fertility and soil erosion, reflecting farmers' concerns about long-term land productivity. In Panel B, we show farmers' perceptions of climate risks. The two most pressing concerns are too little rainfall and excess rainfall, suggesting that farmers are highly sensitive to rainfall variability. Other risks, such as soil erosion, frost, and hail, were also reported but ranked lower in importance compared to rainfall-related concerns. These results indicate that farmers' perceptions of climate risk may not always mirror their reported experience.

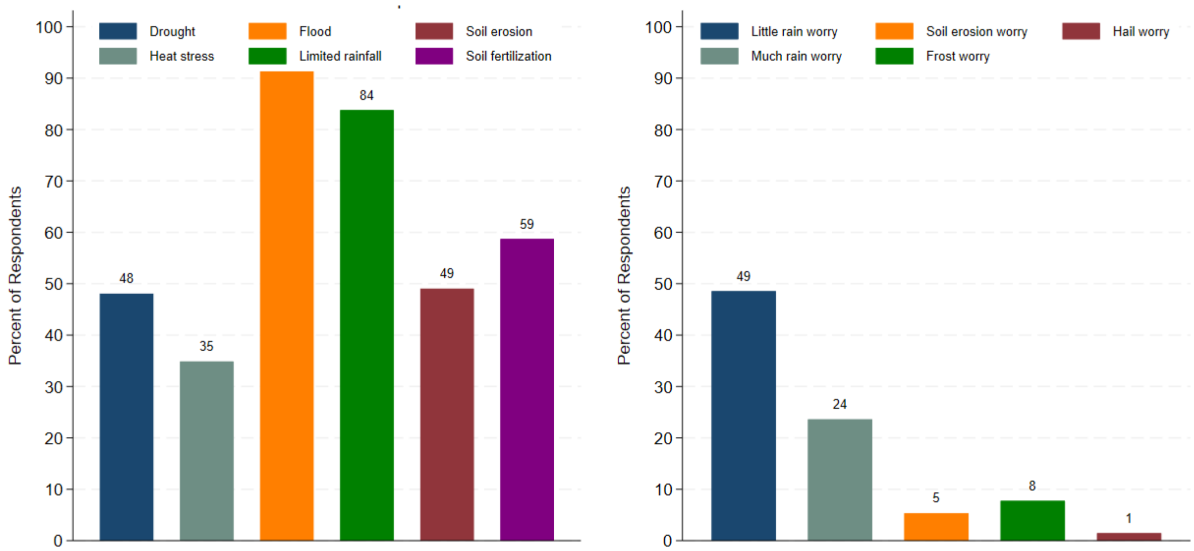


Figure 5: Type of climate risk exposure (left) and type of climate risk concerns (right)

6.1.2 Characteristics Disaggregated by Gender of Plot Manager

In Table 2, we present the summary statistics of the variables used for our analysis disaggregated by the gender of the decision-maker of the plot. Information on sustainable practices was collected at the plot level for the largest or most important plots where the focal crops were cultivated. For each plot, respondents identified the main decision-maker, which enabled us to link plot management to individual demographic characteristics through the household roster. In parallel, climate perception data were obtained through individual interviews. By matching the plot manager's ID to both the household roster and the perception survey, we were able to characterize male- and female-managed plots in terms of managers' demographic profiles, their perceptions of climate risk, and their reported management practices. We discuss the difference by household characteristics, decision maker characteristics, climate risk perception variables and technology risk perception variables. As expected in the Kenyan context, female-managed plots are more frequently observed in households headed by women, while male-managed plots tend to be in male-headed households. Specifically, 34% of female-managed plots are in female-headed households, compared to only 2% of male-managed plots in female-headed households. However, even in male-headed households, we observe women to manage specific plots. This reflects the division of labor and decision-making within households, where men may oversee certain plots (often cash crops), while women manage other plots, (such as subsistence or vegetable plots). Consequently, female-managed plots are not restricted to female-headed households; in our sample, 66% of female-managed plots are in male-headed households. Recognizing this intra-household allocation is important, as it allows us to analyze how gendered management influences the adoption of sustainable practices independently of household headship. Household size also differs marginally, with female-managed plot households having an average of 4 members, compared to 5 members in male-managed plot households. These patterns suggest that female-managed plots tend to be in smaller, female-headed households and lower reliance on farming as the primary occupation.

We also observe several differences in individual characteristics of female- and male-managers. Decision-makers on female-managed plots are slightly younger, with an average age of 53 years compared to 55 years on male-managed plots. The ethnic composition of decision-makers is broadly similar across both groups, with roughly half identifying as Kikuyu, and 42–46% as Meru. In terms of education, decision-makers on female-managed plots are more likely to have secondary schooling (48% compared to 35%) and slightly more likely to have no formal education (5% compared to 2%). However, a smaller share of them has primary education (38% compared to 43%) or post-secondary education (9% compared to 20%). A higher proportion of decision-makers on female-managed plots report farming as their main occupation, at 94%, compared to 87% among their male-managed counterparts. These findings suggest that female-managed plots are typically overseen by slightly younger individuals who are more likely to have secondary education and whose primary livelihood is farming.

Table 2: Summary Statistics Disaggregated by Gender of Decisionmaker of Plot

	(1) All plots		(2) Female managed plots		(3) Male managed plots			
	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation	Mean Difference	Standard error
Household Characteristics								
Age of household head (years)	56.06	12.45	56.88	11.42	55.45	13.15	1.43	0.89
Female household head (dummy)	0.16	0.36	0.34	0.47	0.02	0.13	0.32***	0.02
HH: Main occupation is farming (dummy)	0.78	0.41	0.68	0.47	0.86	0.35	-0.18***	0.03
HH: No schooling (dummy)	0.03	0.18	0.05	0.22	0.02	0.14	0.03**	0.01
HH: Primary schooling (dummy)	0.39	0.49	0.33	0.47	0.43	0.50	-0.11***	0.03
HH: Secondary schooling (dummy)	0.38	0.49	0.44	0.50	0.34	0.48	0.09***	0.03
HH: Post-secondary schooling and above (dummy)	0.20	0.40	0.19	0.39	0.20	0.40	-0.02	0.03
Household size (number)	4.26	2.25	3.99	2.06	4.47	2.37	-0.48***	0.16
Decision maker Characteristics								
Age of decision maker of the plot (years)	53.95	12.60	52.85	11.56	54.82	13.32	-1.97**	0.88
Ethnicity of decision maker: Others (dummy)	0.05	0.21	0.05	0.21	0.05	0.22	-0.00	0.02
Ethnicity of decision maker: Kikuyu (dummy)	0.51	0.50	0.53	0.50	0.49	0.50	0.05	0.04
Ethnicity of decision maker: Meru (dummy)	0.44	0.50	0.42	0.49	0.46	0.50	-0.04	0.03
DM: No schooling (dummy)	0.03	0.18	0.05	0.22	0.02	0.14	0.03**	0.01
DM: Primary schooling (dummy)	0.41	0.49	0.38	0.49	0.43	0.50	-0.06*	0.03
DM: Secondary schooling (dummy)	0.41	0.49	0.48	0.50	0.35	0.48	0.13***	0.03
DM: Post-secondary schooling (dummy)	0.15	0.36	0.09	0.29	0.20	0.40	-0.11***	0.02
DM: main occupation is farming (dummy)	0.90	0.30	0.94	0.23	0.87	0.34	0.07***	0.02
Plot-level Characteristics								
Plot was intercropped (dummy)	0.42	0.49	0.46	0.50	0.39	0.49	0.07*	0.03
Organic inputs were used in plot (dummy)	0.68	0.47	0.72	0.45	0.66	0.48	0.06*	0.03
Plot was irrigated(dummy)	0.23	0.42	0.18	0.38	0.27	0.44	-0.09***	0.03
Crops grown by household (number)	1.41	1.12	1.48	1.18	1.36	1.07	0.13	0.08
Diversified cropping is practiced by household (dummy)	0.70	0.46	0.71	0.45	0.68	0.47	0.03	0.04
Plot was not tilled (dummy)	0.13	0.34	0.16	0.37	0.11	0.31	0.05**	0.02
Water conservation was practiced by the household (dummy)	0.87	0.33	0.91	0.29	0.85	0.36	0.06***	0.02

	(1) All plots		(2) Female managed plots		(3) Male managed plots			
	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation	Mean Difference	Standard error
Sustainable practice index (score)	2.71	1.09	2.83	1.05	2.61	1.11	0.22***	0.08
Bean or Maize cropped on plot (dummy)	0.57	0.50	0.58	0.49	0.56	0.50	0.03	0.03
Plot area (acre)	0.99	1.23	0.79	1.01	1.14	1.35	-0.35***	0.09
Small plot (dummy)	0.53	0.50	0.61	0.49	0.47	0.50	0.14***	0.03
Medium plot (dummy)	0.23	0.42	0.20	0.40	0.26	0.44	-0.05*	0.03
Large plot (dummy)	0.22	0.41	0.17	0.37	0.26	0.44	-0.10***	0.03
Slope of plot (Flat vs steep) (dummy)	0.50	0.50	0.47	0.50	0.52	0.50	-0.05	0.04
Climate Risk Exposure and Concerns								
Climate change experience index (index)	3.62	1.21	3.76	1.11	3.51	1.28	0.25***	0.08
Climate change worry score (score)	1.14	1.06	1.23	1.09	1.06	1.03	0.16**	0.07
Non climate change worry index (score)	1.62	1.17	1.59	1.19	1.64	1.16	-0.05	0.08
Other Behavioral Factors								
Risk preference score (score)	1.17	0.50	1.14	0.47	1.19	0.51	-0.05	0.03
Optimism bias score (score)	1.49	0.65	1.44	0.64	1.53	0.66	-0.08*	0.05
Group membership (number)	1.78	1.09	1.86	0.94	1.72	1.19	0.14*	0.08
Technology Risk Perception variables								
Extension services accessed (number)	2.18	1.10	2.12	1.10	2.23	1.11	-0.11	0.08
Has knowledge about ag-related apps (dummy)	0.33	0.47	0.29	0.45	0.36	0.48	-0.07**	0.03
Has knowledge about use case (dummy)	0.07	0.25	0.10	0.30	0.05	0.21	0.05***	0.02
Has access to credit (dummy)	0.75	0.43	0.79	0.41	0.72	0.45	0.07**	0.03
Adoption ability score (score)	3.35	0.79	3.37	0.76	3.34	0.81	0.03	0.06
Training frequency score (score)	2.56	1.94	2.69	1.86	2.46	2.00	0.24*	0.14
Owns personal mobile phone (dummy)	0.95	0.21	0.95	0.21	0.96	0.21	-0.00	0.02
DM trained in agriculture/adult learning (last 1 yr)	0.62	0.49	0.69	0.46	0.56	0.50	0.13***	0.03
DM trained in agriculture/adult learning (last 5 yr)	0.13	0.34	0.11	0.31	0.15	0.36	-0.04*	0.02
Observations	826		367		459		826	

[a] HH: Household Head; [b] DM: Decision Maker. *** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level. Differences in means were assessed using a two-sample t-test assuming unequal variances.

In terms of climate experience, we find that decision-makers on female-managed plots expressed slightly greater exposure and concerns about climate change compared to male decision makers and the difference is statistically significant. Levels of non-climate-related worry were similar across both groups, showing no statistically meaningful difference. In terms of psychological traits, female plot managers exhibited slightly lower optimism bias, indicating a less overly optimistic outlook. Risk preference scores were comparable between the two groups, suggesting similar attitudes toward taking risks. Finally, group membership—a proxy for social embeddedness and reliance on collective decision-making—was slightly higher among female-managed plot respondents, who were affiliated with an average of 1.86 groups compared to 1.72 for male-managed plot respondents. Overall, while experiences of climate change appear consistent across groups, female decision-makers tend to express greater concern, show lower optimism bias, and demonstrate slightly higher social engagement.

There exist several differences between female- and male-managed plots in terms of exposure to agricultural information, access to financial resources, and training, as well. Both groups accessed a similar number of extension services on average. However, female-managed plot decision-makers were less likely to report knowledge of agriculture-related digital applications but were more likely to be aware of specific agricultural technology use cases, with statistically significant differences. Access to credit was slightly higher among female-managed plots. Adoption ability scores were nearly identical across both groups. Female plot decision-makers reported higher training frequency compared to their male counterparts. Mobile phone ownership was nearly universal and consistent across the two groups. Regarding recent training, a greater share of female plot managers had received agricultural or adult learning training in the past year (69% compared to 56%), though slightly fewer had participated in such training over the past five years (11% compared to 15%). Overall, these patterns suggest that while access to information and technology is broadly similar across groups, female-managed plots are characterized by greater recent training participation and slightly better access to credit, though they show lower familiarity with agricultural mobile applications.

The data indicates that female-managed plots show slightly higher adoption of certain sustainable agricultural practices compared to male-managed plots. In Figure 5 the Sankey diagrams illustrate the relationship between climate change worry (CCWORRY) and the adoption of climate adaptation practices (adapt), separated by gender among plot managers. Both female and male plot managers with higher CCWORRY scores (categorized as very high or high) tend to adopt a greater number of sustainable practices, typically ranging from four to six practices for females and four to five for males. Among those with moderate or some climate experience, adaptation levels are more varied, with females generally implementing two to four practices and males showing a tendency toward fewer adaptation practices. Conversely, plot managers with little or no climate change experience predominantly engage in few or no adaptation practices, highlighting a plausible positive association between experience and adaptive behavior.

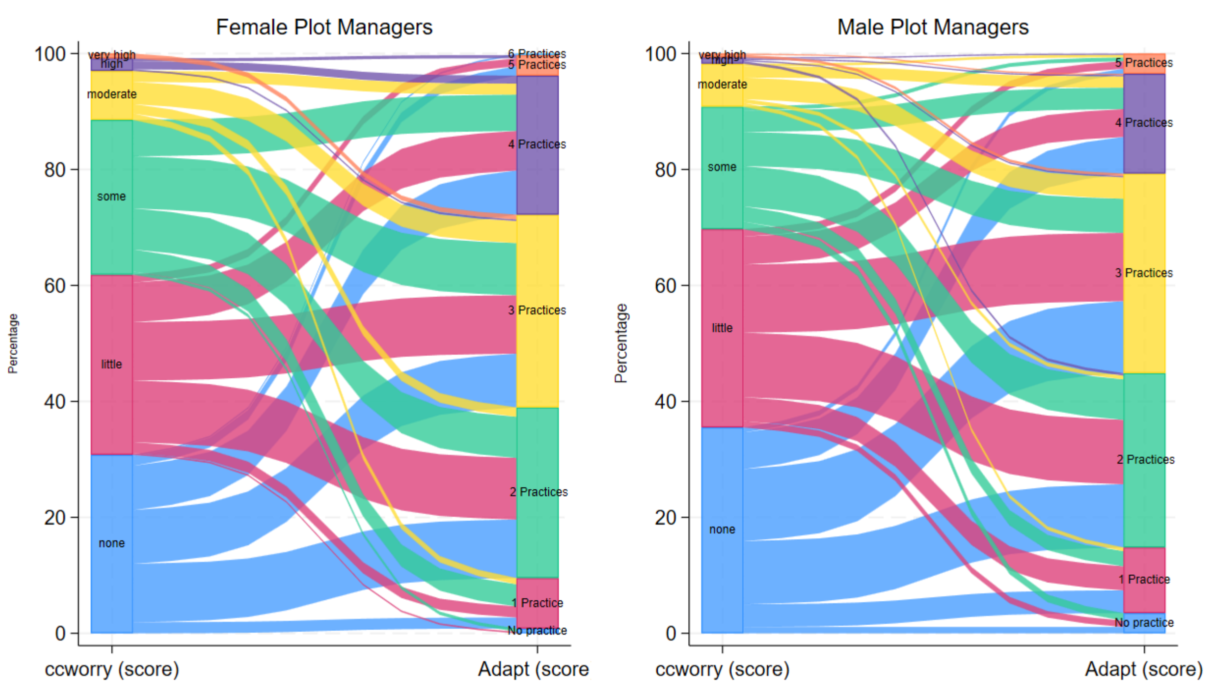


Figure 6: Flow of Responses Between Climate Change Concerns and Adoption of Sustainable Practices.

Further, in Figure 7 we present the distribution of individual practices by gender decision maker of the plot. A larger proportion of female-managed plots were intercropped (46% compared to 39%) and made use of organic inputs (72%

compared to 66%). However, irrigation was less common on female-managed plots, with only 18% being irrigated compared to 27% of male-managed plots. With respect to crop diversity, we do not find significant difference between female-managed plots and male managed plots. Conservation no tillage practices were more common among female-managed plots, with 16% reporting no tillage compared to 11% among male-managed plots. Additionally, water conservation was practiced by a higher share of female-managed plots (91% compared to 85%). Overall, the sustainable practice index, which aggregates these practices into a single score, was marginally higher for female-managed plots, averaging 2.8 compared to 2.6 for male-managed plots, and the difference is statistically significant. In Figure 6 we present the frequency distribution of adoption of different sustainable practices by gender. These patterns suggest that female-managed plots are slightly more likely to incorporate sustainable farming methods, despite lower access to irrigation.

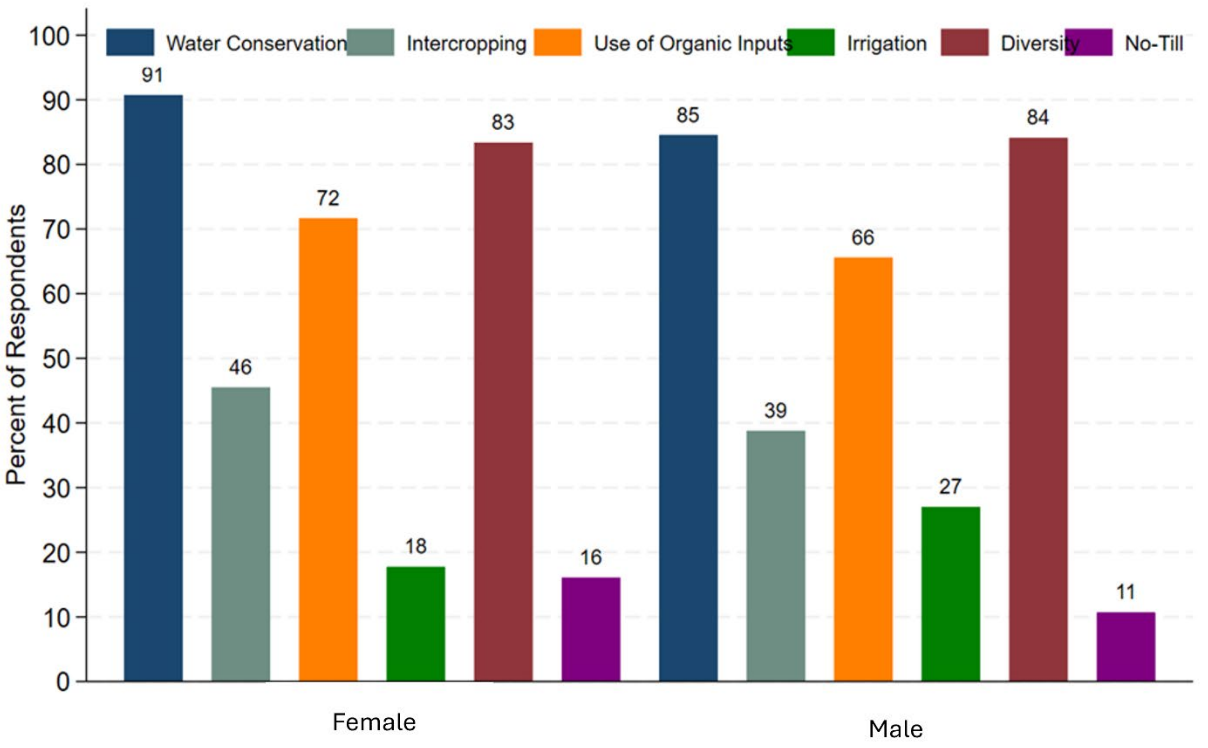


Figure 7: Distribution of Adoption of Sustainable Practices by Gender of the Plot Decision maker

Box 1: Differences in Plot Management Characteristics by Gender

Category	Female-Managed Plots	Male-Managed Plots
Adoption of Sustainable Practices	Slightly higher sustainable practice index; more intercropping and use of organic inputs; less irrigation; more conservation/no-till practices; more soil/water conservation	Lower sustainable practice index; less intercropping and organic inputs; more irrigation; less conservation/no-till practices; fewer soil/water conservation practices
Climate Risk Perception	Greater exposure to and concerned about climate change	Lower exposure/concern
Decision Maker Characteristics	Slightly younger; more secondary education; slightly higher group membership	Slightly older; slightly less secondary education; slightly lower group membership
Behavioral Factors	Slightly lower optimism bias; risk preferences comparable; slightly higher group membership	Slightly higher optimism bias; risk preferences comparable; slightly lower group membership
Exposure to Agricultural Information	Similar access to extension services; less familiar with ag-related digital apps but more aware of specific technology use cases	Similar access to extension services; more familiar with ag-related digital apps; slightly

Category	Female-Managed Plots	Male-Managed Plots
		less awareness of specific technology use cases
Access to Training and Extension Services	Higher training frequency; more recent training (past year)	Participated slightly more in training over the past five years
Access to Credit	Slightly higher	Slightly lower
Access to ICT	Mobile phone ownership nearly universal	Mobile phone ownership nearly universal

Note: Box 1 summarizes the results presented in Table 1

6.2 Econometric Results

6.2.1 Main Specification

This section examines the key determinants of adoption of SAPs in the CHEF region, with a particular focus on how climate risk perceptions (both objective exposure and subjective concerns) shape adoption decisions. The analysis employs a Poisson regression model (as detailed in Section 3), and the marginal effects are presented in Table 3. Column (1) presents the results for the full sample. Here we examine how different components of climate risk perception, such as exposure to climate change and concerns about its impacts are associated with the adoption of sustainable practices at the plot level. The analysis controls other behavioral factors, including the finite pool of worries, a proxy for consensus heuristics, risk-taking preferences, and optimism bias, along with a range of socio-economic characteristics.

Table 3: Factors Influencing Adoption of Sustainable Agricultural Practices (Full sample and disaggregated by the gender of plot manager. Poisson marginal effects)

	(1) Full Sample Sustainable practices adopted (count)		(2) Female managed plots Sustainable practices adopted (count)		(3) Male managed plots Sustainable practices adopted (count)	
	Coeff	SE	Coeff	SE	Coeff	SE
Climate change perceptions						
Climate change worry (score)	-0.150	(0.103)	-0.202	(0.150)	-0.167	(0.139)
Quadratic climate change worry (score)	0.048**	(0.024)	0.048	(0.035)	0.061*	(0.032)
Climate change experience (score)	0.088	(0.201)	0.142	(0.359)	0.042	(0.243)
Quadratic climate change experience (score)	-0.003	(0.028)	-0.000	(0.050)	-0.002	(0.035)
Household characteristics						
Age of household head (years)	0.012*	(0.006)	0.010	(0.011)	0.013*	(0.007)
Gender of household head	-0.017	(0.123)	-0.100	(0.172)	0.381	(0.289)
Household head's main occupation is farming	0.085	(0.103)	-0.044	(0.133)	0.218	(0.154)
Household Size (number)	0.027	(0.019)	0.001	(0.035)	0.038*	(0.023)
Decision-maker characteristics						

	(1) Full Sample Sustainable practices adopted (count)		(2) Female managed plots Sustainable practices adopted (count)		(3) Male managed plots Sustainable practices adopted (count)	
	Coeff	SE	Coeff	SE	Coeff	SE
Age of decision maker (years)	-0.009	(0.007)	-0.001	(0.011)	-0.013*	(0.007)
Male decision maker (dummy)	-0.177	(0.111)				
Ethnicity (Others vs Meru) (dummy)	0.146	(0.293)	0.196	(0.479)	0.180	(0.356)
Ethnicity (Kikuyu vs Meru) (dummy)	0.123	(0.184)	0.014	(0.267)	0.213	(0.230)
DM Education (No schooling vs Post secondary) (dummy)	-0.541**	(0.272)	-0.696*	(0.409)	-0.789***	(0.291)
DM Education (Primary vs Post secondary) (dummy)	-0.355***	(0.127)	-0.611***	(0.197)	-0.291*	(0.169)
DM Education (Secondary vs Post secondary) (dummy)	-0.242**	(0.115)	-0.473***	(0.182)	-0.195	(0.152)
Other behavioral factors						
Non climate change worry (score)	-0.018	(0.100)	0.052	(0.147)	0.005	(0.133)
Quadratic non climate change worry (score)	-0.020	(0.025)	-0.036	(0.038)	-0.029	(0.031)
Risk preference (score)	0.111	(0.099)	0.223	(0.151)	0.052	(0.125)
Optimism bias (score)	-0.026	(0.068)	-0.015	(0.102)	-0.048	(0.085)
Group membership (count)	0.074*	(0.040)	0.085	(0.067)	0.067	(0.053)
Technological risk perception variables						
Access to credit (dummy)	-0.055	(0.105)	-0.089	(0.176)	-0.017	(0.132)
Owns personal mobile phone (dummy)	-0.342*	(0.186)	-0.133	(0.376)	-0.512***	(0.186)
Training frequency (count)	0.061**	(0.026)	0.022	(0.048)	0.088***	(0.030)
Short term agriculture training (dummy)	-0.238**	(0.113)	-0.114	(0.175)	-0.364**	(0.148)
Long term agriculture training (dummy)	-0.167	(0.132)	-0.322	(0.209)	-0.080	(0.170)
Ag-related apps knowledge (dummy)	-0.298***	(0.102)	-0.281*	(0.150)	-0.318**	(0.140)
Extension services accessed (count)	-0.177	(0.146)	-0.125	(0.189)	-0.286	(0.245)
Quadratic Extension services accessed (count)	0.039	(0.031)	0.024	(0.042)	0.068	(0.050)
Plot characteristics						
Bean or Maize cropped on plot (dummy)	0.536***	(0.083)	0.748***	(0.118)	0.392***	(0.111)
Plot size in acre	0.011	(0.031)	-0.039	(0.054)	0.026	(0.037)
Slope of plot (Flat vs steep) (dummy)	0.137*	(0.080)	0.258**	(0.123)	0.007	(0.104)
County FE	Yes		Yes		Yes	
Observations	726		310		416	

*** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level. Standard errors are clustered at the household level.

Table 3 (Column 1) indicates that climate related experience is not significantly associated with the adoption of sustainable agricultural practices, as neither the linear nor the quadratic terms are statistically meaningful. By contrast, concerns about climate hazards show a non-linear pattern. The insignificant linear effect combined with a positive and significant quadratic effect indicates that worry about climate hazards has a curvilinear (U-shaped) relationship with adoption. Farmers with very low or very high levels of worry are more likely to adopt sustainable practices, while those with moderate worry are less likely to adopt This suggests that if an innovation is to go to scale, early efforts should focus on groups with stronger or weaker concerns, who are more receptive and can act as early adopters. From both a development and business perspective, these groups can help drive uptake in the early stages. However, reaching the more moderate group will require specific and targeted strategies to overcome adoption barriers. The fact that actual exposure to climate events was not significant, while subjective climate concerns showed a significant nonlinear effect, suggests that it is farmers' perceptions of risk rather than their experiences that shapes adoption of sustainable agricultural practices. This finding implies that grassroot organizations and policies promoting sustainable practices should actively engage with farmers' perceptions of climate risk through either awareness campaigns, risk communication, or advisory services tailored to different levels of concern.

We also find that several other factors significantly influence the adoption of SAPs amongst the sampled farmers. Education emerges as a key determinant, with households where decision-makers have lower levels of schooling (no schooling, primary, or secondary) adopting significantly fewer practices compared to those with post-secondary education. The adoption of sustainable practices tends to increase with the age of the household head, likely because older farmers, with more experience, better understand the long-term benefits. This implies that scaling strategies can initially target older farmers, who are more likely to adopt. At the same time, to ensure inclusivity, interventions should engage younger farmers through training, financial support, and user-friendly technologies. Older farmers, often respected in the community, can play a key role by encouraging and motivating younger farmers to try and adopt these practices. We also find group membership to be a significant factor in uptake of sustainable practices. This suggests that being part of a group, such as a farmers' association or cooperative, provides access to shared knowledge, peer support, and collective resources, which can encourage uptake. Policies should support the formation and strengthening of such farmer groups to enhance the spread of sustainable practices. Programs can leverage these groups for training, demonstrations, and resource-sharing, making it easier for both young and older farmers and women to adopt sustainable methods.

On the technology side, frequent training encourages adoption, but short-term agricultural training, mobile phone ownership, and knowledge of agricultural apps are negatively associated with sustainable practices. This may reflect information quality and accessibility issues, where farmers have access to phones or apps but face challenges such as unreliable or advice not related to sustainable practices. Moreover, access to digital technologies or ICT may act as a proxy for plot wealth. Since better-off farmers are often engaged in more commercial agriculture that relies on conventional, input-intensive practices, this could help explain the negative relationship observed between mobile phone ownership and the adoption of sustainable methods. Plot-level factors are also important: households cultivating beans or maize, as well as plots on flatter land, are more likely to adopt sustainable practices. However, we interpret these results with caution, as the survey focused on plot-level data from each household's largest plots where the relevant "use-case" crops were grown. Overall, subjective climate concerns, education, demographic characteristics, training quality stand out as the most consistent predictors of sustainable practice adoption.

Box 2: Summarizing Key Learnings by Gender of Plot Manager

Climate Risk Perception
- Nonlinear effects of climate change worry: adoption increases slightly at higher levels of worry.
- Direct climate change experience has no significant effect.

Household Characteristics
- Older household heads slightly more likely to adopt sustainable practices.
- Household size positively influences adoption in male-managed plots but not in female-managed plots.

Decision-Maker Characteristics
- Education is a strong driver: lower education reduces adoption, particularly for female-managed plots.
- Age and ethnicity have limited influence.

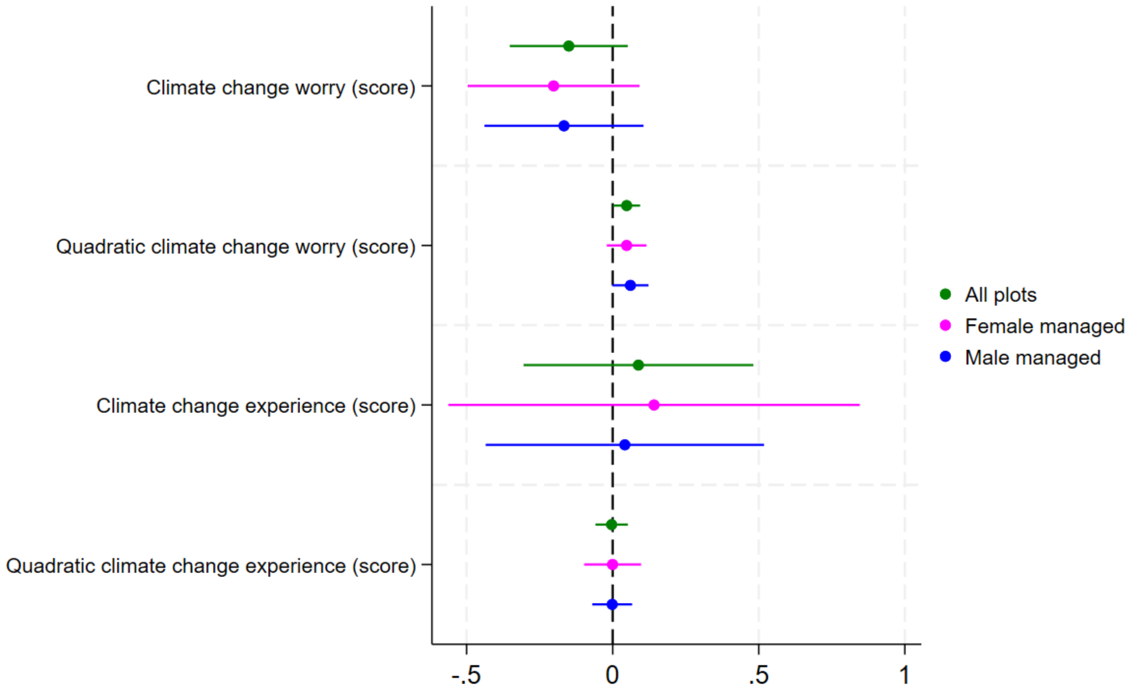
Behavioral Factors • Risk preference, optimism bias, and non-climate worry do not have statistically significant effects. • Group membership slightly increases adoption, especially in female- managed plots.
Technology and Training • Training frequency positively affects adoption, stronger in male- managed plots. • Short-term agricultural training reduces adoption in both genders. • Knowledge of agricultural apps negatively affects adoption. • Mobile phone ownership shows a negative effect, particularly in male-managed plots. • Extension services and long-term training have limited influence.
Overall Takeaways • Key drivers of adoption: education of decision-maker, age of household head, group membership, access to ICT, crop type (beans/maize), training, and plot slope. • Gender differences: female-managed plots are more sensitive to education, crop-type and slope; male-managed plots respond more to climate risk perception, age, household-size, education, training, ownership of mobile phones and crop type.

Note: Box 2 summarizes the results presented in Table 2.

6.2.2 Disaggregating by Gender of Plot-Manager

We further disaggregate the sample by the gender of the primary decision maker of the plot. While many investments decisions are made at the household level, plot-level analysis remains valuable because management decisions often differ across plots within the same household. In many agricultural contexts' different household members (men and women) manage specific plots and make distinct decisions on input use, labor, and practices. Therefore, in Column 2 of Table 3 we present the results for female managed plots and in Column (3) we present the results for male managed plots. In the descriptive analysis, we observed that, on average, women report higher levels of concern about climate change compared to men. Despite this greater concern, our results show that climate change awareness does not significantly influence the adoption of sustainable practices in female-managed plots (Table 3, Column 2). This suggests that while women may be more aware of or worried about climate risks, other structural or socio-economic constraints such as limited access to inputs, credit, labor, or decision-making authority likely prevent this concern from translating into action. We however find that in female managed-plots education level of the decision maker emerges as a significant determinant of adoption of SAPs. Compared to those with post-secondary education, female decision makers with no schooling, primary, or even secondary education are significantly less likely to adopt sustainable practices, suggesting a strong link between formal education and adoption of sustainable practices. This highlights the need for women specific targeted training programs depending on education levels to build knowledge and skills for adopting sustainable practices. Other important determinants of the adoption of sustainable practices in female-managed plots are plot-specific characteristics. We observe higher adoption in plots located on flat terrain and in plots where beans and maize are cultivated. These findings indicate that the programs and advisory services may be more strongly targeted toward flatter areas and staple crops such as beans and maize.

In male-managed plots (Column 3), we find that subjective climate concerns exhibit a non-linear relationship with the adoption of sustainable practices. Adoption tends to be higher when concerns are either low or high, whereas moderate levels of concern are associated with lower adoption. This pattern suggests that moderate concern may lead to uncertainty or indecision, preventing farmers from acting. Interventions targeting male farmers should therefore focus on clarifying risks and providing actionable guidance to convert awareness into concrete adoption of sustainable practices. Furthermore, compared to female-managed plots, male-managed plots demonstrate several other statistically significant and policy-relevant determinants of uptake of sustainable practices, particularly in relation to training, and access to and engagement with agricultural knowledge sources and communication tools (Column 3, Table 3). We find that, for male managed plots, training frequency is strongly and positively associated with uptake of sustainable practices, indicating that repeated learning opportunities are effective in reinforcing knowledge and encouraging behavioral change. However, we find that short term agriculture related training, knowledge about agriculture digital applications and ownership of mobile phones is negatively associated with adoption of sustainable practices.



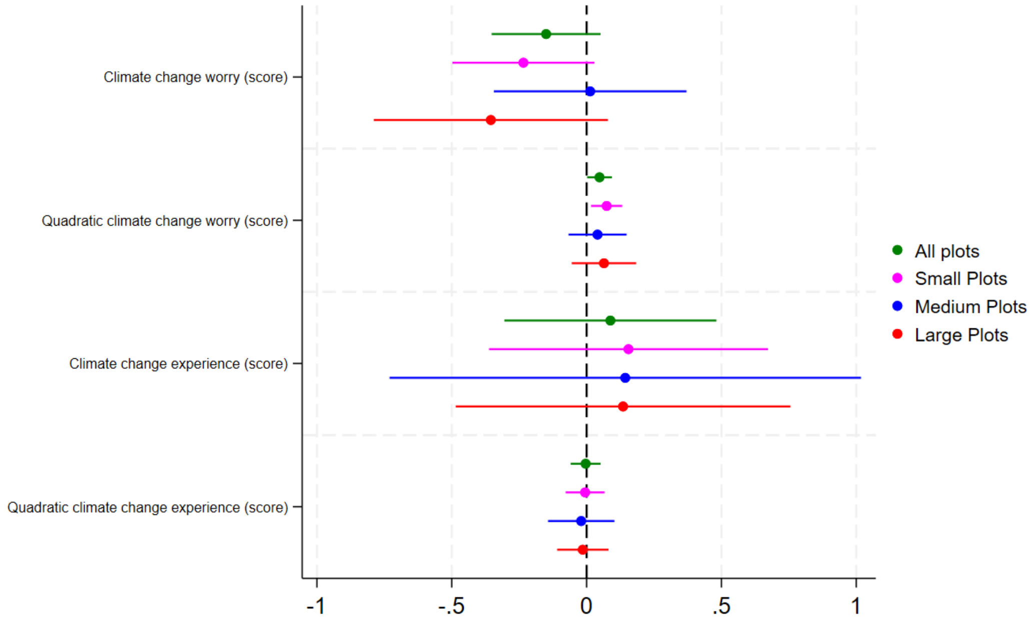
Note: This figure presents the marginal effects of both the linear and quadratic terms of the climate change experience score and climate change worry score presented in Table 2. Both objective and subjective climate experience and concerns are added in the same regression framework. Estimates are obtained from Poisson regression controlling for household and plot decision-maker characteristics, technological risk perception variables, and regional fixed effects. Standard errors are clustered at the household level.

Figure 8: Marginal Effects of Climate Change Experience and Climate Change Worry on Adoption Disaggregated by Gender (Combined Model)

These results highlight significant gender-based differences in the factors influencing the adoption of sustainable practices. In female-managed plots, adoption is primarily shaped by the education level of the decision maker and plot-specific characteristics. In contrast, in male-managed plots, higher subjective climate concerns and the frequency of training are associated with greater adoption.

6.2.3 Disaggregating by Plot-Size

We further break down the analysis by plot size. Farm size categories were created by dividing plot areas into terciles, resulting in three groups representing small, medium, and large plots. Table 4 presents the full regression results for small, medium, and large plots in columns (1) to (3), while Figure 9 summarizes the key coefficients of interest for easier interpretation.



Note: This figure presents the marginal effects of both the linear and quadratic terms of the climate change experience score and climate change worry score presented in Table 3. Both objective and subjective climate experience and concerns are added in the same regression framework. Estimates are obtained from Poisson regression controlling for household and plot decision-maker characteristics, technological risk perception variables, and regional fixed effects. Standard errors are clustered at the household level.

Figure 9: Marginal Effects of Climate Change Experience and Climate Change Worry on Adoption Disaggregated by Plot-Size (Combined Model)

In small plots, we observe a non-linear relationship between subjective climate concerns and the adoption of sustainable agricultural practices, mirroring patterns seen in male-managed plots and the overall sample. Adoption is higher when concerns are either low or high, but lower at moderate levels of concern, suggesting that uncertainty may discourage action. Other key determinants of adoption include the education level of the decision maker and the frequency of training. However, we find short-term training and extension services to be negatively associated with adoption in small plots, contrary to expectations. The limited effectiveness of training and extension on small-plots suggests that either practices are too expensive and less suitable to small plots, or content of training needs to be carefully designed to be practical and actionable for small-plot farmers.

Table 4: Determinants of Sustainable Practice Adoption Disaggregated by the Plot-Size (Poisson Marginal Effects)

	(1) Small Plot Sustainable practices adopted (count)		(2) Medium Plots Sustainable practices adopted (count)		(3) Large Plots Sustainable practices adopted (count)	
	Coeff	SE	Coeff	SE	Coeff	SE
Climate change perceptions						
Climate change worry (score)	-0.234*	(0.134)	0.013	(0.182)	-0.355	(0.222)
Quadratic climate change worry (score)	0.074**	(0.030)	0.041	(0.055)	0.064	(0.061)
Climate change experience (score)	0.155	(0.264)	0.143	(0.446)	0.135	(0.317)

	(1) Small Plot Sustainable practices adopted (count)		(2) Medium Plots Sustainable practices adopted (count)		(3) Large Plots Sustainable practices adopted (count)	
	Coeff	SE	Coeff	SE	Coeff	SE
Quadratic climate change experience (score)	-0.005	(0.037)	-0.020	(0.063)	-0.014	(0.049)
Household characteristics						
Age of household head (years)	0.012	(0.008)	0.009	(0.016)	0.006	(0.012)
Gender of household head	-0.071	(0.166)	-0.019	(0.225)	0.142	(0.237)
Household head's main occupation is farming	0.045	(0.141)	0.322*	(0.173)	-0.011	(0.188)
Household Size (number)	0.049**	(0.024)	0.046	(0.036)	0.014	(0.035)
Decision-maker characteristics						
Age of decision maker (years)	-0.010	(0.008)	-0.013	(0.018)	0.001	(0.013)
Male decision maker (dummy)	-0.277**	(0.126)	-0.100	(0.216)	0.228	(0.202)
Ethnicity (Others vs Meru) (dummy)	0.297	(0.344)	-0.707*	(0.414)	0.546	(0.721)
Ethnicity (Kikuyu vs Meru) (dummy)	-0.019	(0.222)	-0.297	(0.249)	1.344**	(0.549)
DM Education (No schooling vs Post secondary) (dummy)	-0.949**	(0.384)	-0.360	(0.561)	0.867*	(0.485)
DM Education (Primary vs Post secondary) (dummy)	-0.498***	(0.174)	-0.194	(0.203)	-0.281	(0.259)
DM Education (Secondary vs Post secondary) (dummy)	-0.341**	(0.157)	-0.183	(0.198)	-0.108	(0.205)
Other behavioral factors						
Non climate change worry (score)	0.069	(0.129)	0.022	(0.235)	0.004	(0.169)
Quadratic non climate change worry (score)	-0.019	(0.031)	-0.058	(0.061)	-0.006	(0.043)
Risk preference (score)	-0.113	(0.130)	0.188	(0.194)	0.223	(0.161)
Optimism bias (score)	0.045	(0.091)	-0.210*	(0.114)	-0.085	(0.110)
Group membership (count)	0.021	(0.056)	0.076	(0.099)	0.120	(0.076)
Technological risk perception variables						
Access to credit (dummy)	-0.182	(0.138)	-0.126	(0.200)	0.346*	(0.197)
Owns personal mobile phone (dummy)	-0.080	(0.274)	-0.307	(0.318)	-0.666**	(0.261)
Training frequency (count)	0.094***	(0.034)	0.056	(0.051)	-0.031	(0.047)
Short term agriculture training (dummy)	-0.267*	(0.148)	-0.193	(0.204)	0.006	(0.235)
Long term agriculture training (dummy)	-0.224	(0.168)	-0.440	(0.328)	0.101	(0.253)
Ag-related apps knowledge (dummy)	-0.198	(0.132)	-0.429**	(0.178)	-0.081	(0.209)
Extension services accessed (count)	-0.294*	(0.178)	-0.017	(0.353)	0.129	(0.317)
Quadratic Extension services accessed (count)	0.081**	(0.037)	-0.015	(0.072)	-0.022	(0.063)

	(1) Small Plot Sustainable practices adopted (count)		(2) Medium Plots Sustainable practices adopted (count)		(3) Large Plots Sustainable practices adopted (count)	
	Coeff	SE	Coeff	SE	Coeff	SE
Plot characteristics						
Bean or Maize cropped on plot (dummy)	0.309***	(0.100)	0.711***	(0.205)	0.867***	(0.212)
Plot size in acre	-0.173	(0.334)	-1.181**	(0.566)	-0.065	(0.044)
Slope of plot (Flat vs steep) (dummy)	0.171*	(0.104)	0.183	(0.161)	-0.115	(0.164)
County FE	Yes		Yes		Yes	
Observations	387		176		163	

Farm size categories were created by dividing plot areas into terciles, resulting in three groups representing small, medium, and large plots. *** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level. Standard errors are clustered at the household level.

For both medium and large plots, we do not find any statistically significant relationship between climate change perception and the adoption of sustainable practices. This may indicate that farmers managing medium to large plots have greater resources, better access to information, or more diversified income sources, which reduce the role of personal climate risk perception in their adoption decisions. In these plot sizes, ethnicity emerges as an important determinant of adoption, a pattern not observed in other sub-sample analyses. Additionally, for large plots, access to credit is positively associated with uptake of sustainable practices.

Box 3: Summarizing Key Learnings by Plot Size

Climate Risk Perception

- On small plots, climate change worry has a nonlinear effect: initial worry reduces adoption, but higher levels are linked to more adoption.
- On medium and large plots, climate change worry shows weaker or statistically insignificant effects.

Household Characteristics

- Household size encourages adoption on small plots, less so on medium and large plots.
- Farming as the main occupation of household head boosts adoption on medium plots.
- Age and gender of the household head have little influence across all plot sizes.

Decision-Maker Characteristics

- Education is critical for small plots: less schooling strongly reduces adoption.
- Male decision-makers reduce adoption on small plots.
- Ethnic effects appear only on large plots, where Kikuyu vs. Meru shows higher adoption.

Behavioral Factors

- Optimism bias lowers adoption on medium plots, but no clear effects elsewhere.

Technology and Training

- Training frequency drives adoption on small plots, weaker on medium and negative on large plots.
- Short-term training reduces adoption on small plots.
- Knowledge of agricultural apps lowers adoption, especially on medium plots.
- Access to credit encourages adoption on large plots.
- Mobile phone ownership reduces adoption, especially on large plots.
- Extension services are negative on small plots but not significant for medium or large plots.

Plot Characteristics

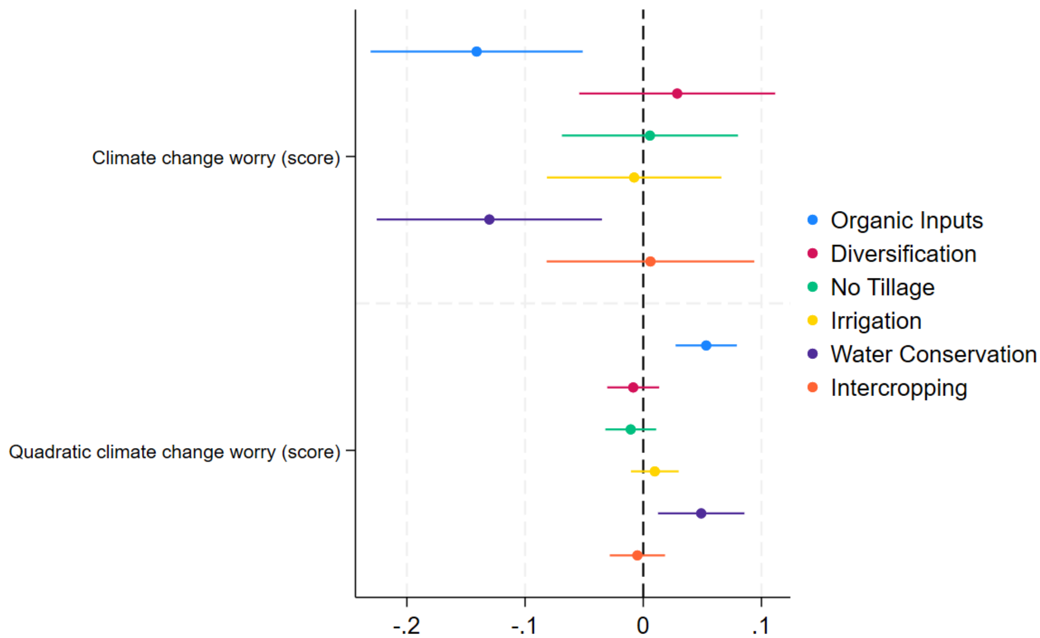
- Bean/maize cropping strongly increases adoption across all plot sizes.
- Flat plots encourage adoption on small plots, but no effect on larger plots.
- Medium plots show a negative association with plot size itself, while small and large plots show no such link.

Overall Takeaways

- On small plots, climate risk perception, education, household size, training, access to extension services and beans/ maize cropping are the strongest drivers.
- On medium plots, farming as a main occupation, beans/maize, and ethnic composition matter most, while optimism bias reduces adoption.
- On large plots, access to credit and beans/maize cropping drive adoption, but mobile phone ownership reduces it.

6.2.4 Climate Risk Perception and Adoption of Individual Sustainable Practices

We further analyze how climate perception influences the adoption of individual sustainable practices. This allows us to see whether the overall patterns are driven by all practices or only a subset. As discussed in Section 4.1, the adoption index is constructed from six binary indicators capturing whether the following practices were implemented on each plot: intercropping, no-tillage, use of organic inputs, irrigation, crop diversification, and soil and water conservation techniques. We therefore use a Probit model to estimate these relationships. The full regression results provided in Table A3 in the Appendix. The corresponding marginal effects of the linear and quadratic terms of subjective climate change concerns are summarized in Figure 10.



Note: This figure presents the marginal effects of CRP index on adoption of individual SAPs such as use of organic inputs, diversification (growing more than a single crop on plot), no tillage, use of irrigation, use of soil and water conservation techniques and intercropping of plot. The full regression of the non-linear model is presented in Table A3 in the Appendix. Each of the graph shows the results of separate Probit regression after regression controlling for climate change experience, household, plot and decision-maker characteristics, technological risk perception variables, and regional fixed effects. Standard errors are clustered at the household level.

Figure 10: Marginal Effects of Climate Risk Perception on Individual SAPs

We find that climate risk perception has a non-linear, U-shaped effect on the adoption of organic inputs and soil and water conservation techniques, with adoption increasing at low and high levels of concern but declining at moderate levels. However, we do not find statistically significant effects on other practices such as crop diversification, no-tillage, irrigation, or intercropping. These findings suggest that awareness-raising alone may be insufficient to promote adoption of all sustainable practices. Targeted interventions could focus on addressing the hesitation observed at moderate concern levels by providing practical guidance, demonstrations, and decision-support tools for organic inputs and soil and water conservation techniques. For input-intensive practices such as irrigation, no-tillage, and crop diversification, interventions would need to address other structural and institutional bottlenecks to enhance access to affordable input, credit, and technical support to reduce barriers and enable broader adoption across all plot types.

7.Recommendations

The study emphasizes strengthening farmer capacity by shifting mindsets through the integration of climate risk and hazard frequency modules into training and providing practical, context-specific packages of sustainable agricultural practices (SAPs) to enhance resilience. Risk communication should be strategically targeted, focusing on small, male-managed plots where perceptions influence adoption, using locally relevant, visual, and experiential approaches to raise awareness, and reinforcing knowledge through multiple sessions. Addressing women's structural barriers is also key—by pairing risk awareness with access to inputs, credit, labor, knowledge, and incentives; co-designing interventions with women farmers; leveraging women's groups; and recruiting more women agents to close information gaps. Scaling low-resource, high-impact interventions such as organic inputs and soil and water conservation can provide scalable entry points. Leveraging ICT and digital platforms to embed climate and SAP content in digital tools, while addressing gendered digital divides through video or community-based training, can expand outreach. Cultivating climate and SAP champions among experienced farmers will help advocate for sustainable practices. Finally, incentivizing adoption through market mechanisms—such as certification and premium pricing for sustainably produced crops, can motivate farmers, especially those managing large and medium plots, to adopt sustainable practices beyond relying solely on risk perception.

Table 5: Recommendations Based on Findings

Recommendation Area	Key Actions / Strategies
Shifting Mindsets to Strengthen Farmer Capacity	✓ Integrate climate risk and hazard frequency modules into training to shift perceptions. ✓ Provide practical, context-specific packages of SAPs to boost resilience.
Target Risk Communication Strategically	✓ Focus awareness on small, male-managed plots where perceptions strongly influence adoption. ✓ Use locally relevant, visual, and experiential approaches to raise climate risk awareness. ✓ Reinforce knowledge and skills through multiple sessions to improve perception and adoption of SAPs.
Address Women's Structural Barriers	✓ Pair risk awareness with access to inputs, credit, labor, knowledge, and incentives. ✓ Co-design interventions with women farmers for greater relevance and uptake. ✓ Leverage women's groups to improve access to knowledge, credit, and markets. ✓ Recruit more women agents and adapt schedules to women's time constraints to close information gaps.
Scale Low-Resource, High-Impact Interventions	✓ Promote organic inputs and soil & water conservation as scalable entry points.
Leverage ICT and Digital Platforms	✓ Embed climate and SAP content in digital extension tools. ✓ Address gendered digital divides by complementing ICT with video or community-based training.
Cultivate Climate and SAP Champions	✓ Engage experienced farmers as advocates for sustainable practices.
Incentivize Adoption via Market Mechanisms	✓ Use certification and premium pricing for sustainably produced crops to motivate farmers, particularly those with large and medium plots.

8. Limitations of the Study

We acknowledge several limitations of this study to ensure that the findings are interpreted with appropriate caution. First, many of the behavioral variables used in the analysis such as climate experience, climate worry, risk preference, optimism bias, and non-climate-related stress, are represented through proxy variables rather than direct psychological assessments. While these proxies are informed by established frameworks in behavioral economics and psychology, and tailored to the survey context, they may not fully capture the complexity or depth of the underlying cognitive and emotional processes. This introduces the possibility of measurement error, which may attenuate or bias the estimated effects. Second, there is potential for endogeneity in the model specification. Specifically, the explanatory variables may be correlated with unobserved factors in the error term due to omitted variable bias, measurement error, or reverse causality—for example, farmers who have adopted sustainable practices may develop different perceptions of climate and technology risk after adoption, rather than prior to it. These forms of endogeneity limit our ability to draw causal inferences from the estimated relationships. Third, the use of cross-sectional data rather than panel data constrains our ability to account for time-invariant unobserved heterogeneity. Factors such as individual risk or historical exposure to extension services or deeply embedded cultural norms could influence both risk perceptions and sustainability adoption but are not directly observed in a single wave of data. Fourth, the study is geographically and contextually bounded. While the findings offer valuable insights into gendered and context-specific decision-making and behavioral mechanisms in climate-vulnerable agricultural systems, their generalizability to other regions or farming systems may be limited without further validation. Given these limitations, we refrain from making causal claims. Instead, our goal is to identify correlational patterns and behavioral trends in the baseline data that can inform grassroot use-case teams to design interventions. Future work using experimental or longitudinal methods would be essential to verify and expand upon these relationships.

9. Conclusion

This study investigates how climate risk perception affects the adoption of sustainable agricultural practices (SAPs) among smallholder farmers. Extending standard technology adoption models that focus on socio-economic and structural determinants, we incorporate a behavioral perspective, emphasizing psychological drivers such as actual exposure to climate events and subjective perceptions of climate risk.

The results reveal that subjective perceptions are more influential than beliefs about climate exposure in shaping adoption decisions. The analysis also highlights important heterogeneity: in female-managed plots, education is the strongest predictors of adoption, whereas in male-managed plots, training frequency and climate concerns play a more prominent role. Furthermore, practice-specific patterns emerge, with organic inputs and soil and water conservation being more likely implemented when a farmer has climate concerns, while resource-intensive practices such as irrigation, intercropping, and no-tillage are less affected by their perceptions. For female-managed plots, practical, low-literacy training programs are critical to increase adoption among women with limited formal education. In male-managed plots, structured and repeated extension services enhance adoption. Heterogenous results from landholding size imply differentiated support strategies: smallholders may require targeted risk awareness campaigns, medium-sized farms benefit from consistent advisory support, and large farms may need incentives or technical guidance to complement existing coping strategies. Taken together, these findings highlight the importance of incorporating behavioral dimensions—particularly climate risk perceptions—into adaptation policies and of tailoring interventions to gender, farm size, and practice type to effectively promote sustainable agricultural practices.

As a recommendation for future survey design for this use-case and beyond, we suggest including a short set of questions specifically targeting climate change awareness, perceptions, and self-efficacy related to adaptation (see Appendix A3 Table A3:3). Such measures would complement the existing behavioral proxies, reduce potential measurement error, and provide richer insights into how farmers perceive their ability to cope with climate risks, allowing for the design of more tailored, context-specific interventions to promote sustainable practices.

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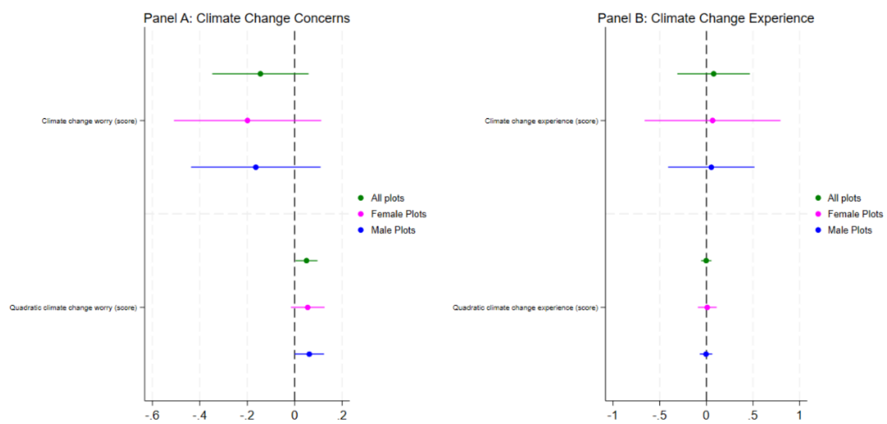
Appendix A1- Robustness Check

1. Separate Models for Climate Worry and Climate Experience score

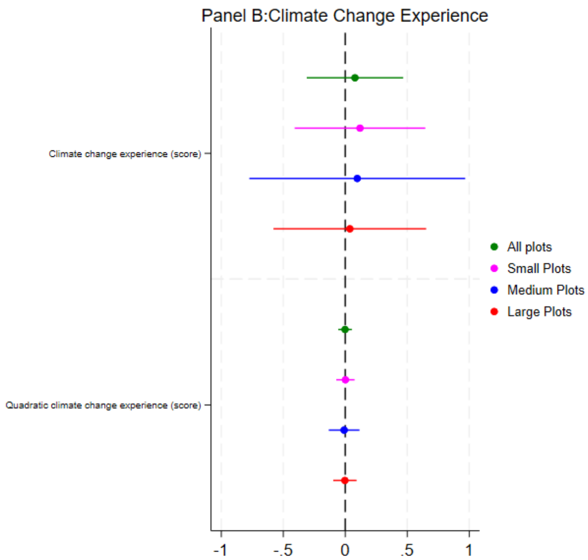
One potential concern when estimating Equation (1) in Table 3 and Table 4 with both objective and subjective measures of climate concerns in the same framework is multicollinearity. It is plausible that individuals who have directly experienced climate events are also more likely to report higher subjective perceptions of climate risk, leading to correlation between these measures. To assess this, we calculate the Variance Inflation Factor (VIF) from an OLS specification of Equation (1). The maximum VIF observed is 6, which indicates moderate collinearity but is well below the conventional threshold of 10 that is typically viewed as problematic. Multicollinearity does not bias coefficient estimates, though it can inflate standard errors and sometimes lead to unstable coefficient signs. To address this possibility, we re-estimate the models including “Climate change experience score” and “Climate change worry score” separately to verify whether the direction of the estimated effects is robust. The association between climate change concerns and the adoption of SAPs disaggregated by gender is reported in Table A4, while Table A5 presents the corresponding results for climate change experience. Figure A1 illustrates the marginal effects of the linear and quadratic terms, after accounting for other control variables. Interpretations of these results are similar to the ones presented in Table 2 and Figure 3.



Note: This figure presents the marginal effects of the linear and quadratic terms of the climate change concern score in Panel A as presented in Table A4 in the Appendix. In Panel B we show the marginal effects of the linear and quadratic terms of the Climate Change experience score as presented in Table A5 in the Appendix. Each of the graph shows the results of separate Poisson regression after regression controlling for household and plot decision-maker characteristics, technological risk perception variables, and regional fixed effects. Standard errors are clustered at the household level.

Figure A1: Marginal Effects of Climate Change Experience and Climate Change Worry on Adoption Disaggregated by Gender (Separate Model)

Similarly, Table A6 we present the relationship between climate change concerns and the adoption of SAPs disaggregated by plot-size, while Table A7 presents the corresponding results for climate change experience. Figure A2 illustrates the marginal effects of the linear and quadratic terms, after accounting for other control variables. Here too, we find similar interpretations to the results presented in Table 3 and Figure 5. These results suggest that adoption of SAPs is largely unrelated to objective climate exposure across all plot types. However, on small plots, adoption rises non-linearly when decision makers’ subjective concern about climate change is high, while for medium plots neither objective nor subjective climate risk perceptions significantly affect adoption, and on large plots, adoption declines as concern increases.

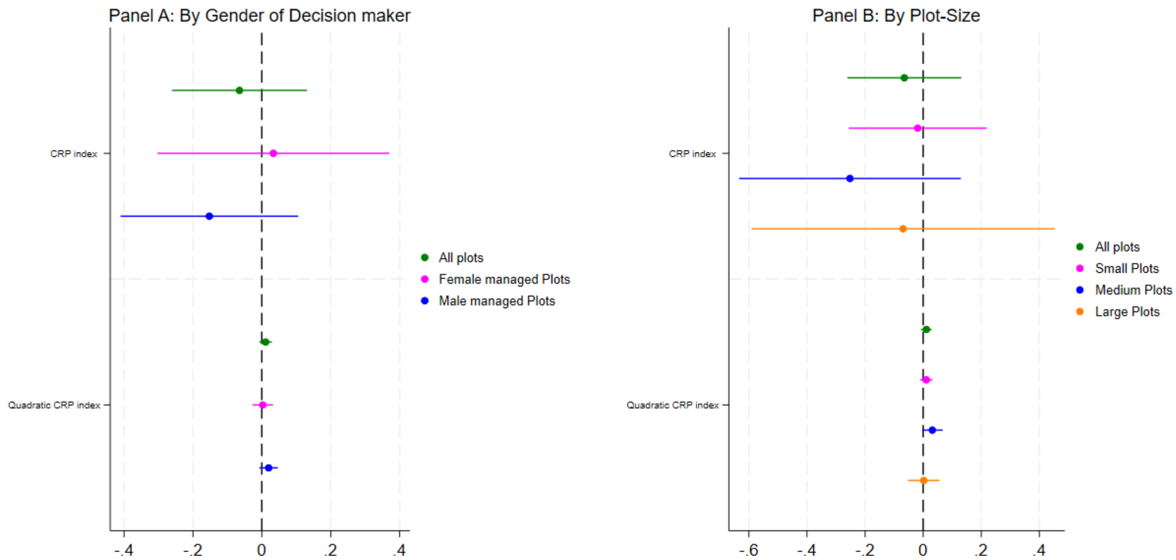


Note: This figure presents the marginal effects of the linear and quadratic terms of the climate change concern score in Panel A as presented in Table A6 in the Appendix. In Panel B we show the marginal effects of the linear and quadratic terms of the Climate Change experience score as presented in Table A7 in the Appendix. Each of the graph shows the results of separate Poisson regression after regression controlling for household and plot decision-maker characteristics, technological risk perception variables, and regional fixed effects. Standard errors are clustered at the household level.

Figure A2: Marginal Effects of Climate Change Experience and Climate Change Worry on Adoption Disaggregated by Gender (Separate Model)

2. Composite Climate Risk Perception Index

The second robustness check we undertake is constructing a single climate risk perception index (CRP) to capture both objective and subjective dimensions of climate exposure in a unified measure, reducing potential multicollinearity and providing a more comprehensive assessment of how overall climate risk perception influences adoption of sustainable agricultural practices. We constructed the CRP index by summing the climate change experience and climate worry scores, producing a scale from 0 to 10. Lower values indicate both low objective exposure and low subjective concern, while higher values reflect greater exposure and concern. This straightforward approach is intuitive, easy to interpret, and effectively captures both dimensions of climate risk in a single measure. Panel A of Figure A3 presents the marginal effects of the CRP index disaggregated by the gender of the decision maker.



Note: This figure presents the marginal effects of CRP index on adoption of SAPs. Panel A presents results disaggregated by the gender of the decision maker, as reported in the Appendix Table A8, while Panel B displays results disaggregated by plot size as presented in Table A9. Each of the graph shows the results of separate Poisson regression after regression controlling for household and plot decision-maker characteristics, technological risk perception variables, and regional fixed effects. Standard errors are clustered at the household level.

Figure A3: Relationship between CRP Index and Adoption of SAPs

The results indicate that for female-managed plots, the relationship between CRP and adoption of SAPs is non-linear. Specifically, at lower levels of climate risk perception, adoption of SAPs tends to decrease, suggesting that mild concerns about climate change may not provide sufficient motivation to alter farming practices. However, as risk perception intensifies, adoption increases, implying that higher levels of concern can act as a catalyst for behavioral change. In contrast, for male-managed plots, no statistically meaningful association is observed between the CRP index and adoption behavior, implying that men's decisions regarding SAPs are less sensitive to variations in perceived climate risks.

Furthermore, Panel B of Figure A3 disaggregates the analysis by plot size. For small plots, the findings mirror those observed for female-managed plots, with adoption showing a non-linear pattern: initial increases in CRP are associated with declines in adoption, followed by a positive association at higher levels of perceived risk. In contrast, for medium- and large-sized plots, no significant relationships between CRP and adoption are detected. Overall, these results highlight important heterogeneities in the role of climate risk perception across gender and landholding size. Women and smallholder farmers appear more responsive to subjective climate concerns, although in a non-linear manner, while men and larger-scale farmers do not show such responsiveness.

Appendix A2-Tables

Table A1: Use-case main crops

Crop Group	Crops
Cereals	Maize, Millet, Sorghum
Legumes	Beans, Cowpea, Pigeon pea, Mung beans (Green gram)
Roots and Tubers	Irish potatoes, Sweet potatoes
Forages	Forages (various types used for livestock feed)

Source: Baseline data

Table A2: Distribution of Sample

County	Sub-County	Sampled respondent
Laikipia	Laikiapia East	89
	Laikiapia West	110
	Laikiapia North	53
Meru	Buuri	52
	Central Imenti	130
	Igembe South	3
	South Imenti	128
Nyandarua	Kinangop	
	Ol_Kalou	
Total	**9**	**622**

Table A3: Association between Climate Risk Perception and Adoption of Individual Sustainable Practice (Probit Marginal Effects)

	(1)		(2)		(3)		(4)		(5)		(6)	
	Organic Inputs		Diversification		No Tillage		Used Irrigation		Used Soil and Water Conservation Technique		Practiced Intercropping	
	Sustainable practices adopted (count)		Sustainable practices adopted (count)		Sustainable practices adopted (count)		Sustainable practices adopted (count)		Sustainable practices adopted (count)		Sustainable practices adopted (count)	
	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE
Climate change worry (score)	- 0.141***	(0.046)	0.029	(0.042)	0.006	(0.038)	-0.008	(0.038)	-0.130***	(0.049)	0.006	(0.045)
Quadratic climate change worry (score)	0.053***	(0.013)	-0.009	(0.011)	-0.011	(0.011)	0.010	(0.010)	0.049***	(0.019)	-0.005	(0.012)
Climate change experience (score)	-0.016	(0.091)	-0.054	(0.082)	0.045	(0.067)	-0.033	(0.075)	-0.014	(0.059)	0.111	(0.083)
Quadratic climate change experience (score)	-0.005	(0.013)	0.012	(0.012)	-0.005	(0.010)	0.003	(0.011)	0.007	(0.009)	-0.008	(0.012)
Age of household head (years)	-0.002	(0.004)	-0.001	(0.003)	0.001	(0.003)	0.003	(0.003)	0.002	(0.003)	0.009***	(0.003)
Gender of household head	-0.093	(0.069)	0.012	(0.062)	-0.004	(0.044)	-0.231***	(0.056)	0.003	(0.046)	0.217***	(0.062)
Household head's main occupation is farming	0.026	(0.052)	-0.015	(0.043)	0.003	(0.039)	0.108**	(0.044)	0.023	(0.041)	-0.068	(0.047)
Household Size (number)	0.026***	(0.009)	0.003	(0.008)	-0.006	(0.007)	-0.007	(0.007)	-0.001	(0.008)	0.012*	(0.007)
Age of decision maker (years)	0.004	(0.004)	-0.000	(0.003)	0.002	(0.003)	-0.004	(0.003)	-0.001	(0.003)	-0.007**	(0.003)
Male decision maker (dummy)	- 0.137***	(0.049)	-0.045	(0.044)	-0.055	(0.037)	0.049	(0.038)	-0.021	(0.039)	0.060	(0.044)
Ethnicity (Others vs Meru) (dummy)	-0.021	(0.112)	0.173*	(0.099)	-0.178*	(0.097)	0.247**	(0.108)	-0.151*	(0.088)	-0.029	(0.109)
Ethnicity (Kikuyu vs Meru) (dummy)	-0.008	(0.090)	0.208***	(0.073)	-0.014	(0.062)	0.052	(0.082)	-0.186**	(0.078)	0.018	(0.085)
DM Education (No schooling vs Post secondary) (dummy)	-0.213*	(0.120)	0.015	(0.096)	-0.026	(0.083)	-0.144	(0.110)	-0.251***	(0.076)	0.035	(0.105)
DM Education (Primary vs Post secondary) (dummy)	-0.149**	(0.063)	-0.036	(0.051)	-0.009	(0.041)	-0.083*	(0.046)	-0.087*	(0.052)	0.007	(0.054)
DM Education (Secondary vs Post secondary) (dummy)	-0.142**	(0.061)	-0.031	(0.051)	0.024	(0.041)	-0.051	(0.044)	-0.050	(0.044)	0.014	(0.053)
Non climate change worry (score)	0.034	(0.042)	0.040	(0.040)	-0.058*	(0.031)	0.033	(0.039)	-0.090**	(0.041)	0.048	(0.043)
Quadratic non climate change worry (score)	-0.013	(0.010)	-0.023**	(0.011)	0.010	(0.008)	-0.006	(0.010)	0.022**	(0.010)	-0.018	(0.011)
Risk preference (score)	-0.000	(0.039)	0.000	(0.037)	0.060**	(0.029)	0.055	(0.035)	-0.010	(0.029)	-0.023	(0.037)
Optimism bias (score)	-0.046	(0.028)	0.004	(0.026)	0.017	(0.022)	-0.007	(0.024)	-0.040**	(0.018)	0.041	(0.028)
Group membership (count)	0.028	(0.019)	-0.014	(0.020)	0.020	(0.013)	0.041**	(0.017)	0.010	(0.017)	-0.016	(0.020)
Access to credit (dummy)	-0.094*	(0.048)	-0.000	(0.044)	0.073*	(0.039)	0.011	(0.042)	-0.010	(0.035)	0.024	(0.045)
Owns personal mobile phone (dummy)	-0.031	(0.082)	-0.166**	(0.067)	0.019	(0.066)	0.070	(0.099)	-0.083	(0.061)	-0.108	(0.076)
Training frequency (count)	0.031**	(0.012)	-0.024**	(0.011)	0.005	(0.009)	0.018*	(0.010)	0.022**	(0.010)	0.001	(0.012)
Short term agriculture training (dummy)	-0.073	(0.050)	-0.014	(0.048)	0.028	(0.038)	-0.072*	(0.040)	0.004	(0.039)	-0.101**	(0.047)
Long term agriculture training (dummy)	0.062	(0.064)	-0.056	(0.055)	0.016	(0.046)	-0.104**	(0.051)	0.039	(0.043)	-0.123**	(0.059)

	(1)		(2)		(3)		(4)		(5)		(6)	
	Organic Inputs		Diversification		No Tillage		Used Irrigation		Used Soil and Water Conservation Technique		Practiced Intercropping	
	Sustainable practices adopted (count)		Sustainable practices adopted (count)		Sustainable practices adopted (count)		Sustainable practices adopted (count)		Sustainable practices adopted (count)		Sustainable practices adopted (count)	
	Coeff	**SE**	**Coeff**	**SE**	**Coeff**	**SE**	**Coeff**	**SE**	**Coeff**	**SE**	**Coeff**	**SE**
Ag-related apps knowledge (dummy)	-0.078*	(0.044)	-0.017	(0.039)	0.002	(0.033)	0.004	(0.036)	-0.138***	(0.035)	-0.057	(0.039)
Extension services accessed (count)	-0.073	(0.077)	0.087	(0.060)	-0.066	(0.057)	-0.070	(0.058)	-0.108*	(0.057)	0.019	(0.066)
Quadratic Extension services accessed (count)	0.020	(0.017)	-0.015	(0.013)	0.003	(0.013)	0.009	(0.013)	0.027**	(0.013)	-0.001	(0.014)
Bean or Maize cropped on plot (dummy)	-0.031	(0.036)	0.412***	(0.024)	-0.053**	(0.025)	-0.125***	(0.026)	0.006	(0.018)	0.281***	(0.030)
Plot size in acre	-0.034**	(0.014)	0.033***	(0.013)	0.023**	(0.009)	-0.022	(0.016)	0.007	(0.008)	-0.004	(0.013)
Slope of plot (Flat vs steep) (dummy)	0.036	(0.035)	0.072**	(0.033)	0.005	(0.028)	0.092***	(0.028)	-0.033	(0.024)	0.002	(0.034)
County FE	Yes		Yes		Yes		Yes		Yes		Yes	
Observations	726		726		726		726		726		726	

*** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level. Standard errors are clustered at the household level.

Table A4: Relationship between Climate Change Worry Index (Subjective Experience) and Adoption of SAPs disaggregated by Gender.

	(1)		(2)		(3)	
	Full Sample		**Female Plots**		**Male Plots**	
	Sustainable practices adopted (count)		**Sustainable practices adopted (count)**		**Sustainable practices adopted (count)**	
	Coeff	**SE**	**Coeff**	**SE**	**Coeff**	**SE**
Climate change worry (score)	-0.144	(0.104)	-0.199	(0.158)	-0.164	(0.139)
Quadratic climate change worry (score)	0.050**	(0.024)	0.055	(0.036)	0.062*	(0.032)
Age of household head (years)	0.011*	(0.006)	0.006	(0.011)	0.012*	(0.007)
Gender of household head	-0.017	(0.124)	-0.090	(0.174)	0.347	(0.280)
Household head's main occupation is farming	0.070	(0.104)	-0.079	(0.137)	0.210	(0.152)
Household Size (number)	0.030	(0.019)	0.008	(0.034)	0.040*	(0.023)
Age of decision maker (years)	-0.008	(0.007)	0.001	(0.011)	-0.012*	(0.007)
Male decision maker (dummy)	-0.189*	(0.110)				
Ethnicity (Others vs Meru) (dummy)	0.122	(0.291)	0.073	(0.463)	0.179	(0.355)
Ethnicity (Kikuyu vs Meru) (dummy)	0.100	(0.188)	-0.052	(0.282)	0.209	(0.234)
DM Education (No schooling vs Post secondary) (dummy)	-0.527**	(0.266)	-0.594	(0.389)	-0.804***	(0.279)
DM Education (Primary vs Post secondary) (dummy)	-0.338***	(0.129)	-0.571***	(0.204)	-0.282	(0.172)
DM Education (Secondary vs Post secondary) (dummy)	-0.237**	(0.118)	-0.465**	(0.191)	-0.190	(0.155)
Non climate change worry (score)	-0.021	(0.101)	0.021	(0.146)	0.008	(0.133)
Quadratic non climate change worry (score)	-0.019	(0.025)	-0.028	(0.039)	-0.030	(0.031)
Risk preference (score)	0.099	(0.097)	0.197	(0.151)	0.047	(0.122)
Optimism bias (score)	-0.075	(0.056)	-0.100	(0.090)	-0.075	(0.067)
Group membership (count)	0.069*	(0.040)	0.081	(0.070)	0.067	(0.053)
Access to credit (dummy)	-0.050	(0.106)	-0.105	(0.177)	-0.012	(0.133)
Owns personal mobile phone (dummy)	-0.387**	(0.186)	-0.271	(0.357)	-0.521***	(0.186)
Training frequency (count)	0.065**	(0.026)	0.027	(0.050)	0.090***	(0.030)
Short term agriculture training (dummy)	-0.251**	(0.112)	-0.139	(0.182)	-0.372**	(0.147)
Long term agriculture training (dummy)	-0.162	(0.132)	-0.300	(0.210)	-0.079	(0.170)
Ag-related apps knowledge (dummy)	-0.276***	(0.102)	-0.232	(0.153)	-0.309**	(0.141)
Extension services accessed (count)	-0.196	(0.146)	-0.122	(0.197)	-0.311	(0.235)
Quadratic Extension services accessed (count)	0.042	(0.031)	0.020	(0.044)	0.074	(0.047)
Bean or Maize cropped on plot (dummy)	0.545***	(0.083)	0.760***	(0.120)	0.398***	(0.113)
Plot size in acre	0.010	(0.031)	-0.039	(0.052)	0.026	(0.036)
Slope of plot (Flat vs steep) (dummy)	0.143*	(0.080)	0.271**	(0.122)	0.009	(0.104)
County FE	Yes		Yes		Yes	
Observations	726		310		416	

*** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level. Standard errors are clustered at the household level.

Table A5: Relationship between Climate Change Experience Index (Objective Experience) and Adoption of SAPs disaggregated by Gender.

	(1)		(2)		(3)	
	Full Sample Sustainable practices adopted (count)		Female Plots Sustainable practices adopted (count)		Male Plots Sustainable practices adopted (count)	
	Coeff	SE	Coeff	SE	Coeff	SE
Climate change experience (score)	0.078	(0.199)	0.067	(0.372)	0.054	(0.236)
Quadratic climate change experience (score)	-0.001	(0.028)	0.010	(0.052)	-0.003	(0.034)
Age of household head (years)	0.011*	(0.006)	0.008	(0.010)	0.012**	(0.006)
Gender of household head	0.001	(0.122)	-0.094	(0.171)	0.362	(0.293)
Household head's main occupation is farming	0.087	(0.102)	-0.046	(0.134)	0.217	(0.154)
Household Size (number)	0.029	(0.018)	0.004	(0.035)	0.041*	(0.023)
Age of decision maker (years)	-0.008	(0.006)	0.001	(0.011)	-0.012*	(0.007)
Male decision maker (dummy)	-0.167	(0.109)				
Ethnicity (Others vs Meru) (dummy)	0.096	(0.292)	0.132	(0.472)	0.116	(0.359)
Ethnicity (Kikuyu vs Meru) (dummy)	0.118	(0.173)	-0.008	(0.254)	0.209	(0.207)
DM Education (No schooling vs Post secondary) (dummy)	-0.519*	(0.271)	-0.647	(0.405)	-0.749***	(0.288)
DM Education (Primary vs Post secondary) (dummy)	-0.367***	(0.122)	-0.594***	(0.198)	-0.305**	(0.154)
DM Education (Secondary vs Post secondary) (dummy)	-0.231**	(0.113)	-0.441**	(0.179)	-0.179	(0.143)
Non climate change worry (score)	-0.048	(0.096)	0.047	(0.143)	-0.050	(0.122)
Quadratic non climate change worry (score)	-0.013	(0.024)	-0.034	(0.037)	-0.017	(0.030)
Risk preference (score)	0.123	(0.100)	0.240	(0.155)	0.057	(0.125)
Optimism bias (score)	-0.022	(0.068)	-0.006	(0.101)	-0.046	(0.085)
Group membership (count)	0.072*	(0.041)	0.070	(0.068)	0.073	(0.055)
Access to credit (dummy)	-0.054	(0.107)	-0.095	(0.178)	-0.023	(0.133)
Owns personal mobile phone (dummy)	-0.308*	(0.184)	-0.105	(0.378)	-0.474***	(0.178)
Training frequency (count)	0.064**	(0.026)	0.024	(0.049)	0.091***	(0.029)
Short term agriculture training (dummy)	-0.227**	(0.114)	-0.099	(0.178)	-0.352**	(0.150)
Long term agriculture training (dummy)	-0.185	(0.131)	-0.343*	(0.206)	-0.107	(0.169)
Ag-related apps knowledge (dummy)	-0.300***	(0.100)	-0.297**	(0.150)	-0.304**	(0.131)
Extension services accessed (count)	-0.182	(0.147)	-0.136	(0.189)	-0.294	(0.247)
Quadratic Extension services accessed (count)	0.038	(0.031)	0.026	(0.042)	0.066	(0.050)
Bean or Maize cropped on plot (dummy)	0.547***	(0.082)	0.757***	(0.118)	0.409***	(0.112)
Plot size in acre	0.008	(0.030)	-0.041	(0.053)	0.022	(0.036)
Slope of plot (Flat vs steep) (dummy)	0.126	(0.080)	0.258**	(0.123)	-0.015	(0.103)
County FE	Yes		Yes		Yes	
Observations	726		310		416	

*** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level. Standard errors are clustered at the household level.

Table A6: Relationship between Climate Change Worry Index (Subjective Experience) and Adoption of SAPs disaggregated by Plot-Size

	(1)		(2)		(3)	
	Small Plot Sustainable practices adopted (count)		Medium Plots Sustainable practices adopted (count)		Large Plots Sustainable practices adopted (count)	
	Coeff	**SE**	**Coeff**	**SE**	**Coeff**	**SE**
Climate change worry (score)	-0.234*	(0.135)	0.015	(0.180)	-0.346	(0.220)
Quadratic climate change worry (score)	0.080***	(0.030)	0.040	(0.053)	0.065	(0.060)
Age of household head (years)	0.012	(0.008)	0.009	(0.016)	0.003	(0.011)
Gender of household head	-0.084	(0.170)	-0.017	(0.227)	0.148	(0.238)
Household head's main occupation is farming	0.033	(0.147)	0.324*	(0.173)	-0.040	(0.182)
Household Size (number)	0.055**	(0.024)	0.044	(0.035)	0.015	(0.035)
Age of decision maker (years)	-0.010	(0.008)	-0.012	(0.018)	0.004	(0.013)
Male decision maker (dummy)	-0.289**	(0.127)	-0.111	(0.208)	0.205	(0.200)
Ethnicity (Others vs Meru) (dummy)	0.241	(0.337)	-0.714*	(0.415)	0.592	(0.723)
Ethnicity (Kikuyu vs Meru) (dummy)	-0.063	(0.232)	-0.315	(0.227)	1.383**	(0.548)
DM Education (No schooling vs Post secondary) (dummy)	-0.944**	(0.374)	-0.381	(0.555)	0.832*	(0.505)
DM Education (Primary vs Post secondary) (dummy)	-0.459**	(0.183)	-0.181	(0.188)	-0.286	(0.259)
DM Education (Secondary vs Post secondary) (dummy)	-0.326*	(0.167)	-0.172	(0.198)	-0.115	(0.205)
dm_edu_cat==Postsecondary+	0.000	(.)	0.000	(.)	0.000	(.)
Non climate change worry (score)	0.073	(0.131)	0.008	(0.228)	-0.000	(0.172)
Quadratic non climate change worry (score)	-0.019	(0.032)	-0.055	(0.060)	-0.006	(0.043)
Risk preference (score)	-0.150	(0.127)	0.180	(0.192)	0.221	(0.160)
Optimism bias (score)	-0.048	(0.078)	-0.214**	(0.099)	-0.117	(0.093)
Group membership (count)	0.015	(0.056)	0.073	(0.096)	0.118	(0.074)
Access to credit (dummy)	-0.183	(0.138)	-0.112	(0.204)	0.339*	(0.193)
Owns personal mobile phone (dummy)	-0.144	(0.264)	-0.316	(0.315)	-0.690***	(0.257)
Training frequency (count)	0.106***	(0.034)	0.055	(0.050)	-0.033	(0.047)
Short term agriculture training (dummy)	-0.312**	(0.149)	-0.190	(0.201)	0.005	(0.231)
Long term agriculture training (dummy)	-0.198	(0.170)	-0.435	(0.324)	0.110	(0.254)
Ag-related apps knowledge (dummy)	-0.180	(0.131)	-0.418**	(0.174)	-0.051	(0.207)
Extension services accessed (count)	-0.338*	(0.180)	-0.031	(0.358)	0.136	(0.322)
Quadratic Extension services accessed (count)	0.088**	(0.037)	-0.011	(0.073)	-0.023	(0.064)
Bean or Maize cropped on plot (dummy)	0.334***	(0.102)	0.710***	(0.203)	0.877***	(0.206)
Plot size in acre	-0.170	(0.335)	-1.172**	(0.546)	-0.066	(0.042)
Slope of plot (Flat vs steep) (dummy)	0.193*	(0.104)	0.185	(0.158)	-0.117	(0.162)
County FE	Yes		Yes		Yes	
Observations	387		176		163	

*** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level. Standard errors are clustered at the household level.

Table A7: Relationship between Climate Change Experience Index (Objective Experience) and Adoption of SAPs disaggregated by Plot-Size.

	(1)		(2)		(3)	
	Small Plot		Medium Plots		Large Plots	
	Sustainable practices adopted (count)		Sustainable practices adopted (count)		Sustainable practices adopted (count)	
	Coeff	SE	Coeff	SE	Coeff	SE
Climate change experience (score)	0.119	(0.269)	0.097	(0.444)	0.037	(0.314)
Quadratic climate change experience (score)	0.001	(0.038)	-0.009	(0.063)	-0.003	(0.048)
Age of household head (years)	0.011	(0.007)	0.009	(0.015)	0.002	(0.013)
Gender of household head	-0.034	(0.167)	0.007	(0.218)	0.079	(0.233)
Household head's main occupation is farming	0.038	(0.138)	0.331*	(0.170)	-0.022	(0.189)
Household Size (number)	0.050**	(0.022)	0.044	(0.036)	0.025	(0.034)
Age of decision maker (years)	-0.009	(0.008)	-0.012	(0.017)	0.008	(0.014)
Male decision maker (dummy)	-0.268**	(0.125)	-0.124	(0.213)	0.181	(0.207)
Ethnicity (Others vs Meru) (dummy)	0.244	(0.341)	-0.684	(0.416)	0.265	(0.681)
Ethnicity (Kikuyu vs Meru) (dummy)	0.002	(0.204)	-0.221	(0.256)	1.114**	(0.517)
DM Education (No schooling vs Post secondary) (dummy)	-0.894**	(0.384)	-0.417	(0.557)	0.881*	(0.489)
DM Education (Primary vs Post secondary) (dummy)	-0.517***	(0.165)	-0.186	(0.203)	-0.363	(0.243)
DM Education (Secondary vs Post secondary) (dummy)	-0.335**	(0.153)	-0.159	(0.197)	-0.145	(0.201)
Non climate change worry (score)	0.014	(0.126)	-0.069	(0.221)	0.019	(0.168)
Quadratic non climate change worry (score)	-0.008	(0.031)	-0.043	(0.058)	-0.005	(0.043)
Risk preference (score)	-0.067	(0.131)	0.187	(0.195)	0.211	(0.167)
Optimism bias (score)	0.053	(0.092)	-0.194	(0.118)	-0.112	(0.109)
Group membership (count)	0.028	(0.056)	0.099	(0.098)	0.080	(0.078)
Access to credit (dummy)	-0.186	(0.140)	-0.136	(0.200)	0.368*	(0.202)
Owns personal mobile phone (dummy)	-0.048	(0.276)	-0.234	(0.308)	-0.574**	(0.263)
Training frequency (count)	0.093***	(0.034)	0.069	(0.050)	-0.029	(0.050)
Short term agriculture training (dummy)	-0.244	(0.151)	-0.215	(0.206)	-0.017	(0.233)
Long term agriculture training (dummy)	-0.276*	(0.165)	-0.414	(0.332)	0.136	(0.252)
Ag-related apps knowledge (dummy)	-0.198	(0.131)	-0.401**	(0.175)	-0.088	(0.203)
Extension services accessed (count)	-0.319*	(0.179)	-0.001	(0.352)	0.146	(0.334)
Quadratic Extension services accessed (count)	0.081**	(0.037)	-0.021	(0.073)	-0.026	(0.066)
Bean or Maize cropped on plot (dummy)	0.336***	(0.099)	0.714***	(0.206)	0.886***	(0.215)
Plot size in acre	-0.199	(0.331)	-1.172**	(0.571)	-0.067	(0.044)
Slope of plot (Flat vs steep) (dummy)	0.159	(0.104)	0.171	(0.166)	-0.153	(0.162)
County FE	Yes		Yes		Yes	
Observations	387		176		163	

*** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level. Standard errors are clustered at the household level.

Table A8: Association between Climate Risk Perception Index and Adoption of Sustainable Practice disaggregated by Gender (Poisson Marginal Effects)

	(1)		(2)		(3)	
	Full Sample		Female managed plots		Male managed plots	
	Sustainable practices adopted (count)		Sustainable practices adopted (count)		Sustainable practices adopted (count)	
	Coeff	**SE**	**Coeff**	**SE**	**Coeff**	**SE**
CRP index	-0.114	(0.094)	-0.046	(0.169)	-0.172	(0.125)
Quadratic CRP index	0.016*	(0.009)	0.010	(0.015)	0.022*	(0.013)
Age of household head (years)	0.013**	(0.006)	0.005	(0.010)	0.016***	(0.006)
Gender of household head	0.037	(0.125)	-0.089	(0.166)	0.548*	(0.323)
Household head's main occupation is farming	0.023	(0.104)	-0.090	(0.138)	0.127	(0.161)
Household Size (number)	0.028	(0.018)	0.015	(0.033)	0.034	(0.023)
Age of decision maker (years)	-0.010	(0.006)	0.003	(0.011)	-0.015**	(0.006)
Male decision maker (dummy)	-0.174	(0.109)	0.000			
Ethnicity (Others vs Meru) (dummy)	0.057	(0.294)	-0.054	(0.491)	0.146	(0.336)
Ethnicity (Kikuyu vs Meru) (dummy)	0.021	(0.193)	-0.183	(0.325)	0.171	(0.190)
DM Education (No schooling vs Post secondary) (dummy)	-0.511*	(0.278)	-0.618*	(0.375)	-0.719**	(0.333)
DM Education (Primary vs Post secondary) (dummy)	-0.329**	(0.129)	-0.588***	(0.200)	-0.271	(0.165)
DM Education (Secondary vs Post secondary) (dummy)	-0.240**	(0.120)	-0.483**	(0.188)	-0.176	(0.150)
Access to credit (dummy)	-0.013	(0.108)	-0.037	(0.179)	0.009	(0.137)
Owns personal mobile phone (dummy)	-0.352*	(0.187)	-0.131	(0.345)	-0.575***	(0.194)
Training frequency (count)	0.058**	(0.026)	0.017	(0.050)	0.079***	(0.029)
Short term agriculture training (dummy)	-0.192*	(0.102)	-0.026	(0.166)	-0.314**	(0.129)
Extension services accessed (count)	-0.148	(0.143)	-0.120	(0.197)	-0.169	(0.233)
Quadratic Extension services accessed (count)	0.030	(0.030)	0.024	(0.044)	0.037	(0.048)
Bean or Maize cropped on plot (dummy)	0.578***	(0.083)	0.773***	(0.121)	0.439***	(0.112)
Plot size in acre	0.004	(0.031)	-0.045	(0.053)	0.021	(0.036)
Slope of plot (Flat vs steep) (dummy)	0.135*	(0.081)	0.207*	(0.122)	0.026	(0.107)
County FE	Yes		Yes		Yes	
Observations	726		310		416	

*** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level. Standard errors are clustered at the household level.

Table A9: Association between Climate Risk Perception Index and Adoption of Sustainable Practice disaggregated by Plot-Size (Poisson Marginal Effects)

	(1)		(2)		(3)		(4)	
	Full Sample		Small Plot		Medium Plots		Large Plots	
	Sustainable practices adopted (count)		Sustainable practices adopted (count)		Sustainable practices adopted (count)		Sustainable practices adopted (count)	
	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE
CRP index	-0.114	(0.094)	-0.025	(0.114)	-0.414**	(0.172)	0.047	(0.236)
Quadratic CRP index	0.016*	(0.009)	0.009	(0.011)	0.050***	(0.016)	-0.006	(0.025)
Age of household head (years)	0.013**	(0.006)	0.011	(0.007)	-0.000	(0.017)	0.004	(0.012)
Gender of household head	0.037	(0.125)	-0.087	(0.169)	0.021	(0.256)	0.112	(0.252)
Household head's main occupation is farming	0.023	(0.104)	-0.015	(0.144)	0.298*	(0.176)	-0.110	(0.190)
Household Size (number)	0.028	(0.018)	0.044*	(0.023)	0.030	(0.035)	0.023	(0.036)
Age of decision maker (years)	-0.010	(0.006)	-0.009	(0.007)	-0.002	(0.019)	0.005	(0.014)
Male decision maker (dummy)	-0.174	(0.109)	-0.298**	(0.124)	-0.277	(0.218)	0.183	(0.206)
Ethnicity (Others vs Meru) (dummy)	0.057	(0.294)	0.217	(0.343)	-0.482	(0.388)	0.068	(0.608)
Ethnicity (Kikuyu vs Meru) (dummy)	0.021	(0.193)	-0.067	(0.227)	-0.305	(0.191)	1.056**	(0.411)
DM Education (No schooling vs Post secondary) (dummy)	-0.511*	(0.278)	-0.816**	(0.371)	-0.641	(0.581)	0.932**	(0.472)
DM Education (Primary vs Post secondary) (dummy)	-0.329**	(0.129)	-0.489***	(0.174)	-0.108	(0.225)	-0.346	(0.233)
DM Education (Secondary vs Post secondary) (dummy)	-0.240**	(0.120)	-0.365**	(0.161)	-0.173	(0.210)	-0.085	(0.205)
Access to credit (dummy)	-0.013	(0.108)	-0.198	(0.142)	-0.095	(0.199)	0.425**	(0.186)
Owns personal mobile phone (dummy)	-0.352*	(0.187)	-0.112	(0.278)	-0.429	(0.274)	-0.641**	(0.260)
Training frequency (count)	0.058**	(0.026)	0.081**	(0.034)	0.040	(0.047)	-0.007	(0.046)
Short term agriculture training (dummy)	-0.192*	(0.102)	-0.168	(0.135)	-0.080	(0.183)	-0.106	(0.186)
Extension services accessed (count)	-0.148	(0.143)	-0.364**	(0.179)	-0.179	(0.377)	0.222	(0.308)
Quadratic Extension services accessed (count)	0.030	(0.030)	0.089**	(0.037)	0.010	(0.080)	-0.041	(0.062)
Bean or Maize cropped on plot (dummy)	0.578***	(0.083)	0.327***	(0.102)	0.771***	(0.205)	0.931***	(0.201)
Plot size in acre	0.004	(0.031)	-0.204	(0.322)	-1.302**	(0.574)	-0.065	(0.043)
Slope of plot (Flat vs steep) (dummy)	0.135*	(0.081)	0.189*	(0.105)	0.202	(0.152)	-0.147	(0.156)
County FE	Yes		Yes		Yes		Yes	
Observations	726		387		176		163	

% level; ** Significant at 5% level; * Significant at 10% level. Standard errors are clustered at the household level.

Annex A3: Questions used for climate risk perception variables

Table A3: 1: Construction of Climate Experience Index

Climate experience index	Response	New variable Created
Please indicate the level at which the following issues were a production constraint in this field in the last cropping season		
Drought	Absent, Moderate, Severe, Very Severe (Crop lost)	No if drought was absent or don't know, otherwise Yes
Heat Stress	Absent, Moderate, Severe, Very Severe (Crop lost)	No if heat stress was absent or don't know, otherwise Yes
Submergence	Absent, Moderate, Severe, Very Severe (Crop lost)	No if submergence was absent or don't know, otherwise Yes
Do you experience problems with insufficient rainfall?	Yes or No	Yes or No
Do you experience problems with soil loss and erosion on your farm?	Yes or No	Yes or No
Do you experience problems with soil fertility on your farm?	Yes or No	Yes or No
Ccexp index		**Summation of binary variables**

Table A3: 2: Construction of Climate Worry Index

Climate Worry Index	Response
Climate related risk that decision maker is worried about	
Too little rainfall (drought)	Yes, No
Too much rainfall (flood)	Yes, No
Soil erosion	Yes, No
Frost	Yes, No
Hail	Yes, No
CCWorry Index	**Summation of Binary Variables**

Note: The respondents identified their top five concerns. From all the risks mentioned, we analyzed the climate-related ones to construct the index.

Table A3: 3: Questions for Survey

#	Climate perception	Response
1	I believe that climate change is real	Strongly agree [ ] Agree [ ] Disagree [ ] Strongly disagree [ ]
2	Climate change will bring about serious negative consequences	Strongly agree [ ] Agree [ ] Disagree [ ] Strongly disagree [ ]
3	My local area will be influenced by climate change	Strongly agree [ ] Agree [ ] Disagree [ ] Strongly disagree [ ]
4	It will be a long time before the consequences of climate change are felt	Strongly agree [ ] Agree [ ] Disagree [ ] Strongly disagree [ ]
5	I believe that the climate in my local area has changed in recent years	Strongly agree [ ] Agree [ ] Disagree [ ] Strongly disagree [ ]

6	Rainfall patterns have become more unpredictable in recent years	Strongly agree [ ] Agree [ ] Disagree [ ] Strongly disagree [ ]
7	Droughts are happening more often than they did in the past	Strongly agree [ ] Agree [ ] Disagree [ ] Strongly disagree [ ]
8	Dry spells during the rainy seasons are now more common	Strongly agree [ ] Agree [ ] Disagree [ ] Strongly disagree [ ]
9	Floods have become more frequent in recent years	Strongly agree [ ] Agree [ ] Disagree [ ] Strongly disagree [ ]
10	I believe it is possible to take action to reduce the impact of climate change on farms like mine	Strongly agree [ ] Agree [ ] Disagree [ ] Strongly disagree [ ]
11	I am willing to try new ways of farming to adapt to the changing climate	Strongly agree [ ] Agree [ ] Disagree [ ] Strongly disagree [ ]
12	I have the ability to try new ways of farming that reduce the impact of climate change on my farm	Strongly agree [ ] Agree [ ] Disagree [ ] Strongly disagree [ ]

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