

Article

Livelihood Capitals and Climate Change Adaptation Among Smallholder Coffee Farmers in Southwestern Uganda [†]

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Abstract

Climate change poses growing risks to coffee farming in Uganda. However, households do not adapt to the same degree, and it remains unclear which household resources contribute to differences in adaptation. This study examines the specific household resources associated with climate adaptation among 376 smallholder coffee-farming households across four districts in Southwestern Uganda. Adaptation was measured using a count of adopted practices and a continuous index derived from Principal Component Analysis (PCA), with Multiple Correspondence Analysis (MCA) used as a robustness check. The analysis examined constituent household resources separately to assess whether broad livelihood-capital categories obscure divergent relationships among their components. Household size, knowledge exchange with other farmers, training, and ownership of basic farm tools were the most consistent positive correlates of adaptation. Years of coffee-farming experience, by contrast, showed a negative relationship with adaptation, opposite to the direction observed for household size despite both being classified within the human-capital domain. A composite human-capital specification showed weaker statistical fit than the disaggregated specification. A similar divergence occurred within financial capital: off-farm income showed a positive relationship with adaptation, whereas access to credit did not. Within physical capital, tool ownership was positively related to adaptation, whereas irrigation equipment, owned by only 1.6% of households, was not statistically significant. These findings suggest that policies to strengthen climate adaptation among smallholder coffee farmers should prioritize farmer-to-farmer knowledge exchange, training, and access to basic farm tools. Additionally, findings caution against treating broad livelihood-capital categories as internally homogeneous because constituent resources may have different or opposing relationships with adaptation.



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1. Introduction

Coffee is the backbone of Uganda's agricultural export economy, contributing substantially to foreign exchange earnings [1] and supporting the livelihoods of an estimated 1.7–1.8 million smallholder households [2,3]. In recent decades, however, the coffee sector has become vulnerable to climate variability and long-term change, manifested through erratic rainfall patterns, prolonged drought episodes, rising temperatures, and shifting pest

and disease dynamics [4,5]. Available evidence indicates that smallholder coffee farmers in Uganda are experiencing climate variability, including changes in temperature and rainfall, and are responding through the adoption of multiple climate-smart agricultural practices [6,7]. Globally and regionally, smallholder crop farmers have responded to these challenges by adopting a portfolio of climate adaptation strategies. These include changes in farm management, soil and water management, agroforestry, climate-informed planning, improved varieties, and diversification, while access to credit, extension, and information can facilitate adaptation [8–11]. In Uganda, adaptation responses are diverse and heterogeneous, with the strategies adopted and the factors shaping their adoption varying across households and locations [12,13]. This unevenness can be linked to disparities in access to productive resources, information, and institutional support systems [14,15].

Consequently, empirical knowledge progressively emphasizes that adaptation is both a technical and socioeconomic process shaped by households' asset endowments and institutional contexts [16–18]. Within this perspective, the Sustainable Livelihoods Framework (SLF) has gained prominence as a holistic analytical approach for understanding household livelihood strategies under conditions of stress and change. It emphasizes how households draw upon and combine different forms of livelihood capital in responding to these conditions. The framework recognizes five key livelihood assets, namely, human, natural, physical, financial, and social capital, and emphasizes that households' access to, and ability to combine and transform, these assets shapes their capacity to cope with and adapt to shocks [19–21]. Empirical applications of the SLF in climate change research have expanded in recent years, demonstrating that human capital (education, skills, and experience) and social capital (networks, group membership, and trust) are often critical for enabling knowledge exchange, collective action, market information, and access to extension services [22–24]. Simultaneously, natural and physical capitals, particularly land holdings and farm equipment, influence farmers' capacity to adopt specific climate change adaptation practices [25–27]. Financial capital, through access to credit and savings, can enhance households' capacity to invest in adaptation practices and strengthen their resilience to shocks [28–30].

Despite these advances, important gaps remain. While an increasing body of research has applied econometric approaches to identify the contributing factors to climate change adaptation relatively limited attention has been given to quantifying the distinct contributions of disaggregated livelihood capitals to adaptation behavior. Existing studies have examined socioeconomic, institutional, and environmental correlates of adaptation across diverse contexts, including Ethiopia, Kenya, and Mesoamerica [22,28,31,32]. However, these studies generally focus on individual contributing factors, adaptation choices, or aggregate measures of vulnerability and adaptive capacity, and rarely systematically estimate the relative contribution of distinct livelihood-capital domains to adaptation intensity. Within Uganda, recent studies have examined livelihood vulnerability and coffee-specific climate adaptation. Ntakyo et al. [33] applied the SLF to assess livelihood vulnerability among smallholder farmers in Southwestern Uganda, but did not examine climate adaptation intensity econometrically. Recent coffee studies have focused on factors contributing to climate-smart technology adoption, with limited attention to disaggregated livelihood-capital domains [6]. To our knowledge, no study has used econometric modeling to examine whether disaggregating the SLF's capital domains into their constituent variables helps explain climate adaptation intensity among smallholder coffee farmers in Southwestern Uganda. Addressing this gap is important given the strategic importance of coffee to Uganda's development trajectory and the increasing need to strengthen climate resilience. A more precise understanding of how individual livelihood assets shape adapta-

tion decisions can inform targeted policies and stakeholder interventions, improve resource allocation, and strengthen institutional support mechanisms.

This study modelled the influence of livelihood capitals on the extent of climate change adaptation among smallholder coffee farmers in Southwestern Uganda. Specifically, the study pursues four objectives: (i) to characterize the extent and spatial distribution of climate change adaptation among smallholder coffee farmers across the study districts; (ii) to examine the relationship between each constituent variable of the five livelihood-capital domains, human, natural, physical, financial, and social, and the intensity of adoption of adaptation-enhancing practices, defined here as the farm-level agronomic and management responses described in Section 2.3 (for example, intercropping, mulching, irrigation, and varietal substitution) that farmers adopt specifically to reduce their exposure or sensitivity to climate-related risks to coffee production; (iii) to test whether aggregating these constituent variables into composite capital indices, as is common in the prior literature, obscures relationships that are visible when the same variables are entered separately; and (iv) to derive policy-relevant implications for strengthening adaptive capacity among smallholder coffee farmers.

This study does not assume in advance that each capital domain has a uniform or predictable relationship with adaptation. Instead, it treats this as an empirical question, letting the disaggregated evidence indicate which specific constituent variables, and by extension which capital domains, are associated with adaptation intensity. Examining how different livelihood capitals influence adaptation intensity contributes to understanding the household-level factors associated with adaptive capacity and climate risk management in smallholder coffee systems. Enhancing adaptive capacity in the face of climate change remains a pressing development priority. Strengthening the resilience of farming systems and livelihoods is essential for managing increasing climate risks and safeguarding food security [34].

2. Materials and Methods

2.1. Study Area

The study was conducted in Southwestern Uganda, covering the districts of Kanungu, Ntungamo, Rukungiri, and Sheema. The study area lies approximately between 29°50' E and 30°36' E longitude and 0°24' S and 1°45' S latitude (Figure 1). The region is one of Uganda's major coffee-producing landscapes and is characterized by a mix of Robusta and Arabica coffee systems, mainly managed under smallholder farming conditions. Sheema and Ntungamo are predominantly located within the Southwestern Agroecological Zone (SWAEZ), which is associated mainly with Robusta production, while Kanungu and Rukungiri fall within the Southwestern Highland Agroecological Zone (SWHAEZ), where Arabica coffee is more prominent, although mixed coffee systems are also present across the study area [35,36]. This distribution is consistent with the differing agroecological suitability of the two coffee types. Arabica generally performs better under cooler, higher-elevation conditions, whereas Robusta is better suited to comparatively warmer, lower-elevation environments [36].

The area lies within the greater Ankole and Kigezi highlands, with elevations ranging from approximately 1200 to 2200 m above sea level. These altitudinal conditions have previously supported favorable coffee production, but the region has become gradually vulnerable to climate variability. A mean temperature range of 17 °C to 26 °C and average annual rainfall of 1000 to 1500 mm distributed bimodally are reported for the broader study area, not separately for the SWAEZ and SWHAEZ [37,38]; zone-specific climate normals for Southwestern Uganda's Arabica- and Robusta-growing areas were not available from these sources at the resolution required to attribute distinct values to each district. Recent

work directly characterizing climate patterns in Uganda's Arabica and Robusta coffee regions confirms that measurable differences between the two exist [39]. Therefore, the area-wide climate range reported here represents a general characterization and should not be interpreted as indicating uniform conditions across the study area. Recent years have been associated with rising rainfall irregularity, delayed onset of rains, prolonged dry spells, and temperature-related stress. These and other factors pose significant risks to coffee productivity and household livelihoods [40]. The area, therefore, provides a relevant setting for examining heterogeneity in climate change adaptation among smallholder coffee farmers [4,41]. What distinguishes Southwestern Uganda from other Ugandan coffee-growing regions studied in this literature is that it hosts both major coffee production systems, Robusta and Arabica, within a single, geographically compact and directly comparable area, unlike regions where quantitative coffee-adaptation research has concentrated on one system alone. In addition to this ecological distinctiveness, the study area exhibits differences in market access, farmer organization, extension exposure, and institutional support systems. This is appropriate for investigating how livelihood assets shape household adaptation behavior.

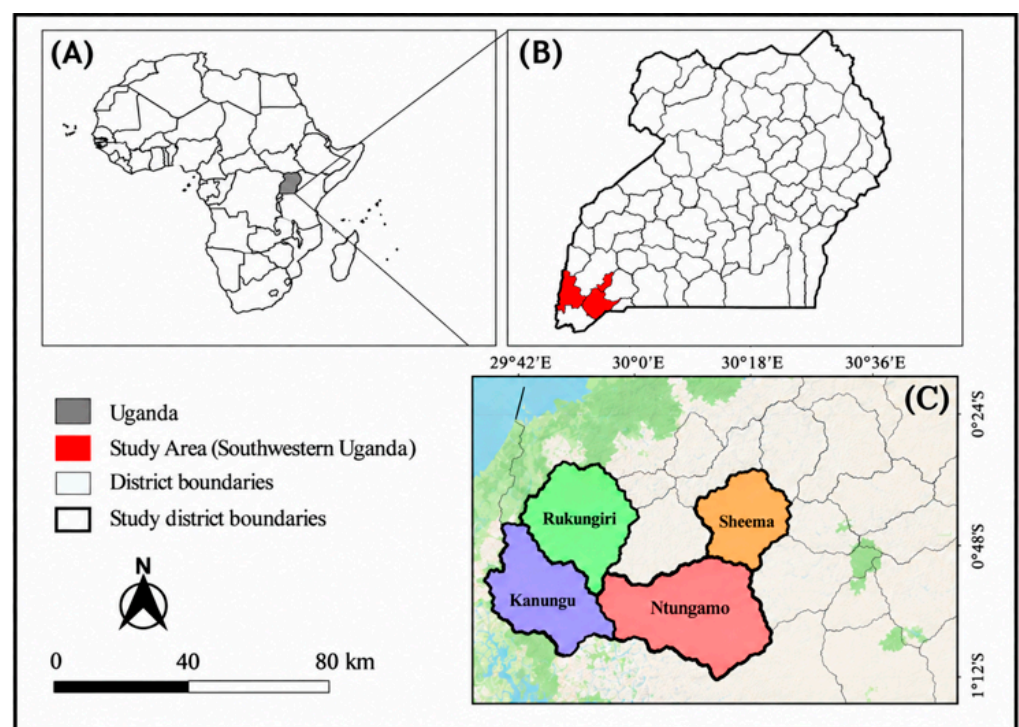


Figure 1. Map of the study area. (A) Location of Uganda within the African continent. (B) Location of the study area (shaded red) within Uganda. (C) Detailed map of the four study districts (Kanungu, Ntungamo, Rukungiri, and Sheema), showing district boundaries.

2.2. Research Design, Sampling, and Data Collection

This study employed a cross-sectional household survey design, which enables the analysis of variation in adaptation behavior across households using comparable socioeconomic and farm-level data. Such designs are commonly used in agricultural adaptation empirical studies [31]. However, they are primarily suited to identifying associations and are less suitable for establishing causal relationships. They allow for the collection of household-level data on production practices, livelihood assets, institutional access, and adaptation responses at a specific point in time. This is vital where the objective was to analyze variation in adaptive behavior across households and locations using comparable socioeconomic and farm-level information.

A multistage stratified random sampling procedure was used to select the study respondents. In the first stage, four districts were purposively selected as the two highest coffee-producing districts within each of the two agroecological zones present in the study region (Sheema and Ntungamo in the SWAEZ; Kanungu and Rukungiri in the SWHAEZ), based on coffee production volumes reported by the Uganda Coffee Development Authority [36]. In the second stage, two sub-counties, four parishes, and four villages were purposively selected within each district, with guidance from District and Sub-County Agricultural Officers who maintained coffee production records for their respective jurisdictions. In the final stage, coffee-producing households were randomly selected from village-level farmer lists compiled with the assistance of area Agricultural Officers (AOs) and Local Council Chairpersons (LCIs). Sixteen villages were initially targeted across the four districts; the realized analytic sample, following data cleaning, was distributed across 21 villages, reflecting fieldwork adjustments where some initially targeted villages did not yield their full household quota. The required sample size was determined using the standard formula (Equation (1)) for estimating a population proportion at a specified level of precision [42].

$$n = \frac{z^2 p(1-p)}{e^2} \quad (1)$$

where (n) is the required sample size, (z) is the z -value corresponding to the desired confidence level, p is the estimated population proportion, and (e) is the acceptable margin of error. Assuming a 95% confidence level ($z = 1.96$), a 5% margin of error ($e = 0.05$), and maximum variability ($p = 0.5$), the minimum sample size was calculated (Equation (2)).

$$n = \frac{1.96^2 \times 0.5(1-0.5)}{0.05^2} = 384 \quad (2)$$

A sample of 388 households was initially targeted, exceeding the minimum required sample size of 384 (Equation (2)) to allow for possible non-response. The target sample was allocated equally across the four study districts, with 97 households per district. Following field validation, data collection, and data cleaning, 376 completed and valid household questionnaires were retained for analysis. The sampling procedure was independent of the construction of the count-based, PCA-based, and MCA-based adaptation indices described in Section 2.3. These indices were constructed after data collection from the survey responses of the selected households and were not used in household selection.

District was retained as the primary spatial unit for analysis because it is the administrative unit through which the sampling design was operationalized. Sub-counties, parishes, and villages were selected within each of the four districts. The districts, however, correspond closely to two agroecological contexts, with Sheema and Ntungamo located in the SWAEZ and Kanungu and Rukungiri in the SWHAEZ. Since each sampled district falls within a single AEZ, AEZ membership can be assigned unambiguously to each sampled household from its district. Thus, districts capture the administrative and sampling structure of the study, whereas AEZs provide an ecological basis for examining spatial heterogeneity. To assess whether the observed district-level patterns were sensitive to the choice of spatial unit, Section 3.6 re-estimates the main disaggregated models using the two-level AEZ indicator in place of the four-level district indicator. The analysis, therefore, serves as a robustness assessment of the spatial patterns identified in the district-level models.

Primary data were collected using a structured household questionnaire administered to randomly sampled coffee farming households. Data collection was conducted between November 2025 and February 2026. The survey instrument captured information on household socioeconomic characteristics, farm resources, adaptation practices, access to training and extension services, institutional support, and indicators related to the five

livelihood capitals under the SLF. Ethical considerations were observed throughout the research process. The study protocol was registered with the Uganda National Council for Science and Technology (UNCST) under Protocol No. A551ES, with board approval dated 10 March 2025. Participation was voluntary, respondents provided informed consent before participation, and confidentiality and anonymity were maintained throughout data collection, processing, and analysis [43].

This study is anchored in the SLF, which conceptualizes household adaptive capacity as being shaped by access to five forms of capital, namely, human, natural, physical, financial, and social capital [44]. Within this perspective, adaptation behavior is understood both as a technical response to climate stress and an outcome of households' differential access to productive resources, knowledge, labor, institutions, and social networks. In this study, the SLF is used as an organizing framework for identifying which household characteristics to measure. In contrast to studies that combine each capital's constituent variables into a single composite score before estimation, each constituent variable is entered separately into the regression models below (Section 2.4), so that variables nominally grouped under the same capital are not assumed a priori to move together or in the same direction. A composite-capital specification, constructed in the manner of prior studies in this literature, is nonetheless also estimated and retained as a robustness check for comparability with that body of work (Section 3.4).

2.3. Measurement of Household Climate Change Adaptation

Climate change adaptation among smallholder coffee farmers was conceptualized as a multi-practice behavioral response involving multiple adaptation decisions instead of a single binary outcome. This approach recognizes that farmers often respond to climatic stress through a portfolio of strategies, combining agronomic, technical, and livelihood adjustments depending on their resources, knowledge, and local production conditions. Treating adaptation as a bundle of responses is consistent with the broader smallholder adaptation literature. This emphasizes that adaptation is cumulative, multidimensional, and context-specific, and manifests through multiple discrete actions instead of a single one-off choice [10,45,46]. Adaptation was measured using twelve farm-level practices reported by coffee-growing households: intercropping, mulching, planting shade trees, planting resistant coffee varieties, changing coffee type, irrigation, trench construction, pest and disease management, manure use, inorganic fertilizer application, reduction in coffee acreage, and pruning and de-suckering. These practices represent key dimensions of climate adaptation in coffee systems, including crop management, soil and water conservation, varietal substitution, and input intensification [47,48]. Each practice was coded as a binary variable (Equation (3)).

$$A_{ij} = \begin{cases} 1, & \text{if household } i \text{ adopted practice } j \\ 0, & \text{otherwise} \end{cases} \quad (3)$$

where (A_{ij}) denotes the adoption of adaptation strategy j by household i . All variables were standardized into a consistent binary format by converting textual responses "Yes/No" into numerical values. Missing values on individual adaptation items (4 of 376 households, 1.1%) were conservatively re-coded as zero (non-adoption), to avoid potentially overstating adoption. Given the very small proportion of missing observations, this coding decision was unlikely to materially affect the results. To assess the sensitivity of the results to this convention, the main regression models were re-estimated on the subsample of 372 households with no missing adaptation-item responses.

To operationalize climate change adaptation, this study identified twelve household-level adaptation practices that are widely recognized in the climate-smart agriculture and

coffee adaptation literature and are relevant to the agronomic conditions of smallholder coffee farming in Southwestern Uganda. These practices comprised intercropping, increased mulching, planting of shade trees, planting of resistant coffee varieties, changing coffee type, introducing irrigation, digging trenches, pest and disease management, manure use, inorganic fertilizer application, reducing coffee acreage, and pruning, de-suckering, and stumping (Table 1). Several practices in this inventory consolidate related items from the broader technology set documented by Kirungi et al. [6]: weed control (mechanical and chemical) is captured within pest and disease management; cover crop planting is captured within intercropping; and gap filling, where replacement plants involved a different variety, is captured within changing coffee type. Of the twelve practices, four are inherently specific to coffee production and have no direct equivalent for other crops: planting resistant coffee varieties, changing coffee type, reducing coffee acreage, and shade-tree management. The remaining eight are general farm-management techniques, but the survey questions asked specifically about their application to coffee production as a climate-adaptation response, not about the household's general farming practices; all twelve practices therefore refer to coffee-specific adaptation behavior. Applicability across coffee systems is most conceptually relevant to the four coffee-specific practices identified above, since resistant-variety choice, coffee-type switching, and shade-tree requirements plausibly differ between Robusta and Arabica production; the general farm-management practices are less likely to be system-dependent in this respect. This distinction could not be tested statistically given the data limitations discussed in Section 7.1, but is offered here as a conceptual basis for interpreting the applicability limitation. A single instrument covering all twelve practices was applied across both coffee systems. This approach was adopted because mixed coffee systems occur across the study area, making separation of the survey instrument by coffee type impractical at the sampling stage. The practices were therefore assessed using common definitions across households, while recognizing that their specific application may differ between Arabica and Robusta systems; for example, changing coffee type may involve switching among cultivars within the farmer's existing coffee system.

Twelve practices were classified as climate-adaptation responses when farmers reported adopting them in response to perceived or experienced climate-related changes or risks. This classification is consistent with evidence from Ugandan smallholder coffee systems, where pruning, de-suckering, pest and disease management, shade-tree management, improved coffee varieties, mulching, manure application, irrigation, soil and water conservation, and inorganic fertilizer application have been documented as climate-smart agricultural technologies [6]. Evidence from smallholder coffee systems in the Eastern African Highlands further supports the relevance of mulch and fertilizer management to coffee production under resource constraints [49], while a systematic review of 80 studies identifies crop, soil, and water management practices as potential approaches to enhancing coffee climate resilience [50]. Table 1 presents the operational definition, climate-adaptation relevance, and measurement of each practice.

Collectively, these practices represent farm-level management strategies that enhance resilience by improving soil and water conservation, reducing pest and disease risks, sustaining productivity, and strengthening the capacity of coffee production systems to cope with climatic variability and change [51–53]. Two complementary dependent variables, a count-based adaptation index and a Principal Component Analysis (PCA)-based adaptation index, were constructed to capture both the breadth and the relative configuration of adaptation behavior.

Table 1. Adaptation practices, operational definitions, climate-adaptation relevance, and measurement.

Adaptation Practice	Operational Definition	Relevance to Climate Adaptation	Measurement
Intercropping	Growing coffee alongside other crops on the same plot	Diversifies production and reduces reliance on coffee under climate-related yield risks	Binary (0/1)
Mulching	Applying organic material around coffee plants	Conserves soil moisture and helps buffer drought and heat stress	Binary (0/1)
Planting shade trees	Establishing tree cover over coffee plots	Moderates coffee-plot microclimate and reduces heat and moisture stress	Binary (0/1)
Planting resistant coffee varieties	Adopting varieties with tolerance to relevant pests, diseases or climatic stresses	Reduces vulnerability to climate-related pest, disease and drought pressure	Binary (0/1)
Changing coffee type	Changing the type of coffee grown	Predominantly switching between cultivars within the same coffee type (Robusta or Arabica); a smaller subset of households switched from Arabica to Robusta	Binary (0/1)
Introducing irrigation	Applying supplementary water to coffee plots	Reduces exposure to rainfall deficits and dry periods	Binary (0/1)
Digging trenches	Constructing trenches for water management	Helps manage excess or deficient soil moisture under erratic rainfall	Binary (0/1)
Pest and disease management	Implementing measures to control pests and diseases	Reduces vulnerability to climate-related changes in pest and disease pressure	Binary (0/1)
Manure use	Applying organic manure to coffee plots	Improves soil condition and moisture retention under water stress	Binary (0/1)
Inorganic fertilizer application	Applying inorganic fertilizer to coffee plots	Supports crop productivity under climate-related production stress	Binary (0/1)
Reducing coffee acreage	Decreasing land allocated to coffee production	Reduces exposure to climate-related production risks through defensive land-use adjustment	Binary (0/1)
Pruning, de-suckering, and stumping	Removing excess growth and unproductive shoots	Helps maintain plant vigor and resource-use efficiency under climatic stress	Binary (0/1)

Note: The twelve practices were coded as binary indicators (1 = adopted; 0 = not adopted). A farmer-level classification by coffee variety was not constructed for this analysis; practice-level applicability to Robusta and Arabica production could not therefore be verified directly, and this is acknowledged as a limitation (Section 7.1).

2.3.1. Count-Based Adaptation Measure

The first outcome variable was defined as the number of climate change adaptation practices adopted by each household. Each of the twelve practices was coded as a binary indicator, taking the value of “1” if the household reported adopting the practice and “0” otherwise. This approach provides a direct measure of the breadth of adaptation behavior and has been widely applied in studies of agricultural adaptation and technology adoption [10,54]. The total number of practices adopted by the household i was then computed (Equation (4)). The survey instrument did not collect the duration for which each practice had been in use; adoption is therefore measured as a current binary status (currently practicing or not) instead of a length of adoption, a scope limitation discussed further in Section 7.2.

$$AdaptCount_i = \sum_{k=1}^K A_{ik} \quad (4)$$

where A_{ik} is a binary variable indicating whether the household (i) adopted an adaptation practice (k), and (K) is the total number of identified adaptation practices ($K = 12$). This

variable ranges from 0 to 12 and captures the breadth of household adaptation behavior, that is, the number of distinct practices implemented. The count-based measure is appropriate when adaptation is conceptualized as a portfolio of responses, as opposed to a single intervention. While this measure is intuitive and easy to interpret, it assumes that all adaptation practices contribute equally to adaptive capacity and does not account for correlations or complementarities among practices.

2.3.2. PCA-Based Adaptation Index

Although the count of adopted practices captures the breadth of adaptation, it does not reflect differences in the structure, co-occurrence, or relative intensity of adaptation strategies across households. To address this limitation, a second dependent variable was constructed using Principal Component Analysis (PCA). PCA was applied to the set of binary adaptation indicators to extract the dominant dimension of variation in household adaptation behavior. The first principal component, which captures the largest share of common variation, was kept as a continuous adaptation index (AI_PCA). This approach moves beyond a simple count by incorporating the underlying configuration and relative importance of adaptation practices, a common approach in adaptation studies [10,55]. Consequently, while the count-based measure reflects the number of strategies adopted, the PCA-based index captures variation in the overall adaptation profile and the way practices are combined across households [56]. Before PCA estimation, all adaptation variables were standardized (Equation (5)).

$$Z_{ij} = \frac{A_{ij} - \bar{A}_j}{\sigma_j} \quad (5)$$

where (Z_{ij}) is the standardized value of the adaptation variable (j), ($\bar{A}_j$) is its mean, and (σ_j) it is the standard deviation. The PCA model can be expressed as a linear combination of standardized variables (Equation (6)).

$$PC_m = \sum_{j=1}^K w_{jm} Z_{ij} \quad (6)$$

where (PC_m) is the (m -th) principal component and (w_{jm}) are the associated loadings. The first principal component (PC1), which captures the largest share of total variance, was retained as the adaptation index (Equation (7)); PC1 explained 14.67% of total variance across the twelve binary indicators.

$$AI_i^{PCA} = \sum_{j=1}^K w_j Z_{ij} \quad (7)$$

This PCA-based index provides a continuous measure of adaptation, with higher values indicating stronger engagement with dominant adaptation patterns. Unlike the count index, PCA assigns data-driven weights to each practice, reflecting their relative contribution to overall adaptation behavior and accounting for correlations among strategies [57].

Since all twelve adaptation indicators are binary, PCA's standard assumptions of continuous, linearly correlated variables with meaningful covariances are not strictly satisfied, and Multiple Correspondence Analysis (MCA) is, in principle, better suited to this type of data [58,59]. A parallel MCA-based adaptation index (AI_MCA) was constructed from the same indicators as a robustness check. Each binary indicator was represented by its two mutually exclusive categories (adopted/not adopted), and MCA was applied to the resulting indicator matrix using chi-square weighting. As with PCA, the first dimension was retained as the adaptation index. The first MCA dimension explained 14.67% of total inertia, coincidentally the same proportion as the first PCA component explained, and the resulting household indices were perfectly rank-correlated (Spearman's $\rho = 1.00$; $p < 0.001$).

PCA and MCA are exploratory, not confirmatory, multivariate techniques, and their agreement is therefore not interpreted as external validation of the adaptation construct. The comparison instead assesses whether the choice of index-construction method materially affects the resulting household rankings. PCA and MCA apply different mathematical treatments to the same twelve binary indicators, with PCA based on covariance structure and MCA designed for categorical data. The near-perfect correspondence between the resulting indices indicates that the substantive ranking of households is highly robust to the choice between these two methods. Thus, the findings reported in Section 3 are unlikely to be driven solely by the choice of PCA over MCA. Given this equivalence, AI^{PCA} is retained as the primary continuous adaptation measure, following common practice in the construction of asset, wealth, and livelihood indices in agricultural and development studies [58], with AI^{MCA} reported as a robustness check.

2.4. Explanatory Variables

The explanatory variables were selected based on the Sustainable Livelihoods Framework (SLF) and the broader empirical literature on smallholder adaptation to climate change [60,61]. The SLF provides a well-established analytical framework for examining how households' access to different forms of livelihood capital influences their capacity to respond to environmental and climate-related shocks, and has been applied directly to climate change adaptation in smallholder agricultural systems [24]. Five livelihood-capital domains were identified: human, natural, physical, financial, and social capital (Table 2). Instead of aggregating each domain's constituent variables into a single composite score, the main specification entered each constituent variable separately. This approach was adopted because aggregating several indicators into one index assumes that they move together and contribute equally to the underlying construct, an assumption that does not always hold and can obscure heterogeneous or offsetting relationships among conceptually related variables [58,59]. The explanatory variables were complemented by selected contextual and institutional factors, including training and extension access, district location, and gender of the household head.

Human capital comprised education, household size, and years of coffee-farming experience, representing farmers' knowledge, labor availability, and accumulated production experience that may influence their capacity to perceive climate risks and implement adaptation measures. Natural capital included land size, perceived soil fertility, and access to a permanent water source, reflecting the natural resource base available for agricultural production. Physical capital represented productive assets and infrastructure that facilitate on-farm adaptation, including irrigation equipment, distance to the nearest agro-input shop, and ownership of essential farm tools (secateurs, tarpaulins, pruning saws, forked hoes, and watering equipment). Financial capital comprised access to credit and off-farm income, capturing households' financial capacity to invest in adaptation. Social capital included cooperative membership and participation in farmer-to-farmer knowledge exchange, reflecting access to information, collective action, and social support. Training in coffee production or climate-smart agriculture was included as an institutional variable to account for farmers' exposure to extension and advisory services. District fixed effects were included to control for broad spatial differences in agroecological and institutional conditions, while gender was included to account for potential differences in access to productive resources and household decision-making.

Although the explanatory variables were conceptually grouped into livelihood-capital domains following the Sustainable Livelihoods Framework [60,61], the primary regression models treated the constituent variables individually. Composite indices were not used as the primary predictors in these models. This modeling strategy recognizes that variables

within a livelihood-capital domain may influence adaptation through different pathways and with differing magnitudes or directions of effect, as shown empirically in Section 3.4, where combining a positively signed and a negatively signed variable into one human-capital index produced a weaker, worse-fitting summary than the disaggregated variables themselves [58,59]. Composite-capital models were estimated separately as robustness checks to facilitate comparison with previous studies that have operationalized livelihood capitals as aggregated indices [19].

Table 2. Operationalization of livelihood-capital variables (disaggregated main specification).

Capital	Constituent Variable	Type	Coding
Human capital	Years of schooling	Ordinal	1–4 scale
	Household size	Continuous	Count
	Years of experience in coffee farming	Continuous	Years
Natural capital	Land size under coffee (acres)	Continuous	Continuous
	Soil fertility rating	Ordinal	1–3 scale
	Access to a permanent water source	Binary	0/1
Physical capital	Irrigation equipment ownership	Binary	0/1
	Distance to the agro-input shop	Continuous	Continuous
	Tool ownership count (secateur, tarpaulins, pruning saw, forked hoe, watering equipment)	Continuous	0–5 count
	Access to credit for farming operations	Binary	0/1
Financial capital	Off-farm income (any ranked source)	Binary	0/1
	Cooperative membership	Binary	0/1
Social capital	Knowledge exchange with other farmers	Binary	0/1

Note: A corresponding composite-capital construction, aggregating each domain's constituent variables via a normalized mean, following prior studies in this literature, is used (Section 3.4).

2.5. Econometric Analysis

To examine the factors associated with climate change adaptation, this study employed two estimators corresponding to two distinct assumed data-generating processes for the two dependent variables: Ordinary Least Squares (OLS) for a linear conditional-mean process governing the continuous PCA-based adaptation index, and Poisson regression for an exponential conditional-mean (log-link) process governing the count-based number of practices adopted [62]. OLS and Poisson are treated here as estimators for different outcome structures, not as directly comparable models of the same underlying process. Accordingly, coefficients are not compared in magnitude across the two estimators because they use different link functions and outcome scale.

2.5.1. OLS Model for PCA-Based Adaptation Index

The main specification estimates the relationship between the disaggregated household characteristics in Table 1 and the continuous PCA-based adaptation index (AI_PCA). The estimator is specified (Equation (8))

$$\begin{aligned}
 AI_PCA_i = & \beta_0 + \beta_1 Educ_i + \beta_2 HHsize_i + \beta_3 Exp_i + \beta_4 LandSize_i + \beta_5 SoilFert_i + \beta_6 Water_i \\
 & + \beta_7 Irrig_i + \beta_8 Dist_i + \beta_9 Tools_i + \beta_{10} Credit_i + \beta_{11} OffFarm_i + \beta_{12} Coop_i \\
 & + \beta_{13} KnowEx_i + \beta_{14} TR_i + \beta_{15} D_i + \beta_{16} G_i + \varepsilon_i
 \end{aligned} \tag{8}$$

where AI_PCA_i = PCA-based adaptation index for household i ; $Educ_i$, $HHsize_i$, Exp_i , $LandSize_i$, $SoilFert_i$, $Water_i$, $Irrig_i$, $Dist_i$, $Tools_i$, $Credit_i$, $OffFarm_i$, $Coop_i$, and $KnowEx_i$ are the thirteen disaggregated constituent variables listed in Table 1 (Exp_i = years of experience in coffee farming; $Tools_i$ = count of five farm tools owned; TR_i = training/extension access; D_i = district dummy variables; G_i = gender of household head; ε_i = error term). Aggregating constituent variables into composite capital indices assumes that variables within the same livelihood-capital domain exert homogeneous effects on adaptation. This assumption may obscure heterogeneous or offsetting relationships among conceptually related variables by averaging them into a single score. Estimating the constituent variables individually allows their independent contributions to adaptation to be identified, while the composite-index specification (Section 3.4) is retained as a robustness check and to facilitate comparison with previous studies.

2.5.2. Poisson Model for Count-Based Adaptation Measure

The second estimator assessed the factors associated with the number of adaptation practices adopted using a Poisson regression model with the same set of disaggregated covariates. The estimator is specified (Equation (9)).

$$E(AdaptCount_i | X_i) = \exp(\beta_0 + \beta_1 Educ_i + \beta_2 HHsize_i + \beta_3 Exp_i + \dots + \beta_{16} G_i) \quad (9)$$

where $AdaptCount_i$ is the total number of adaptation practices adopted by the household i , and X_i represents the vector of explanatory variables. The Poisson specification was preferred because the dependent variable is a discrete count bounded at zero. Poisson regression is consistent under distributional misspecification of the conditional variance whereas the Negative Binomial estimator is not [62], a Negative Binomial specification is also estimated and reported for completeness, but the two count estimators are not compared via a formal information-criterion selection test; instead, the Poisson deviance-to-degrees-of-freedom ratio is reported descriptively as evidence on the presence or absence of overdispersion (Section 3.5). For ease of interpretation, the Poisson coefficients were also transformed into Incidence Rate Ratios (IRRs), which indicate the multiplicative effect of each explanatory variable on the expected count of adaptation practices. A composite-capital specification, aggregating the constituent variables (Section 3.4) into the five capital indices following prior studies in this literature, is estimated in parallel using the same OLS, Poisson, and Negative Binomial estimators, and is reported in Section 3.4 for comparability with that body of work.

2.5.3. Diagnostic and Robustness Checks

Several diagnostic and robustness procedures were conducted to assess model validity. First, for the Poisson model, overdispersion was assessed using the ratio of residual deviance to residual degrees of freedom; a value substantially greater than one would suggest overdispersion and indicate that the Poisson model may underestimate standard errors. Second, a Negative Binomial model was also estimated as a robustness check for the count outcome (Section 2.5.2). Third, all standard errors are clustered at the village level, with 21 village clusters in the analytic sample. This approach does not assume that observations are independent conditional on the observed covariates and allows for unrestricted correlation among farmers residing in the same village [63]. Fourth, the sensitivity of the results to the choice between the PCA- and MCA-based adaptation indices was assessed by comparing the two indices directly (Table A1). Fifth, the sensitivity of the results to the missing-data recoding convention for adaptation items was assessed by re-estimating the main specification on the subsample of households with no missing adaptation responses (Table A2). Lastly, multicollinearity among explanatory variables in both the disaggregated

main specification and the composite-capital specification was examined using variance inflation factors (VIFs) and generalized variance inflation factors (GVIFs) for categorical variables (Table A3); all values are well below conventional thresholds of concern, indicating no meaningful multicollinearity among the disaggregated covariates. Following Fox and Monette [64], adjusted $\text{GVIF}^{(1/2df)}$ values below 2 are indicative of negligible multicollinearity; all values in the present models fall well below this threshold, confirming no meaningful collinearity among the disaggregated covariates. All statistical analyses were conducted using the R-statistical software environment (version 4.6.1; R Core Team, 2026).

3. Results

3.1. District-Level Socioeconomic Attributes and Adaptation Levels

Table 3 shows variation in selected household characteristics across districts. Male-headed households constituted the majority in all districts, although the proportion of female respondents was relatively higher in Ntungamo and Sheema than in Kanungu and Rukungiri. Training/extension access also differed across districts. Sheema recorded the highest proportion of respondents with extension access (42.7%), followed by Kanungu (36.5%), while Ntungamo (35.8%) and Rukungiri (30.3%) had relatively lower participation rates. These differences are relevant because access to information and extension-related learning opportunities may shape awareness, experimentation, and eventual adoption of adaptation practices.

Table 3. Selected district-level sample characteristics.

Variable	Kanungu	Ntungamo	Rukungiri	Sheema
Male respondents (%)	73.96	55.79	69.66	59.38
Female respondents (%)	26.04	44.21	30.34	40.63
Above primary education (%)	31.25	40.00	41.57	33.33
Training/extension access (Yes) (%)	36.46	35.79	30.34	42.72
Mean adaptation index (mean)	1.34 (1.10)	1.81 (1.5)	1.34 (1.11)	1.71 (1.24)

Notes: Standard deviation in parentheses.

District-level mean adaptation figures show that adaptation was not uniformly distributed across the study area. Ntungamo recorded the highest mean adaptation index (1.81), followed by Sheema (1.71), while Kanungu and Rukungiri had lower, identical mean values of (1.34) each. These results imply that farmers in Ntungamo and Sheema were more actively engaged in climate adaptation strategies than those in the other districts. These district-level disparities may reflect differences in access to information, local institutional support, agroecological conditions, infrastructure, and social learning environments. In the regression models (Section 3.3), district indicators capture average time-invariant differences across districts, including common shocks, institutions, and agroecological conditions, and are not interpreted as causal effects of district affiliation.

3.2. Descriptive Statistics of Key Variables

Table 4 presents the descriptive statistics for the principal outcome variables used in the analysis. The mean adaptation index was 1.55 (SD = 1.26), indicating that, on average, households adopted approximately one to two climate change adaptation practices. The adaptation index ranged from zero to eight, suggesting considerable variation in the number of practices adopted across households. The PCA-based adaptation index (AI_PCA) had a mean of 0.00 (SD = 1.33), as expected for standardized principal component scores, with a range of −2.17 to 9.28 indicating heterogeneity in the intensity of adaptation

behavior across households. The MCA-based adaptation index (AI_MCA), estimated as a robustness check, had a mean of 0.00 (SD = 0.38). Generally, 36.4% of respondents reported having received training in coffee or climate-smart agriculture in the preceding three years.

Table 4. Descriptive statistics of the main outcome variables.

Variable	Mean (SD)	Theoretical Range	Observed Range
Adaptation Index (count-based)	1.55 (1.26)	0–12	0–8
PCA-based Adaptation Index	0.00 (1.33)	Unbounded *	−2.17–9.28
MCA-based Adaptation Index	0.00 (0.38)	Unbounded *	−0.63–2.68
Training/extension access (%)	36.40	0–100	—

Notes: Standard deviation in parentheses. * The PCA- and MCA-based indices are standardized principal component/dimension scores with no fixed theoretical minimum or maximum; their scale is data-determined, unlike the count-based index, whose theoretical range (0–12) is fixed by the number of practices measured.

Table 5 reports the prevalence of each adaptation practice among the 376 sampled households. Intercropping (44.1%) and increased mulching (41.5%) were the most commonly reported practices. Adoption declined substantially among the remaining practices, with irrigation (4.8%), inorganic fertilizer application (1.6%), and pruning and de-suckering (0.8%) among the least frequently reported. The very low adoption of soil-input and management-intensive practices, including manure use (1.9%), inorganic fertilizer application (1.6%), and pruning, de-suckering, and stumping (0.8%), suggests that resource and knowledge constraints are particularly binding for these practices.

Table 5. Prevalence of climate-adaptation practices among sampled households.

Adaptation Practice	Households, <i>n</i> (%)
Intercropping	166 (44.1)
Increased mulching	156 (41.5)
Planting shade trees	90 (23.9)
Planting resistant coffee varieties	59 (15.7)
Changing coffee type	49 (13.0)
Introducing irrigation	18 (4.8)
Digging trenches	14 (3.7)
Pest and disease management	11 (2.9)
Manure use	7 (1.9)
Inorganic fertilizer application	6 (1.6)
Reducing coffee acreage	5 (1.3)
Pruning, de-suckering, and stumping	3 (0.8)

Note: *n* = number of households reporting adoption of the respective practice; percentages are calculated as $n/376 \times 100$. Practices were measured as binary indicators (1 = adopted; 0 = not adopted).

3.3. Correlates of Climate Change Adaptation: Disaggregated Specification

Table 6 reports the main disaggregated specification, with standard errors clustered at the village level (21 clusters). Across the OLS, Poisson, and Negative Binomial estimators, several constituent variables show consistent, statistically significant associations with adaptation. The disaggregated OLS specification explains approximately 29% of the variance in adaptation intensity ($R^2 = 0.294$), a reasonable fit for a cross-sectional behavioral study of this type.

Table 6. Factors influencing climate change adaptation among smallholder coffee farmers in South-western Uganda.

Variable	OLS (AIPCA)	Poisson (β)	IRR ($e\beta$)
<i>Human capital</i>			
Education level	0.161 † (0.100)	0.101 * (0.047)	1.106
Household size	0.073 ** (0.023)	0.047 * (0.019)	1.048
Coffee-farming experience (years)	−0.013 * (0.005)	−0.009 * (0.004)	0.991
<i>Natural capital</i>			
Land size (acres)	0.040 † (0.023)	0.017 (0.013)	1.017
Soil fertility rating	0.178 † (0.092)	0.141 (0.096)	1.152
Access to permanent water source	0.195 † (0.103)	0.132 † (0.070)	1.141
<i>Physical capital</i>			
Irrigation equipment	−0.187 (0.324)	−0.122 (0.174)	0.886
Distance to agro-input shop	0.013 (0.010)	0.006 (0.008)	1.006
Farm-tool ownership (0–5)	0.151 * (0.059)	0.094 * (0.037)	1.099
<i>Financial capital</i>			
Credit access	−0.183 (0.113)	−0.095 (0.089)	0.910
Off-farm income	0.305 * (0.151)	0.090 (0.103)	1.094
<i>Social capital</i>			
Cooperative membership	0.492 † (0.271)	0.326 * (0.139)	1.385
Farmer-to-farmer knowledge exchange	0.301 ** (0.106)	0.297 *** (0.057)	1.346
<i>Other covariates</i>			
Climate-smart agriculture training	0.420 *** (0.123)	0.204 ** (0.078)	1.227
District: Ntungamo	0.813 *** (0.242)	0.266 (0.238)	1.305
District: Rukungiri	0.180 (0.265)	−0.054 (0.230)	0.947
District: Sheema	0.411 (0.266)	0.086 (0.246)	1.089
Gender (Male)	0.194 † (0.107)	0.031 (0.092)	1.031
Constant	−2.358 *** (0.369)	−0.938 * (0.381)	0.391

Notes: Standard errors clustered at the village level (N = 376; 21 clusters), reported in parentheses. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; † $p < 0.10$. District reference category = Kanungu; gender reference = Female. IRR = Incidence Rate Ratio, computed from the Poisson coefficient. Model fit: OLS residual SE = 1.14 on 357 df; $R^2 = 0.294$; adjusted $R^2 = 0.258$; $F(18, 357) = 8.25$; $p < 0.001$. Poisson null deviance = 435.22 (375 df); residual deviance = 328.60 (357 df); AIC = 1105.8. Negative Binomial null deviance = 435.20 (375 df); residual deviance = 328.59 (357 df); AIC = 1107.8; $\theta \approx 29,261$.

Household size and, more weakly, education level are positively associated with the adaptation index: household size is significant across every estimator (IRR = 1.048), while education level is significant under the count estimators (IRR = 1.106) but only marginal under OLS ($p = 0.108$) once village clustering and tool ownership are both accounted for. Years of experience in coffee farming remains significant and negative across every estimator and both standard-error specifications ($\beta = -0.013$; $p = 0.011$; OLS, village-clustered; IRR = 0.991), the opposite sign from education and household size despite all three belonging to the same nominal capital domain; we return to the implications (Section 4.2). Within natural capital, land size, soil fertility, and water access are all marginally significant under OLS ($p = 0.06$ – 0.08) but not significant under the count estimators. Within physical capital, tool ownership count is significant and positive across every estimator (IRR = 1.099; that

is, each additional tool owned is associated with a 9.9% increase in the expected number of practices adopted). While neither irrigation equipment ownership nor distance to the agro-input shop is significant, irrigation equipment is owned by only six of 376 households (1.6%) in this sample, which likely explains its unstable, non-significant estimate.

Within financial capital, the two constituent variables diverge sharply. Off-farm income is significant and positive under OLS ($\beta = 0.305$; $p = 0.044$) though not significant under the count estimators ($p = 0.28$ – 0.39). Credit access is not significant in any specification and trends negative ($\beta = -0.183$ to -0.095 ; $p = 0.11$ – 0.29 across estimators). This disaggregation clarifies that a null composite result for financial capital (Section 3.4) masks an offsetting pattern between its two constituent variables. Within social capital, knowledge exchange with other farmers is significant and positive across every estimator ($p < 0.01$ throughout; IRR = 1.346), the single most robust covariate in the model. Cooperative membership is significant in the count models (IRR = 1.385) and marginally significant under OLS ($p = 0.071$). Having received training is significant and positive across all specifications (IRR = 1.227). Among the contextual variables, district effects are evident under OLS, where households in Ntungamo ($\beta = 0.813$; $p < 0.001$) recorded significantly higher adaptation scores relative to Kanungu (the reference category), though this difference is not significant in the count models ($p = 0.26$) once village-clustered standard errors are applied. Gender is marginally associated with adaptation intensity under OLS (male respondents scoring higher; $p = 0.071$) but is not significant in the count models.

3.4. Composite-Capital Specification

Table 7 reports the composite-capital specification, in which the constituent variables in Table 1 are aggregated into the five SLF capital domains following prior studies in this literature, estimated with the same OLS, Poisson, and Negative Binomial estimators (model-based standard errors, for direct comparability with that body of work). Human capital ($\beta = 1.272$; $p = 0.035$, OLS) and social capital ($\beta = 0.705$; $p = 0.001$, OLS) are significant and positive across every specification, consistent with the disaggregated results above. Natural capital is marginally significant under OLS ($p = 0.093$) and Poisson ($p = 0.064$). Physical capital is significant and positive under OLS ($\beta = 1.239$; $p = 0.041$) and marginally significant under the count estimators ($p = 0.053$), the first specification in this analysis in which physical capital reaches significance; this follows directly from including tool ownership as a third component, since the earlier two-component index (irrigation equipment and distance) was built almost entirely from a near-constant variable (only 1.6% of households own irrigation equipment) and consequently carried little signal. Financial capital is not statistically significant as a composite measure ($p = 0.06$ – 0.31). This null result may reflect offsetting associations between its two constituent variables, with the composite effect therefore masking differences in the direction or strength of the individual association. In practical terms, the disaggregated specification fits the data better than the composite specification: Poisson AIC was 1105.8 under the disaggregated model compared with 1117.5 under the composite, a difference of 12 AIC units, which by conventional interpretation represents substantially stronger support for the disaggregated approach.

The human-capital composite is noticeably weaker here than it would be without the addition of farming experience; adding this third, negatively signed constituent to the two-component (education and household size) index reduces the OLS coefficient from 1.885 to 1.478 and its Poisson counterpart from 1.177 to 0.917 (both remain significant, but less strongly so). The composite specification's overall fit also worsened on adding this variable, Poisson AIC rose from 1107.3 to 1121, and residual deviance rose from 346.19 to 359.80 on the same degrees of freedom, even though the same variable firmly improved the disaggregated model's fit (Poisson AIC fell from 1112.3 to 1109.6). This contrast is a direct

empirical demonstration that, averaging a positively and a negatively signed variable into one composite index does not merely fail to reveal the offsetting relationship; it can make the composite a strictly worse summary of the underlying data than the disaggregated variables it was built from.

Table 7. Composite-capital specification.

Variable	OLS (AI_PCA)	Poisson	Neg. Binomial	OLS (AI_MCA)
Human capital	1.272 * (0.600)	0.775 † (0.403)	0.775 † (0.403)	0.368 * (0.174)
Natural capital	0.525 † (0.312)	0.401 † (0.217)	0.401 † (0.217)	0.152 † (0.090)
Physical capital	1.239 * (0.603)	0.723 † (0.374)	0.723 † (0.374)	0.358 * (0.174)
Financial capital	0.347 † (0.184)	0.129 (0.128)	0.129 (0.128)	0.100 † (0.053)
Social capital	0.705 ** (0.218)	0.592 *** (0.141)	0.592 *** (0.141)	0.204 ** (0.063)
Training	0.425 ** (0.140)	0.209 * (0.093)	0.209 * (0.093)	0.123 ** (0.040)
Ntungamo	0.623 *** (0.182)	0.146 (0.124)	0.146 (0.124)	0.180 *** (0.053)
Rukungiri	0.221 (0.179)	−0.027 (0.130)	−0.027 (0.130)	0.064 (0.052)
Sheema	0.257 (0.183)	−0.015 (0.127)	−0.015 (0.127)	0.074 (0.053)
Gender: Male	0.274 * (0.134)	0.090 (0.092)	0.090 (0.092)	0.079 * (0.039)
Intercept	−2.202 *** (0.304)	−0.775 *** (0.207)	−0.775 *** (0.207)	−0.636 *** (0.088)

Notes: Standard errors are model-based (not clustered), for direct comparability using this specification. Significance: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; † $p < 0.10$. Model fit: OLS— $R^2 = 0.215$; adjusted $R^2 = 0.193$; $F(10, 365) = 9.98$; $p < 0.001$. Poisson—null deviance = 435.22 (375 df); residual deviance = 356.39 (365 df); AIC = 1117.5. Negative Binomial—null deviance = 435.20 (375 df); residual deviance = 356.38 (365 df); AIC = 1119.6; $\theta \approx 25,330$.

Physical capital's tool-ownership addition provides an instructive contrast. Unlike experience, tool ownership does not offset the other constituents of its capital domain. Irrigation equipment and distance are both weak, near-null signals, so adding a genuinely informative variable improves the composite model fit instead of diluting the contribution of the other variables. The composite Poisson AIC decreases from 1121 to 1117.5 after adding tool ownership, alongside a corresponding improvement in the disaggregated model, where Poisson AIC decreases from 1109.6 to 1105.8 (Section 3.5). The two additions show that aggregation is not uniformly harmful or harmless; its cost depends on whether a capital domain's constituent variables actually move together in the data, which is testable, and should not be assumed.

3.5. Model Diagnostics and Robustness

The appropriateness of the Poisson specification for the disaggregated main model was confirmed through the dispersion ratio, calculated as the ratio of residual deviance to residual degrees of freedom, that is $328.60/357 = 0.920$. As this value is close to unity, there is no evidence of overdispersion in the data. The corresponding ratio for the composite-capital specification was $356.39/365 = 0.976$. The Akaike Information Criterion (AIC) was lower for the Poisson than for the Negative Binomial specification in both the disaggregated model (1105.8 vs. 1107.8) and the composite model (1117.5 vs. 1119.6). Given the absence of overdispersion, these AIC values are reported descriptively and are not used as the basis for a formal model-selection test between the two count estimators.

Two additional robustness checks support the main findings. First, the PCA- and MCA-based adaptation indices are essentially identical in the ranking of households they produce (Spearman's $\rho = 1.00$; Table A1), indicating that the choice of dimension-reduction method does not drive the reported results. Second, re-estimating the disaggregated specification

on the subsample of 372 households with no missing adaptation-item responses produces coefficients materially unchanged from the full-sample results, with no sign reversals and no changes in significance classification of substantive consequence for any covariate, including years of coffee-farming experience ($\beta = -0.013 \rightarrow -0.014$, OLS; both $p < 0.01$) and tool ownership count ($\beta = 0.151 \rightarrow 0.166$, OLS; both $p < 0.02$) (Table A2). Multicollinearity diagnostics (VIF/GVIF) for both the disaggregated main specification and the composite-capital specification are reported in Table A3; all values are well below conventional thresholds of concern (maximum GVIF ≈ 1.7 , for the three-level district factor), indicating that the results above are not distorted by multicollinearity among the disaggregated household-characteristic covariates. Third, several adaptation practices show low adoption rates (Table 2), including pruning/de-suckering/stumping (0.8%) and inorganic fertilizer application (1.6%). Rare practices contribute little variance to either index or are unlikely to individually drive the reported associations. However, their sparsity limits the precision of any practice-specific relationships, similar to the near-constant irrigation-equipment covariate discussed in Section 3.3.

3.6. Agroecological Zone (AEZ) Robustness Check

The four study districts fall within two agroecological zones. Ntungamo and Sheema in the Southwestern Agroecological Zone (SWAEZ, $n = 191$), and Kanungu and Rukungiri in the Southwestern Highland Agroecological Zone (SWHAEZ, $n = 185$). Mean adaptation intensity was higher in the SWAEZ (1.76; SD = 1.37) than in the SWHAEZ (1.34; SD = 1.10), consistent with the district-level pattern (Section 3.2; Table 4). As a robustness check, the main disaggregated OLS and Poisson models were re-estimated using a two-level AEZ indicator, with SWAEZ as the reference category, in place of the four-level district indicator (Table A4). Standard errors were clustered at the village level. The covariates significant in the district specification, including household size, years of coffee-farming experience, tool ownership, off-farm income, knowledge exchange, and training, retained the same direction and statistical significance under the AEZ specification. Soil fertility became significant under the AEZ specification (OLS; $p = 0.028$), while education remained marginally significant. The SWHAEZ coefficient was negative and significant in the OLS model ($\beta = -0.521$; $p = 0.002$), but not in the Poisson model ($p = 0.149$). Since SWAEZ corresponds predominantly to Robusta production and SWHAEZ to Arabica, this negative coefficient suggests that Arabica-zone households adopted fewer adaptation practices than Robusta-zone households under comparable household resource endowments, although this interpretation should be treated with caution given that the AEZ indicator is a district-level proxy instead of a household-level measure of coffee type. Model fit was broadly comparable across specifications, with a marginally lower Poisson AIC for the AEZ model (1104.4 vs. 1105.8) and a marginally lower adjusted R^2 under OLS (0.249 vs. 0.258). These results indicate that the principal associations are broadly robust to replacing the four-level district specification with the two-level AEZ specification. District was therefore retained as the primary spatial unit because it corresponds to the study's sampling design, while the AEZ specification is reported as a robustness check.

Four household resources showed the most consistent positive relationships with the number of climate-adaptation practices adopted: household size, knowledge exchange with other farmers, training, and ownership of basic farm tools. In contrast, irrigation-equipment ownership and access to credit were not statistically significant after accounting for the other explanatory variables. Years of coffee-farming experience showed a negative relationship with adaptation, indicating that more experienced farmers reported fewer adaptation practices, conditional on the other model covariates. District-level and gender

differences were less robust to alternative standard-error specifications and are therefore interpreted with greater caution.

4. Discussion

Three findings from Section 3 anchor this discussion; that is, knowledge-related resources (education, farmer-to-farmer exchange, and training) are the most consistent predictors of adaptation; land and basic farm tools matter more than large capital items like irrigation equipment; and years of farming experience predict less adaptation, not more, once education is held constant. These results push back against a common assumption in the livelihoods literature that human, physical, and financial capital each act as internally consistent domains [27,65,66].

4.1. Descriptive Patterns

Adaptation varies across both households and districts in this sample. Households in Ntungamo and Sheema show higher average adaptation levels than those in Kanungu and Rukungiri, despite only modest differences in observable characteristics, such as education and extension access. This pattern is consistent with evidence that smallholder adaptation is shaped by local enabling conditions, including institutional support, climate information, and farmer learning networks. These factors may influence adaptation alongside household-level attributes [13,17]. One result challenges a simple institutional-access explanation. Sheema records the highest extension access (42.7%) but not the highest adaptation level, which instead occurs in Ntungamo. Extension access alone therefore does not appear sufficient to explain the observed differences in adaptation. Its effectiveness could depend on farmers' capacity to implement recommendations. It may also depend on the local relevance of the information provided, and on how much knowledge circulates through peer learning. This is consistent with evidence that extension systems are more effective when embedded in broader local support and learning environments [67,68].

4.2. Human, Social, and Physical Capitals as Central Adaptation Capitals

Across the estimators and standard-error specifications, education level and knowledge exchange with other farmers were among the most consistent positive predictors of adaptation intensity. This aligns with Deressa et al. [28], who identified education and social capital as significant positive correlates of adaptation among Nile Basin farmers in Ethiopia. It is also consistent with Hassan and Nhemachena [69], who reported comparable patterns across African farming systems. Farmers with higher levels of education may be better able to interpret climate risks, evaluate response options, and implement management adjustments. This aligns with the capability-based perspective, which emphasizes the ability to use resources effectively [70]. Household size was also positively associated with adaptation. This matches findings by Mulinde et al. [71], among Ugandan coffee farmers, and Nabikolo et al. [72], among farmers in Eastern Uganda. This relationship may partly reflect the availability of household labor for practices, such as mulching, trenching, and pruning [73].

Land size under coffee and, to a lesser extent, soil fertility rating were positively associated with adaptation. The composite natural-capital index was also significant in both the OLS and Poisson specifications (Section 3.4). These findings are consistent with Deressa et al. [28] and Hassan and Nhemachena [69], who linked land size and agroecological conditions to adaptation choices among African smallholders. Knowledge exchange and cooperative membership in the count models further highlight the importance of social relationships in adaptation. Farmer networks may reduce uncertainty surrounding unfamiliar practices. They may also facilitate access to relevant information and allow farmers

to observe the experiences of others before adopting new practices. This is consistent with evidence on social networks and technology adoption [74], and network-based learning in climate adaptation [68,75,76]. The significance of human, natural, and social capital variables supports the Sustainable Livelihoods Framework's emphasis on the interaction of multiple asset domains in shaping livelihood responses [21,77,78].

An unexpected finding within human capital is the negative association between years of coffee-farming experience and adaptation. This relationship was consistent across the estimators, standard-error specifications, and the missingness-exclusion check, with more experienced farmers reporting fewer adaptation practices after accounting for other model covariates. Years of farming experience were found to be a significant negative predictor of both climate change perception and adaptation measures among smallholder farmers in Cameroon. This pattern was attributed to “cognitive inertia”, in which established mental frameworks built up over decades make experienced farmers less receptive to interpreting recent conditions as systemic change [79]. This mechanism cannot be confirmed as causal with the present data; it is offered as a possible interpretation, not an established explanation. A second possible explanation relates to investment horizons. More experienced farmers tend to be older. Older farmers may perceive a shorter period over which the returns from adopting new practices would be realized, potentially reducing the expected benefit of adaptation investments relative to continuing with established methods [23,80]. A third possibility is that farmers who have remained in coffee production for many years may have found their established management practices sufficient to sustain production. Such sufficiency may reduce the perceived urgency of adopting additional adaptation measures. Distinguishing among these three mechanisms, i.e., cognitive inertia, shortened investment horizons, and survivorship selection, requires longitudinal data tracking the same households over time. The present study does not provide such data, making this an important priority for future research.

This finding, however, has an important implication for the treatment of livelihood-capital domains. Human capital cannot be assumed to have a uniformly positive relationship with adaptation when its constituent variables operate in different directions. In this study, incorporating years of experience into the composite human-capital index weakened the estimated relationship and worsened the composite model's AIC. By contrast, experience contributed to the fit of the disaggregated specification. This provides empirical evidence that aggregating constituent variables with opposing relationships can reduce the information captured by a composite capital measure.

4.3. Financial Capital, an Offsetting Pattern Within a Single Domain

Financial capital's two constituent variables, credit access and off-farm income, show materially different relationships with adaptation, a pattern that a composite financial-capital index, non-significant in every specification, does not reveal on its own. Off-farm income is a significant positive predictor of the adaptation index under OLS, while credit access is directionally negative and non-significant in every specification. A negative point estimate for formal credit access is not without precedent in this literature. In some studies, farmers who report needing or holding credit are disproportionately those already facing financial constraints on adaptation, which can even reverse a naively expected positive relationship [28]. We do not over-interpret this directionality given its lack of statistical significance. However, the pattern illustrates a more general point. Aggregating variables with potentially offsetting relationships into a single composite index can mask both effects, leaving neither relationship clearly visible. This reinforces the case for entering constituent variables separately whenever the underlying data permit. This is also consistent with the broader literature, which indicates that financial resources in smallholder settings are often

limited or unstable. Available resources may also be directed toward immediate household needs, leaving fewer resources for longer-term adaptation investments [29]. Several of the adaptation practices examined in this study may also be more strongly constrained by knowledge, labor availability, and local coordination than by cash expenditure alone.

4.4. Training, Institutional Support, and Physical Capital

Training and extension access have a positive but comparatively modest effect. Institutional support matters, but on its own it is not enough to drive adaptation. Extension systems remain vital for transmitting climate information and introducing climate-responsive practices [81]. However, adaptation depends on the interaction between knowledge, resources, and local context, not information alone [80]. Consistent with this, adaptation support in Uganda and elsewhere works best when it is locally grounded and aligned with farmers' practical realities [13,81]. Climate information services may also be more effective when integrated into social networks and participatory learning systems, instead of being delivered as standalone advisory content [82].

Physical capital is significant once measured with a broader inventory of farm tools. Neither irrigation-equipment ownership nor distance to the agro-input shop predicts adaptation in any specification. Tool ownership count, covering secateurs, tarpaulins, pruning saws, forked hoes, and watering equipment, is significant and positive across every estimator. The composite physical-capital index also becomes significant under OLS once tool ownership count is included (Section 3.4). These results suggest that some forms of physical capital are more closely related to adaptation than others. Irrigation equipment, a physical asset distinct from the broader practice of introducing irrigation reported in Table 5, is owned by only 1.6% of the sampled households, too rare to estimate a stable effect. Distance to the agro-input shop captures market access and does not directly measure a household's own productive assets. A broader set of farm tools captures implementation capacity more directly. This is consistent with evidence from technology-adoption studies showing that physical-capital measures predict adoption most effectively when they reflect assets directly used in the practices being measured. General access proxies may provide weaker measures of the physical capital relevant to adoption [25,26].

4.5. Spatiality, Gender, and Context-Specificity of Adaptation

District effects persist after controlling for household-level covariates. The Ntungamo effect, however, is significant under OLS but not under the count estimators once village-clustered standard errors are applied. This indicates that inference about place-based effects is sensitive to how within-location correlation is handled. The finding is consistent with evidence that adaptation is context-specific and shaped by local agroecological conditions, institutional environments, and socioeconomic structures [18]. It also aligns with global evidence showing that adaptation strategies vary across regions in response to local enabling conditions. Climate exposure does not fully explain these differences in adaptation responses. District differences may shape the risks farmers face, as well as the feasibility and perceived benefits of specific practices. Adaptation is therefore shaped by local production environments and institutional realities, not a universally transferable package. This is consistent with evidence of uneven climate-smart practice adoption across Ugandan coffee-farming contexts [6]. The AEZ-level robustness check reported in Section 3.6 further indicates that the main covariate relationships are not materially altered when the spatial unit is changed from district to AEZ.

The gender results provide a more nuanced picture of adaptation inequality. Male respondents recorded higher adaptation intensity under OLS, but gender was not significant under Poisson. This difference across model specifications suggests that the relationship be-

tween gender and adaptation is not uniform across the measures and estimators used here. Gender may also operate through access to other enabling resources, including information, tools, training, and decision-making authority. This is consistent with evidence that gender differences in adaptation often reflect unequal access to such resources instead of gender alone [83–85]. The district and gender results indicate that adaptation is influenced by household-level resources, as well as by wider spatial, institutional, and social conditions.

5. Conclusions

This study offers an exploratory, pilot-scale examination of livelihood capitals and climate change adaptation among smallholder coffee farming households in four districts of Southwestern Uganda. Analysis was conducted using both a count-based adaptation index and a PCA-based measure of adaptation intensity. Given the study's geographically bounded scope and sample size, the findings should be interpreted as indicative of patterns within this specific coffee-growing context. They should not be generalized to all smallholder coffee systems without further evidence from other settings. Instead of only aggregating livelihood capitals into composite indices, the analysis also estimated the constituent household characteristics individually, enabling a more detailed, context-specific assessment of their respective contributions to adaptation.

The findings suggest that adaptation is neither random nor uniformly distributed across households and districts. Instead, it appears shaped by heterogeneous combinations of human, social, financial, natural, and physical capital. The constituent variables within several livelihood-capital domains showed distinct, and in some cases opposing, associations with adaptation. Within human capital, education and household size were positively associated with adaptation, whereas years of coffee-farming experience showed a negative association. Similarly, within financial capital, off-farm income was positively associated with adaptation, whereas access to credit was not. Knowledge exchange among farmers emerged as the most consistent predictor across model specifications, pointing to the importance of social learning and farmer networks. The positive associations of training and extension services further suggest a role for institutional support in strengthening adaptive capacity. Within physical capital, ownership of basic farm implements was positively associated with adaptation, while irrigation equipment, owned by only 1.6% of sampled households, showed no significant association in any specification. The observed district-level differences hint that adaptation may be sensitive to local agroecological and institutional contexts, given the pilot nature of this study and its coverage of only four districts. We present these associations as hypotheses that warrant testing in larger and more geographically diverse samples. They should not be interpreted as an established basis for place-based policy design.

Methodologically, this study offers a preliminary but instructive contribution to the climate change adaptation literature. It does so by estimating the constituent variables of livelihood capitals individually, which revealed relationships that a composite-index approach would have concealed, illustrating how aggregated capital indices can obscure heterogeneous mechanisms among their constituent variables. Future research should extend this disaggregated approach to larger, multi-regional samples of smallholder coffee farmers to test whether the specific capital–adaptation relationships identified here, i.e., the roles of knowledge exchange, education, and off-farm income, hold beyond Southwestern Uganda. Future work should also examine whether these relationships differ systematically between Robusta and Arabica production systems, a distinction that the present study could only approximate through the AEZ-level indicator.

6. Policy Recommendations

The regression results identify five specific areas where policy can strengthen climate adaptation among smallholder coffee farmers in Southwestern Uganda.

- i. Invest in farmer-to-farmer learning and extension. Knowledge exchange with other farmers was the strongest and most consistent predictor of adaptation across all models, and training was significant and positive in every specification (IRR = 1.227). Extension programs should be participatory, continuous, and embedded in local farmer networks. Guidance on shade-tree management, soil-moisture conservation, pest control, and other critical adaptation practices in both Robusta and Arabica farming systems is needed.
- ii. Improve access to basic farm tools. Farm-tool ownership was significant and positive across all estimators (IRR = 1.099). Subsidized tool packages and cooperative equipment-sharing schemes targeting basic implements, such as secateurs, pruning saws, tarpaulins, forked hoes, and watering equipment, are more actionable for most households than investment in high-cost technologies.
- iii. Design adaptation programs at the district and agroecological zone level. Under the AEZ specification, Arabica-zone households adapted less intensively than Robusta-zone households. These differences persist after controlling for household-level variables. Uniform national programs will miss this variation; adaptation programs should therefore be designed around local agroecological and institutional conditions rather than applied uniformly.
- iv. Support income diversification. Off-farm income was a significant positive predictor under OLS. Policy should support non-farm employment, value addition, and market linkages. Where financial instruments are used, matching grants and group-based mechanisms tied to specific adaptation practices are more appropriate than general credit schemes.
- v. Address structural barriers to women's participation. Gender was marginally significant under OLS but not under the count models. Programs should focus on removing specific access barriers for women. They should be supported in joining and participating in farmer groups, extension activities, and tool/input distribution schemes.

7. Study Limitations and Future Research

Despite providing new evidence on the relationships between livelihood capitals and climate change adaptation among smallholder coffee farmers in Southwestern Uganda, this study has several limitations that should be considered when interpreting the findings.

7.1. Methodological and Data Limitations

The analysis is based on cross-sectional household survey data, which provide a snapshot of adaptation at a single point in time and therefore do not permit causal inference or capture the dynamic nature of adaptation processes. Potential endogeneity and reverse causality cannot be entirely ruled out, as adaptation decisions may themselves influence the accumulation of livelihood capitals. Although village-clustered standard errors were used to account for within-village correlation, the relatively small number of village clusters (21) may reduce the reliability of cluster-robust inference, warranting caution when one is interpreting village- and district-level differences. In addition, while district fixed effects account for broad spatial variation, the models do not explicitly capture fine-scale spatial heterogeneity or spatial dependence that may influence adaptation decisions.

A farmer-level classification by coffee variety was not constructed for this analysis; the Southwestern and Southwestern Highland Agroecological Zones referenced in Section 2.1 are used as a district-level proxy for this distinction, and the possibility that elements of

adaptation differ systematically by coffee type was not tested with an individual-level interaction. Similarly, district- or zone-specific climate normals for the SWAEZ and SWHAEZ could not be sourced at the resolution required for this study; the area-wide climate range reported in Section 2.1 is accordingly a simplification of conditions across the study area.

7.2. Measurement and Variable Scope

This study evaluates adaptation using a defined set of observed household practices. Although these indicators capture the principal adaptation strategies adopted by coffee farmers, they may not fully represent informal, seasonal, or context-specific responses to climatic variability. Similarly, gender is represented by the sex of the household head, which does not capture intra-household processes, such as decision-making authority, bargaining power, labor allocation, or control over productive resources, that may shape adaptive capacity. The measurement of physical capital was expanded to include ownership of five farm tools alongside irrigation equipment and distance to the nearest agro-input supplier; however, other potentially relevant dimensions, including transport infrastructure, storage facilities, and market accessibility, were beyond the scope of the present analysis and warrant further investigation. The survey did not capture how long each adaptation practice had been in use. Adoption was therefore measured as current status, which limits the ability to distinguish recently adopted practices from long-established ones. Adaptation practices were measured through farmer self-report instead of direct observation. This might have introduced possible recall bias, social-desirability reporting, and variation in how farmers attribute a practice to climate change versus routine farm management. Reported prevalence and regression estimates therefore reflect perceived, self-reported adaptation, not independently verified adoption. This may partly explain the low reported prevalence of pruning, de-suckering, and stumping (0.8% of households; Table 2), a routine coffee-management practice that farmers may not have explicitly framed as a climate response even where it occurred.

7.3. Directions for Future Research

Longitudinal household surveys would provide greater insight into how adaptation evolves over time and strengthen causal understanding of the relationships between livelihood capitals and adaptive behavior. Greater attention should also be given to the institutional environment, specifically, the roles of climate information services and value-chain actors in shaping adaptation outcomes. Integrating quantitative and qualitative approaches with more comprehensive gender-sensitive indicators and broader measures of physical and institutional capital would provide a more nuanced understanding of the socio-institutional mechanisms that facilitate or constrain adaptation to climate change among smallholder coffee farming households.

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Informed Consent Statement: All procedures performed in this study involving human participants were in accordance with the ethical standards of the relevant institutional and/or national research committee. Informed consent was obtained from each individual participant included in the study. Confidentiality and anonymity were maintained throughout data collection, processing, and analysis.

Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors on request.

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Abbreviations

AIC	Akaike Information Criterion
GVIFFs	Generalized Variance Inflation Factors
IRR	Incidence Rate Ratio
MCA	Multiple Correspondence Analysis
PCA	Principal Component Analysis
OLS	Ordinary Least Squares
UNCST	Uganda National Council for Science and Technology
VIFs	Variance Inflation Factors

Appendix A. Model Diagnostic Tests

Table A1. PCA vs. MCA robustness check.

Metric	PCA	MCA
Variance explained (1st component/dimension)	14.67%	14.67%
Spearman correlation with the other index (ρ)	1.00 ($p < 0.001$)	1.00 ($p < 0.001$)

Table A2. Robustness of OLS and Poisson regression estimates to exclusion of observations with missing adaptation responses.

Variable	Baseline (N = 376)	Excluding Missing (N = 372)
<i>OLS specification</i>		
Education level	0.161 ($p = 0.0864$)	0.140 ($p = 0.139$)
Household size	0.073 ($p = 0.0060$)	0.071 ($p = 0.0078$)
Years of coffee-farming experience	−0.013 ($p = 0.0030$)	−0.014 ($p = 0.0016$)
Land size, acres	0.040 ($p = 0.103$)	0.038 ($p = 0.124$)
Soil fertility rating	0.178 ($p = 0.0802$)	0.176 ($p = 0.0861$)
Water access	0.195 ($p = 0.141$)	0.212 ($p = 0.108$)
Irrigation equipment	−0.187 ($p = 0.612$)	−0.259 ($p = 0.486$)
Distance to agro-input shop	0.013 ($p = 0.309$)	0.013 ($p = 0.320$)
Tool ownership count	0.151 ($p = 0.0237$)	0.166 ($p = 0.0131$)
Credit access	−0.183 ($p = 0.129$)	−0.197 ($p = 0.102$)

Table A2. *Cont.*

Variable	Baseline (N = 376)	Excluding Missing (N = 372)
Off-farm income	0.305 ($p = 0.0127$)	0.315 ($p = 0.0104$)
Cooperative membership	0.492 ($p = 0.124$)	0.538 ($p = 0.100$)
Knowledge exchange	0.301 ($p = 0.0249$)	0.312 ($p = 0.0202$)
Training	0.420 ($p = 0.0033$)	0.394 ($p = 0.0058$)
District: Ntungamo	0.813 ($p < 0.0001$)	0.807 ($p < 0.0001$)
District: Rukungiri	0.180 ($p = 0.255$)	0.183 ($p = 0.248$)
District: Sheema	0.411 ($p = 0.0129$)	0.437 ($p = 0.0083$)
Gender: Male	0.194 ($p = 0.0917$)	0.193 ($p = 0.0918$)
<i>Poisson specification</i>		
Education level	0.101 ($p = 0.0453$)	0.085 ($p = 0.0916$)
Household size	0.047 ($p = 0.0104$)	0.045 ($p = 0.0144$)
Years of coffee-farming experience	−0.009 ($p = 0.0116$)	−0.009 ($p = 0.0063$)
Land size, acres	0.017 ($p = 0.174$)	0.016 ($p = 0.195$)
Soil fertility rating	0.141 ($p = 0.0560$)	0.134 ($p = 0.0687$)
Water access	0.132 ($p = 0.129$)	0.152 ($p = 0.0752$)
Irrigation equipment	−0.122 ($p = 0.501$)	−0.165 ($p = 0.359$)
Distance to agro-input shop	0.006 ($p = 0.400$)	0.006 ($p = 0.425$)
Tool ownership count	0.094 ($p = 0.0070$)	0.104 ($p = 0.0022$)
Credit access	−0.095 ($p = 0.237$)	−0.108 ($p = 0.169$)
Off-farm income	0.090 ($p = 0.313$)	0.094 ($p = 0.288$)
Cooperative membership	0.326 ($p = 0.0042$)	0.353 ($p = 0.0017$)
Knowledge exchange	0.297 ($p = 0.0006$)	0.302 ($p = 0.0004$)
Training	0.204 ($p = 0.0118$)	0.180 ($p = 0.0247$)
District: Ntungamo	0.266 ($p = 0.0259$)	0.253 ($p = 0.0333$)
District: Rukungiri	−0.054 ($p = 0.639$)	−0.056 ($p = 0.623$)
District: Sheema	0.086 ($p = 0.452$)	0.097 ($p = 0.388$)
Gender: Male	0.031 ($p = 0.707$)	0.032 ($p = 0.696$)

Notes: Robust (HC1) standard errors are reported. Results compare the baseline sample with the complete-case sample after excluding households with missing adaptation responses. Across both OLS and Poisson models, coefficient signs and statistical significance are substantively unchanged, indicating that the findings are robust to the treatment of missing adaptation data.

Table A3. Generalized variance inflation factor (GVIF) diagnostics for the disaggregated regression specification.

Predictor Variable	df	GVIF	GVIF ^{1/2} (1/2df)
Education level	1	1.439	1.200
Household size	1	1.143	1.069
Years of coffee-farming experience	1	1.372	1.172
Land size, acres	1	1.319	1.149
Soil fertility rating	1	1.142	1.069
Water access	1	1.259	1.122
Irrigation equipment	1	1.168	1.081

Table A3. *Cont.*

Predictor Variable	df	GVIF	GVIF ^{1/2} (1/2df)
Distance to agro-input shop	1	1.247	1.116
Tool ownership count	1	1.431	1.196
Credit access	1	1.233	1.110
Off-farm income	1	1.097	1.047
Cooperative membership	1	1.327	1.152
Knowledge exchange	1	1.263	1.124
Training	1	1.253	1.119
District	3	1.699	1.092
Gender	1	1.180	1.086

Notes: GVIF values are substantially below commonly used thresholds for problematic multicollinearity.

Table A4. Correlates of climate change adaptation across agroecological-zones.

Variable	OLS (AIPCA)	Poisson
<i>Human capital</i>		
Education level	0.183 † (0.100)	0.107 * (0.048)
Household size	0.069 ** (0.022)	0.046 * (0.019)
Years of coffee-farming experience	−0.012 * (0.005)	−0.008 † (0.004)
<i>Natural capital</i>		
Land size (acres)	0.041 † (0.024)	0.017 (0.013)
Soil fertility rating	0.196 * (0.089)	0.155 † (0.093)
Water access	0.152 (0.118)	0.104 (0.085)
<i>Physical capital</i>		
Irrigation equipment	−0.295 (0.359)	−0.181 (0.160)
Distance to agro-input shop	0.012 (0.012)	0.004 (0.009)
Tool ownership count (0–5)	0.158 ** (0.054)	0.093 ** (0.035)
<i>Financial capital</i>		
Credit access	−0.205 (0.126)	−0.094 (0.085)
Off-farm income	0.302 * (0.147)	0.087 (0.102)
<i>Social capital</i>		
Cooperative membership	0.490 (0.340)	0.330 * (0.159)
Knowledge exchange	0.261 * (0.107)	0.285 *** (0.053)
<i>Other covariates</i>		
Training (last 3 years)	0.413 ** (0.125)	0.208 ** (0.074)
AEZ: SWHAEZ (ref. SWAEZ)	−0.521 ** (0.165)	−0.201 (0.140)
Gender: Male (ref. Female)	0.183 † (0.108)	0.031 (0.088)
Constant	−1.790 *** (0.344)	−0.764 ** (0.284)

Notes: Coefficients are reported with village-clustered standard errors in parentheses. N = 376 households and 21 village clusters. AIPCA = PCA-based adaptation index. The OLS model estimates the continuous AIPCA, whereas the Poisson model estimates the count-based adaptation index. SWAEZ is a reference agroecological zone. Female is the reference category for gender. † $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

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