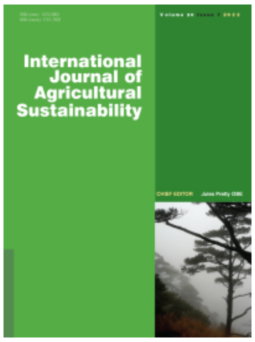

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Smallholder coffee farmers' perceptions of climate variability and the adoption intensity of climate-smart agriculture technologies in Uganda

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ABSTRACT

The current adoption intensity of Climate-Smart Agriculture Technologies (CSATs) among smallholder farmers is below the desired level despite the increasing climate change challenges. This study analysed the perceptions of smallholder coffee farmers towards climate variability and how these influence the adoption intensity of CSATs. A survey was conducted with 226 randomly selected coffee farming households in Luweero district, Uganda. Multivariate regression, Multivariate probit and Poisson regression were used to assess the determinants of farmers' perceptions of climate variability, the determinants of adoption among the different CSATs and the influence of farmers' perceptions of climate variability on the adoption intensity of CSATs, respectively. The findings show that smallholder farmers are aware of climate variability, as their perceptions about the increase in temperature and decrease in rainfall align with the available meteorological data. Additionally, farmers' perceptions of changes in rainfall and temperature, credit access, interaction with an extension worker and access to climate information positively influence their adoption intensity of CSATs. The study recommends that efforts to enhance the adaptive capacity of smallholder farmers should consider enhancing farmers' climate variability awareness through the provision of climate information, enhancing farmers' access to credit facilities, and strengthening extension service delivery to support farmers in implementing multiple healthy and environmentally friendly CSATs.

KEYWORDS

Adoption intensity; climate variability; climate-smart agriculture; perceptions; smallholder farmers; Uganda; regenerative agriculture

1. Introduction

Uganda is vulnerable to the effects of climate change due to various mechanisms that contribute to climate variability in the country (Nsubuga & Rautenbach, 2018; Nyenje & Batellan, 2009). Among these is its geo-location and as such the temperatures are determined by the heat emission from the earth's surface, the Inter-Tropical Convergence Zone (ITCZ), subtropical anticyclones, monsoonal winds and the moist westerly winds from the Congo basin (Nsubuga et al., 2011). Other major elements like large water masses and topography also affect Uganda's climate (Nsubuga et al., 2011; Nsubuga & Rautenbach, 2018; Nyenje & Batellan, 2009). The climate change vulnerability is worsened by undesirable human activities including deforestation, ecosystem degradation, environmental pollution, urban and wildfires and poor land use (Sserwadda, 2011). Some scholars have indicated that over the past years in Uganda, the temperatures have increased (Nsubuga & Rautenbach, 2018), while the rainfall has decreased (Nsubuga et al., 2014a; Nsubuga & Rautenbach, 2018). Severe drought periods have also been identified (Phillips & McIntyre, 2000), yet with extreme rainfall events characterized by floods (Nsubuga et al., 2014b). Forward predictions show a potential 1.5–2°C surface

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temperature increase in 20 years under any of the Representative Concentration Pathways (RCP) scenarios (Nsubuga & Rautenbach, 2018). Similarly, overall rainfall is unlikely to change much, but extreme weather events, especially droughts and flooding, are foreseen (Nsubuga et al., 2014b). The situation will worsen if business stays as usual for both daily and seasonal temperatures and rainfall (Nsubuga & Rautenbach, 2018). This means that action needs to be taken to counter the potential negative effects of the changing climate in the country (Nsubuga et al., 2014a; Nsubuga & Rautenbach, 2018).

Among all sectors in the country, the agriculture sector is the most vulnerable to the changing climate (Nsubuga & Rautenbach, 2018). Like in many other developing countries, the sector is a major economic and livelihood contributor to Uganda's economy, employing more than 72% of the population (UBOS, 2015). A lot of evidence exists where climate change has impacted agriculture. In 2006, it was estimated that about 800,000 hectares of crops on average were destroyed annually by climate-related effects, resulting in losses of an equivalent of over $32,432,432 (UNWDR, 2005). In 2010, flood disasters hit the Teso sub-region, leading to crop damage and loss worth $2,162,162, through rotting cassava, sweet potato tubers and groundnuts (Government of Uganda, 2015). Climate variability has also lowered the productivity of major cash crops like coffee in major producing districts like Luweero (Jassogne et al., 2013b) and lowered the productivity of food crops like maize, cassava, bananas and beans (Tumwine et al., 2019). This means that farmers, in particular smallholder farmers, who make up the largest population of Ugandan farmers, are the most vulnerable considering the adverse effects of climate change on agricultural productivity (Deressa, Hassan, Ringler, Alemu, et al., 2009). The fact that Uganda relies majorly on rainfed agriculture worsens its vulnerability to the changing climate (Nakabugo et al., 2019; Nsubuga & Rautenbach, 2018). Adaptation is particularly important in agriculture, given the climate sensitivity of the sector (Nsubuga & Rautenbach, 2018). The questions, therefore, are whether farmers, more so the smallholders, are aware of climate change and whether their perceptions of climate change match or vary from the actual meteorological data. These are two crucial questions that in part this study seeks to address.

The coffee sub-sector is expected to be one of the worst hit by climate change since coffee is a very fragile crop and highly sensitive to climate variability (Bunn et al., 2015; Kath et al., 2020). Many studies have predicted that climate change will have a massive impact on the coffee-growing regions of Uganda (Jassogne et al., 2013a; Mulinde et al., 2019). The surface temperature rise will force the Arabica coffee *(Coffea arabica)* growing areas to move uphill, causing forest encroachment, risks of landslides on steep hills, and biodiversity loss (Caffrey et al., 2013; World Bank, 2012). Areas suitable for growing coffee will also reduce drastically (Jassogne et al., 2013a). The Robusta coffee (*Coffea canephora*) growing areas in central Uganda like Luweero need to fundamentally transform their cropping system for coffee to survive even under low RCP scenarios. Specifically, high temperatures and unpredictable rains increase the plant water stress and coffee's susceptibility to pests and diseases like Black Coffee Twig Borer (BCTB) and Coffee Wilt Disease (Adhikari et al., 2020). These cause early ripening of coffee beans and loss of berries, which negatively affect coffee quality and yields (Jassogne et al., 2013a). Indeed, in a survey by Infante et al. (2023), farmers highlighted that coffee pests like leaf miners, coffee berry borer, mealy bugs and skeletonizes that were not common in the past had increased in incidence, severity, seasonality and trends. In areas where the suitability for coffee will be reduced, adaptation strategies will need to be undertaken to sustain its production (Jassogne et al., 2013a). It is estimated that if nothing is done, climate change will continue to have more adverse effects on coffee growth and productivity (Jassogne et al., 2013a). Coffee is Uganda's largest agricultural export product. It is produced by more than 14.4% of the smallholder farming households (Kagezi et al., 2019) and is a main livelihood source for over 33% of the households in Uganda (UBOS, 2018). As coffee contributes to 20% of the total export revenue (BOU, 2018), climate change impacts on coffee productivity will result in a negative impact on the national economy (UCDA, 2012). This means that climate change adaptation strategies for coffee cannot be ignored by smallholder farmers. As such, smallholder farmers need to realize that the climate is changing and they should also be able to identify and implement suitable CSATs at appropriate intensities. There is limited literature on climate variability awareness and perceptions among smallholder coffee farmers in Uganda (Mulinde et al., 2019). To ensure more sustainable coffee production in the country, smallholder coffee farmers' perceptions of climate variability and the possible effects this could have on their adaptation of CSATs need to be explored broadly.

The severity of the future impacts of climate change is largely determined by peoples' present ability and action to adapt (Wolf & Moser, 2011). Farmers' perceptions of climate variability must also be considered (Zakaria et al., 2020). Many scholars have used different measures of climate change for rainfall and temperature (Mairura et al., 2021; Tesfahunegn et al., 2016). Indicators of rainfall changes include; crop failure due to water shortage, changes in planting time/date, changes in rainy season frequency, decrease in rainfall, delayed onset, prolonged dry seasons, short rain seasons, increased volume of rainfall, early onset and early exit of rainfall, and switch to drought-tolerant crops. Whereas the indicators of temperature changes include: quick water source disappearance, temperature rise, hotter dry seasons, frequent crop diseases, high day temperature, frequent human diseases, frequent livestock diseases, switch to heat-tolerant crops and emergency of new plant species (Mairura et al., 2021; Tesfahunegn et al., 2016). This shows that there are so many climate risks that farmers need to face (Mairura et al., 2021; Tesfahunegn et al., 2016). To secure agricultural productivity and rural livelihoods, farmers must adapt to climate change (Nsubuga et al., 2014a; Nsubuga & Rautenbach, 2018). Understanding the motivating factors leading to adaptive behaviour is key to promoting climate change adaptation. An important precondition to understanding individual climate adaptive behaviour is revealing farmers' cognitive processes (Azadi et al., 2019), which are shaped by their perceptions of climatic variability (Hyland et al., 2016; Wiid & Ziervogel, 2012). A positive relationship has been found between farmers' perceptions of climate change and agriculture technology adoption (Saguye, 2017; Zakaria et al., 2020). However, a lack of knowledge of climate variability and its impacts has been noted as a barrier to CSAT adoption among farmers (Kumar & Sidana, 2018; Ndambiri et al., 2013), meaning that farmers who are unaware of climate change may lack knowledge of appropriate strategies to adapt to its impacts. The link between smallholder farmers' perceptions of climate change and the adoption of agricultural technologies has been studied but only to a limited extent (Kumar & Sidana, 2018; Ndambiri et al., 2013). Previous research reveals that these relations are not adequately understood, addressed or considered (Meijer et al., 2015). This study, therefore, aims to further expound on the evidence base of how farmers' perceptions of climate variability influence their adoption of CSATs. While the perception of climate change and its impacts can motivate adaptive behaviour (Hyland et al., 2016), farmers' adaptive behaviours are also strongly shaped by personal, environmental and socio-economic contexts (Satterfield et al., 2018). To better understand farmers' adaptative behaviour to climate change, it is necessary to investigate both internal (e.g., cognitive) and external (e.g., institutional) factors. This study explores the influence of factors such as gender, education level, farming experience, familiarity with CSA, household size, access to credit, farmers' interaction with extension agents and attendance of business skills trainings, not only on CSATs adoption but also on farmers' climate variability perceptions.

As farmers are confronted with multiple climate-related risks (Mairura et al., 2021; Tesfahunegn et al., 2016), a CSAT portfolio may be considered to simultaneously tackle some of those risks and exploit the possible adaptation benefits (Aryal, Jat, et al., 2018). A combination of multiple CSA technologies also contributes to the achievement of the objectives of regenerative agriculture, including tree restoration and maintenance, preventing land degradation, soil fertility and soil health enhancement through restoring degraded soils (Leu, 2004). Some CSATs are complementary and work better in combination. For example, laser land levelling facilitates minimum tillage because it is easier to operate zero tillage seed drills on a laser-levelled field (Aryal, Jat, et al., 2018). Hence, enabling farmers to get both services as a package can enhance their adoption. A CSAT portfolio potentially helps overcome adoption challenges, which often undermine the farmer's ability to achieve the full economic and environmental benefits of adoption (Nakabugo et al., 2019). Complementarities among CSATs can also increase income (Kassie et al., 2015), stimulate further adoption (Sharma et al., 2016) and enhance adaptive capacity (Fleischer et al., 2011; Nakabugo et al., 2019). This supports a more positive transition to self-regenerating land management as well as regenerative food (Lal, 2020) and farming systems as a whole (Leu). Existing studies on multiple CSATs adoption considered the influence of socio-demographics like age, gender, and family size but not climate variability perceptions (Aryal, Rahut, et al., 2018). Aryal, Rahut, et al. (2018) examined the influence of the main climate risks farmers had experienced during the last years on CSATs adoption in the Indo-Gangetic Plains of India. The study hypothesized that farmers experiencing high temperatures and low rainfall were more likely to adopt CSATs, but this needs to be proven further with evidence from other localities. Additionally, most CSA studies have only assessed the influence of farmers' climate variability perceptions on the adoption of a particular CSAT (Nakawuka et al., 2018). As such, there is limited literature on how farmers' climate variability perceptions affect the adoption of multiple CSATs, particularly adoption intensity, which reflects the number of agriculture technologies a farmer adopts (Kolady et al., 2021). As there are more benefits of adopting multiple CSATs, this study fills the existing literature gap by assessing the influence of farmers' climate variability perceptions on the adoption intensity of multiple (18) CSATs for coffee production consisting of pruning, de-suckering, mechanical weeding, gap filling, stumping, soil and water conservation, planting and management of shade trees, intercropping with bananas, chemical pest management, chemical disease management, mulching, cultural pest and disease control, planting of cover crops, manure application, irrigation, and application of inorganic fertilizers, planting improved coffee varieties and herbicide application (Alemu & Dufera, 2017; Jassogne et al., 2013a, 2013b; Kirungi et al., 2023). As climate change is complex and multifaceted, the more CSATs adopted by a farmer, the higher the resilience to climate change effects and the more CSA benefits would be realized as compared to fewer technologies (Kolady et al., 2021). Therefore, the desired and most appropriate situation, if resources were not limited, would be the adoption of all the 18 CSATs reflected in step 4 of the coffee Climate Smart Investment Pathways (CSIPs), generating the highest coffee yield amidst the changing climate (Jassogne et al., 2017; Kirungi et al., 2023). However, since farmers are resource-constrained, adopting at least more than half of the CSATs (10 or more, CSIP steps 3 and 4) would be adequately appropriate for farmers to realize higher benefits of CSA than if they adopted fewer CSATs (steps 1 and 2 of the CSIPs) (Jassogne et al., 2017). Indeed, CSATs can increase crop yields and enhance food security, adaptation and resilience to climate change (Aryal, Jat, et al., 2018). However, a few of the CSATs could be detrimental to health and the environment, including the use of chemicals (Banjo et al., 2010) and inorganic fertilizers (Ketema & Kabete, 2017). These result in the emission of GHG, pollute the water and environment and destroy biodiversity (Banjo et al., 2010; Ketema & Kabete, 2017). There is no substantial evidence on the adoption rate of these would-be detrimental technologies among smallholder farming systems. This calls for more research in this aspect and how this can be overcome, which the current research will explore to fill the existing knowledge gap.

Several studies have highlighted that a lack of CSA knowledge and awareness is a key barrier to CSAT adoption in developing countries (Manda et al., 2019; Moutouama et al., 2022). Therefore, before adopting CSATs, farmers must understand what CSA entails (Gwambene et al., 2015). Beyond this, they can identify CSATs to adapt to climate change (Gwambene et al., 2015). As such, there is limited literature on farmers' familiarity with CSA in developing countries and less on how this influences the adoption intensities of CSATs. The present study will contribute new knowledge on smallholder coffee farmers' familiarity with CSA, their perceptions of climate variability and how these influence their adoption and adoption intensity of various coffee CSATs.

2. Conceptual framework of the study

To study individuals' responses to climate change, the Model of Private Proactive Adaptation to Climate Change (MPPACC) was created by Grothmann and Patt (2005) and has been widely used by various scholars (Abid et al., 2019; Talanow et al., 2021; Zobeidi et al., 2022). The MPPACC categorizes the diversity of internal and external factors that may determine a person's adaptation intention and the resulting adaptive behaviour. This study adapted the MPPACC as was used by other scholars (Abid et al., 2019; Kolady et al., 2021; Talanow et al., 2021) and modified it to the CSA adoption in the farmer context. As climate change has adverse effects on agricultural productivity, farmers should recognize this challenge and adjust their farming practices (Abid et al., 2019). In this case, we assume that adoption is a linear process that can occur in three main stages, as shown in the MPPACC modified in this study, as shown in Figure 1. In the *first stage*, the adaptation to climate change based on the adoption of CSATs depends on farm and farmer characteristics and their perception of variations in temperature and rainfall. In addition to the usual socio-demographics like gender, education, household size, and farm characteristics like land size (Abid et al., 2019; Kolady et al., 2021; Talanow et al., 2021), other key components like access to climate information (Tesfahunegn et al., 2016), farmers' interaction with an

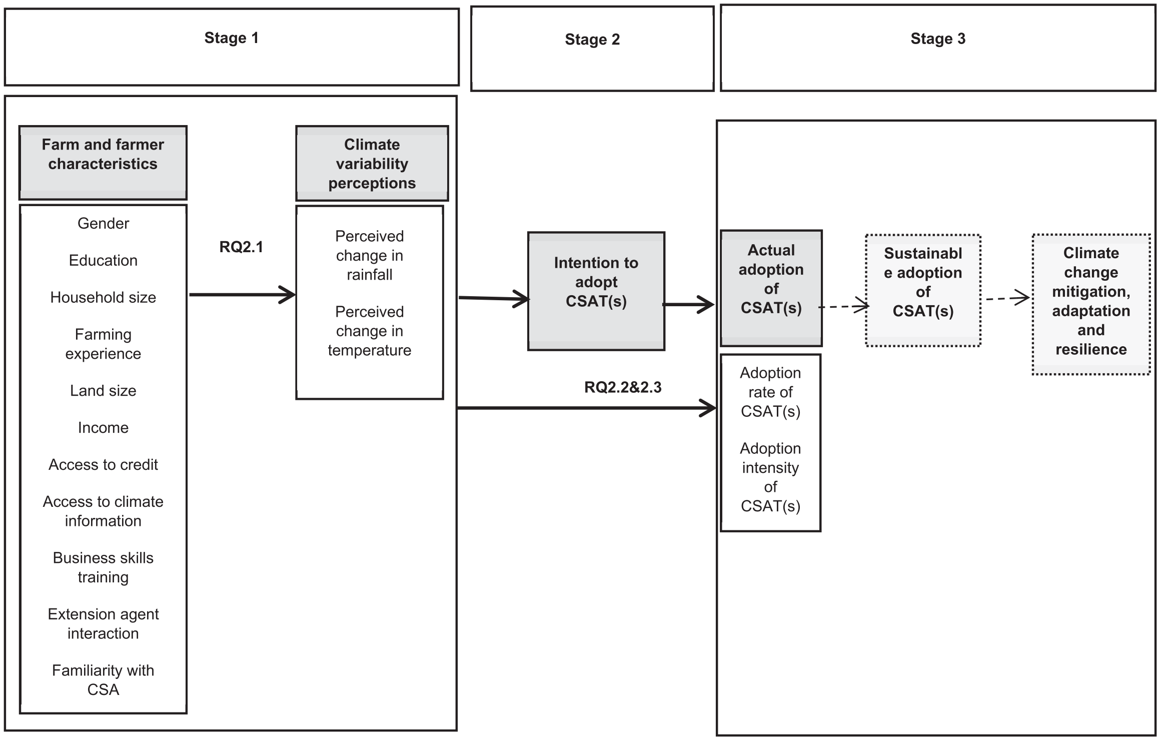

Figure 1. Conceptual framework of the relationship between climate variability, farmer's perceptions and adoption of CSATs (Adapted and modified from [Abid et al., 2019; Grothmann & Patt, 2005; Talanow et al., 2021].).

extension agent (Zamasiya et al., 2017) and farming experience (Grazhdani, 2013; Zakaria et al., 2020) can also influence farmers' climate variability perceptions, consequently influencing their adaptation. In the modified model, these key components have been included. Farmers' accurate perceptions of climate variability and perceived benefits of CSATs in mitigating and adapting to climate change are an important determinant of their intentions and the choice of adaptation methods (Deressa et al., 2011). In the current framework, climate variability perceptions are measured by farmers' perceived changes in rainfall and temperatures (Mairura et al., 2021; Tesfahunegn et al., 2016). In the *second stage,* the intention stage, once the farmers have attained the right perceptions of the changing climate, they become aware of the potential damage it can have on agriculture, and they consider and plan to take on appropriate CSATs (Saguye, 2016; Zakaria et al., 2020). These intentions depend on the accuracy of farmers' perceptions and various internal and external factors; the farm and farmer characteristics, as well as institutional factors like access to climate information. In the *final and third stage*, farmers implement their adaptation measures, which, in the modified model, can be considered at varying rates and intensities. This enables them to ultimately mitigate climate change damages in the long run (Abid et al., 2019). A farmer will adopt a CSAT if its expected utility of adoption and incentive payment exceeds the farmer's utility of not adopting the CSAT, meaning that this is subject to the availability of required resources and affordability of the technologies (Zakaria et al., 2020). The uptake of CSATs at higher rates and intensities can lead to more sustainable adoption of these technologies. We further modify the model to include the contribution of the CSAT adoption in achieving climate change mitigation, adaptation and resilience against climate shocks and damage (Hussain et al., 2022).

As such, this article assesses smallholder coffee farmers' perceptions of climate variability and their influence on the adoption intensity of multiple CSATs utilizing the framework in Figure 1. The study seeks to respond to the following key research questions: (1) How do smallholder farm and farmer characteristics influence their perceptions of climate variability?; (2) How do smallholder farm and farmer characteristics influence their adoption of CSATs?, and (3) How do smallholder farmer perceptions of the climate variability influence their adoption of CSATs? The contribution of this study is four-pronged. Firstly, it examines the correlation between farmers' perception of climate variability and the available meteorological data. Secondly, it highlights the interdependence between different CSATs and analyses the decision to adopt the technologies. Thirdly, it examines the role of key factors determining the adoption of CSATs, such as farmers' perceptions of climate change, farming experience, access to climate information and familiarity with CSA, phenomena that are not widely covered in CSA adoption literature. Lastly, the study separately analyses the determinants of adoption and adoption intensity of multiple CSATs. By this, the study informs future programmes and policies that seek to scale up the adoption and diffusion of CSATs by increasing not only the adoption rate but also the adoption intensity of CSATs. The results of this study will contribute immensely to a better understanding of farmers' climate variability perceptions and other factors influencing CSA technology adoption intensity. These will also be useful as a guide in programme formulation, and advanced climate change and adaptation policies while planning climate change adaptation programmes for farmers. The subsequent sections of the article present the materials and methods, results and discussion, conclusion and recommendations.

3. Materials and methods

3.1. Study area

The study was conducted in the Luweero district, Central Uganda. The district is approximately 75 kilometres, by road, North of Kampala, Uganda's capital. The annual average rainfall is 1300 mm. The mean annual maximum temperature falls between 27.5°C and 30°C, whereas the mean annual minimum temperature is between 15°C and 17.5°C (UCC, 2011). Luweero district is one of the districts in the country that leads in Robusta coffee production (UBOS, 2018), yet is heavily impacted by climate change (Mulinde et al., 2019). Luweero district lies within the dry cattle corridor characterized by erratic swings in seasons with an increased frequency of water shortage and high crop pests and disease incidences that lead to massive crop failure in the district (Opio, 2019). The district has one of the highest prevalences of the Black Coffee Twig Borer (BCTB) and Coffee Wilt Disease in the region (Mulinde et al., 2019), yet the adoption rate of appropriate CSATs by farmers in the district is still low (Kirungi et al., 2023). It is therefore evident that farmers in Luweero are battling with the impacts of climate change, making adopting CSATs of paramount importance to enhance their resilience and adaptation to climate change (Nakabugo et al., 2019).

3.2. Sampling technique and sample size

The participants were purposively selected from Bakyabumba Farmers' Cooperative Society Limited (BFCSL), located in the Butuntumula sub-county. This is the largest farmer cooperative in the Luweero district (NAAS, 2020). As a cooperative, farmers come together and engage in different coffee-related activities, including coffee bulking, coffee management-related trainings and marketing among other activities (Mugoya, 2019). It is also one of the cooperatives through which different organizations promote CSATs adoption in the region (Mulinde et al., 2019) due to the large number of over 1000 smallholder coffee farmers belonging to 23 farmer producer organizations (POs) spread in 4 out of the 9 parishes of the sub-county, i.e. Kyawangabi, Kakabala, Bukambaga and Bamugolodde. This makes the cooperative a suitable pool to provide a representative sample for this study assessing the adoption intensities of CSATs. A cross-sectional study design was used in the study. Multi-stage sampling technique was used to select the sample; that is a purposive sampling of the Luweero district due to its vulnerability to climate change and having coffee as the main cash crop in the district; subjective sampling in selecting farmers with homogeneous characteristics including being smallholders, practicing coffee farming as a main means of livelihood and having participated in interventions that promote CSATs in coffee (Alemu & Dufera, 2017; Faisal Salad et al., 2021; Kirungi et al., 2023) and implementing different coffee CSATs and cluster sampling technique to select participants from the parishes (Lambert & Loiselle, 2008; Sedgwick, 2014). Simple random sampling was used to select the participants from a list of all the farmers in the cooperative. A total of 226 farmers representing 226 coffee farming households spread over the four parishes were randomly selected and participated in the study.

3.3. Data collection

A structured digitized questionnaire was used for data collection. This consisted of simple formulated questions about the farm and farmer characteristics; perceptions on climate variability; perceived awareness of the term Climate-smart agriculture and the type and number of CSATs a farmer adopted. Five research assistants were recruited and trained on the modalities for questionnaire administration. The two-day training of the research assistants ensured uniformity in questionnaire administration and enhanced the credibility of the data collected (Bryan et al., 2009). The terms CSA and CSAT(s) were evaluated by smallholder farmers based on the three pillars of Climate-Smart Agriculture: productivity, adaptation, and mitigation (Moutouama et al., 2022). Ethical approval was obtained from the International Institute of Tropical Agriculture (IITA), and an ethical clearance certificate was obtained from its Internal Review Board (IITA IRB) in accordance with the IITA Research Ethics Policy, with the Reference number of IRB/003/2022. Participants' consent was obtained to be able to partake in the survey. Primary data was collected through a household survey by trained enumerators, ensuring anonymity and confidentiality during data collection. Secondary data were also collected and consisted of Luweero meteorological data for rainfall and temperature for 1951–2020 (World Bank, 2020). The data were collected from 11th April to 23rd April 2022.

3.4. Data analysis

Quantitative primary data were analysed in STATA V15. Preliminary analysis, such as normality and outlier tests, was performed using line graphs, box and scatter plots (Mishra et al., 2019). To understand the farm and farmer characteristics, descriptive statistics were calculated using frequencies, percentages, means and standard deviations, which were presented using tables (Hothorn & Everitt, 2009; Maindonald, 2008). Inferential statistics, such as independent sample t-test and one-way analysis of variance (ANOVA), were also calculated using demographic independent variables and dependent variables. A correlation matrix was used to check for the presence of collinearity and multicollinearity among the explanatory variables (farm and farmer characteristics). There was only collinearity between farmers' age and farming experience (0.73). This means that older farmers also had high farming experience. Farmers' age was taken out of the model and farming experience was taken as the dependent variable to ensure model stability (Mundry, 2014). The study also checked for homogeneity of variance, which exceeded 0.05, indicating no violation of assumptions (Pallant, 2016). The level of significance of different variables was taken at 5% and 95% confidence intervals. The effect size for the t-test as well as the ANOVA was computed. Climate change perception statements, which were measured on a five-point Likert scale, were aggregated for inferential analysis (t-test and ANOVA) (Kothari, 2004), following the approach of Ofuoko, (2011). For each statement, the total score was divided by the number of respondents; for instance, a statement like 'hotter afternoons are experienced these days' may have responses of strongly agree ($f = 65$); agree ($f = 26$); neutral ($f = 23$); disagree ($f = 28$) and strongly disagree ($f = 12$). It will now be worked as $65 \times 5 = 325$, $26 \times 4 = 104$, $23 \times 3 = 69$, $28 \times 2 = 56$ and $12 \times 1 = 12$. Then $325 + 104 + 69 + 56 + 12 = 566$. 9. The sum was divided by the total f thus, $566 \ / \ 154 = 3.6$. In this case, 3.6 is the mean score, which is greater than the cut-off mean score of 2.50 (Ofuoku, 2011). Therefore, for an observation to be important, it had a mean score above 3.6 (Ofuoku, 2011).

3.4.1. Perceptions of climate variability

To assess the determinants of farmers' perceptions of the changing climate (RQ1), the Multivariate Analysis of Variance (MANOVA) was utilized (Ofuoku, 2011). This was an appropriate approach since farmers' perceptions of climate variability consisted of several dependent variables as indicators for rainfall and temperature variations that were condensed into composite variables, allowing for the analysis of how the different farm and farmer characteristics influence these dependent variables collectively (Ofuoku, 2011). The null hypothesis states that farm and farmer characteristics such as gender, farm size, level of formal educational attainment, extension agent interaction, access to climate information and farming experience do not affect farmers' perception of climate variability. It is expected that these variables will affect farmers' perception of climate variability. The implicit form of the model for the analysis is given in equation 1 (Ofuoku, 2011):

$$Y1, Y2 = f(X1, X2, X3, X4, X5, X6, U) \tag{1}$$

where $Y1$ =perception of temperature, $Y2$ = perceptions of rainfall (total Likert's type scale of each respondent); X1 =gender (male = 1, female = 0); $X2$ = farm size (ha); $X3$ = formal education attainment (number of years of formal schooling); $X4$ = interaction with extension agent (yes or no); $X5$ = access to climate information (yes or no); $X6$ = farming experience (years); U = error term

To predict the determinants of the adoption of CSATs (RQ2 and RQ3), we applied a theoretical model, in which it was assumed that the adoption process involves two different decision steps (Mairura et al., 2021; Noltze et al., 2012). First (RQ2), the farmer decides whether or not to adopt the technology (a dichotomous choice-*a*), and second (RQ3), the intensity of adoption-*b* (a metric variable).

3.4.2. Adoption of CSATs (a)

The farmer's process of deciding on whether to adopt or not to adopt a CSAT was modelled using the expected random utility model approach (Cooper & Giovanni, 2002). From the utility model, it can be considered that a farmer i will adopt a CSAT if the expected utility of adoption of the CSAT and the incentive payment exceeds the farmer's utility of not adopting the CSAT. The function Yi = 1 represents the farmers' decision i to adopt a CSAT and Yi = 0 as the farmers' decision not to adopt the CSAT. Assuming that the perceived benefit associated with the farmers' adoption decision (including mitigation and adaptation to climate change) is i^{Yi}, then adoption of a CSAT would actually occur as in equation 2 if

$$E(U(1, \pi_i^1, X)) > E(U(0, \pi_i^0, X)) \tag{2}$$

In this case, X is the explanatory variable that includes the descriptive statistics of the farm and farmer.

Since we do not know the farmer's utility function U (Yi, iYi; X), the deterministic part of the utility function V (Yi, iYi; X), we could estimate the inequality in (1) and represent it as in equation 3:

$$V(1, \pi_i^1, X) + U_1 > V(0, \pi_i^0, X) + U_0, \tag{3}$$

From equation ii, U1 and U0 are distributed independently and identically with random disturbances having means=0 and unit variances.

We can further formulate model 3 above using a latent equation 4

$$Y_i^* = \beta' X_i + \in_i , \tag{4}$$

Y_i^* is the latent variable, X_i are the descriptive statistics of the farm and farmer characteristics. The decision to adopt or not adopt the CSAT is a binary outcome Yi and since it is the observed variable, we can empirically estimate the outcome using a univariate probit model embracing the maximum likelihood estimation as suggested by Karlı et al. (2006) and Kolady et al. (2021) to generate the fourth and final empirical model as in equation 5:

$$Y_i = \beta' X_i + \in_i , \tag{5}$$

here β represents the parameters to be estimated by the model.

To see whether the determinants of adoption vary among the different technologies, the study employed the Multivariate Probit (MVP) model for each CSAT separately. This is a powerful statistical analysis tool that allows for possible association among the unobserved disturbances in the adoption decision equations and the relationships that might exist between adopting a combination of CSATs (Zakaria et al., 2020). MVP model concerns the possibility of complementarities (positive correlation) and substitutability (negative correlation) among the CSATs. Estimating multiple innovations like CSATs without considering the trade-off and combined effect of technology adoption gives biased and inefficient estimates of the factors influencing adoption decisions (Greene, 2003).

3.4.3. Adoption intensity of CSATs (b)

To investigate the determinants of the adoption intensity of CSATs, the study utilized the count models as previously used by Greene (2003) and Kolady et al. (2021) for Precision Agricultural Technologies (PATs). The count model was also used by Karlı et al. (2006) to assess Turkey farmers' decisions to join agricultural cooperatives. It is confirmed that count models based on the number of CSATs a farmer adopts are appropriate when multiple technologies are studied and adoption intensity is the focus (Isgin et al., 2008). As this study focused on coffee farmers' adoption of 18 CSATs for climate change management, the number of CSATs a farmer adopted was used as a proxy measure for technology adoption intensity (Ferrer et al., 2023).

Table 1. Included variables, their description and the expected outcome in relation to the dependent variables.

Variable	Description and measurement type	Variable type	Expected outcome (+/−)
Dependent variables			
Adoption			
Adoption of CSATs	Farmer adopts CSAT(s) (1 = Adopt, 0 = Do not Adopt)	Categorical	
Adoption intensity of CSATs	The total number of CSATs that a farmer was implementing	Metric	
Independent variables			
Farm and farmer characteristics			
Gender	Gender of a farmer (1 = female, 0 = male)	Categorical	
Education years	Years of formal education	Metric	+
Household size	Total number of people in the household	Metric	+
Farming experience	Years spent practicing farming	Metric	+
Land size	Land under farming (Ha)	Metric	+
Income	Total household income ($)	Metric	+
Access to credit	For credit used in production (1 = Yes received, 0 = otherwise)	Categorical	+
Extension agent interaction	Farmers' interaction with an extension agent(1 = Yes interact, 0 = otherwise)	Categorical	+
Access to climate information	Access to climate information (1 = Yes received, 0 = otherwise)	Categorical	+
Business skills training	Farmers attendance to business skills training (1 = Yes, 0 = otherwise)	Categorical	+
Familiarity with CSA	Farmers' familiarity with CSA (1 = Yes, 0 = otherwise)	Categorical	+
Climate variability perceptions			
Perceived change in rainfall	Farmer has perceived changes in rainfall (1 = strongly agree, 2 = agree, 3 = neutral, 4 = disagree, 5 strongly disagree)	Categorical	+
Perceived change in temperature	Farmer has perceived changes in temperature (1 = strongly agree, 2 = agree, 3 = neutral, 4 = disagree, 5 strongly disagree)	Categorical	+

The 18 CSATs for coffee production were used in the model as derived from past literature (Alemu & Dufera, 2017; Faisal Salad et al., 2021; Kirungi et al., 2023). The count value for adoption intensity ranged from zero (0) to eighteen (18). As such, 18 count model analyses were carried out (Kolady et al., 2021).

Adoption intensity was estimated using the model indicated in equation 6 for the count variables separately:

$$\text{Adoption intensity}_i = \gamma' X_i \in_i \qquad (6)$$

where γ is the parameters to be estimated by the equation.

The dependent variable from the count model analysis is assumed to follow a Poisson distribution since it takes a non-negative integer value whose average is small and therefore assumes an equal mean and variance (Greene, 2003). The Poisson regression model was checked for overdispersion (*p*-value less than 0.05). If this was confirmed, then the Poisson regression model would be used and Goodness Of Fit (GOF) indices interpreted accordingly to confirm whether the Poisson regression was a suitable model.

The trend of CSAT adoption by the farmers was analysed using a pairwise correlation matrix (Kolady et al., 2021) to see which technologies were complementary and which ones were not. Table 1 describes the potential explanatory variables for the Multivariate Probit and Poisson Regression model, which are expected to affect, respectively, CSAT adoption and adoption intensity, along with their expected signs. The literature guided the choice of independent variables.

4. Results and discussion

4.1. Sample descriptives

Table 2 presents the characteristics of the sample. The majority of coffee farmers were males, which reflects country statistics (UCDA, 2019). Most respondents were aged above 50 years with more than 10 years of farming experience. This means that coffee farmers are predominantly older males, which is not surprising (Chiputwa & Qaim, 2016; Wairegi et al., 2018). Also, most respondents had less than seven years of formal education. This is common among smallholder communities where most farmers only attended primary school or never attended formal education (Chingala et al., 2017; Okello et al., 2012). Regarding household size, most respondents had an average of six to 10 members. Household size matters in farm labour arrangements since resource-constrained farmers mostly depend

Table 2. Farm and farmer characteristics.

Variable	Category	Frequency	%
Gender	Male	136	58.9
	Female	90	41.1
Age (yrs)	<25	3	1.3
	26–50	108	47.8
	>50	115	50.9
Education (yrs)	<7	166	73.5
	8–11	46	20.4
	9–12	7	3.1
	>13	7	3.1
Household size	<5	83	36.7
	6–10	116	51.3
	>10	27	12.0
Farming experience (yrs)	<10	35	15.5
	11–30	114	50.4
	>30	77	34.1
Credit access	Yes	96	42.5
	No	130	57.5
Access to climate information	Never	14	6.2
	Not sure	33	14.6
	Often	143	63.3
	Very often	36	15.9
Business skills training attendance	Yes	112	49.6
	No	114	50.4
Familiarity with CSA	Yes	217	96.0
	No	9	4.0
Extension agent interaction	Yes	214	94.7
	No	16	5.3
Role of CSA	Food security	161	71.2
	Adaptation	40	17.7
	Mitigation	17	7.5
	Reduce risks	8	3.5
		$\bar{x}$	**SD**
Household income ($)		1201,50	0.4
Land size (ha)		2.2	2.6
Awareness of temperature change		3.4	0.8
Awareness of rainfall change		3.7	0.7

on family labour to manage their farms (Adeoti, 2008; Ogada et al., 2010). Farmers had an average land size of 2.2 ha, a mean annual income of $1,201.5 and limited access to credit. This aligns with previous research that smallholder farmers usually own less than 2.5 ha of farmland (Etonihu et al., 2013; Lowder et al., 2016; Wiggins et al., 2010), have low annual income (Billah et al., 2015; Ketema et al., 2016) and lack access to credit (Chandio et al., 2020; Dzadze et al., 2012; Mukasa et al., 2017). As reported by other scholars, the majority of the farmers interacted with extension agents (Amadu, 2022; Zakaria et al., 2020).

Most farmers never attended business skills training, but often had access to climate information. The mean awareness of farmers to changes in temperature and rainfall was 3.4 and 3.7, respectively. This confirms the fact that farmers are more aware of changes in rainfall than temperature (Aryal, Rahut, et al., 2018). Farmers were familiar with CSA and mostly associated it with roles towards improving food security, then adaptation, reducing climate risks and lastly mitigation. This affirms previous research that farmers related the importance of CSA more to improving productivity and adaptation than mitigation (Gwambene et al., 2015). Possibly, farmers prioritize productivity and adaptability because these are easily observable and measurable, unlike mitigation (Gwambene et al., 2015).

4.2. Farmers' perceptions of climate variability

From Figure A1, the 1951–2020 climate statistics for Luweero show that over the past 20 years, the annual rainfall has declined while the annual mean temperature has increased (World Bank, 2020). The minimum temperature has risen by 0.5–1.2°C while the maximum by 0.6–0.9°C, and since the 1960s, the temperature has risen by 1.3°C (USAID, 2012). The temperature change has caused more hot days and nights (MoWE, 2015). The changes in rainfall reliability, onset and cessation may cause soil degradation, crop failure, food insecurity and hunger (Lyon & DeWitt, 2012). Therefore, farmers must be aware of climate change and take precautions to overcome these obstacles.

The sampled farmers did observe climatic variations over the past 20 years (Figures 2 and 3). Out of the several indicators of climate change and long-term climate variability in literature (Atube, Okello, et al., 2022; Bryan et al., 2009; Mairura et al., 2021; Tesfahunegn et al., 2016), the most observed rainfall changes by farmers in Luweero are crop failure due to water shortage, changes in planting time/date, changes in the frequency of rainy seasons, decrease in rainfall, delayed onset of rainfall, late onset of the rainy season, prolonged dry seasons, short rain seasons, shortened length of rainy season increased volume of rainfall at a time, early onset and early exit of rainfall at a time, switch to drought-tolerant crops. Additionally, the farmers also perceived temperature changes. Based on the mean scores for temperature (>2.5°C), the most perceived changes are; quick water source disappearance, increase in temperature, hotter dry seasons, frequent crop diseases, high day temperature, frequent human diseases, frequent livestock diseases, switch to heat-tolerant crops, and emergency to new plant species.

The perceptions of climate variability among farmers in Luweero reflect actual regional and

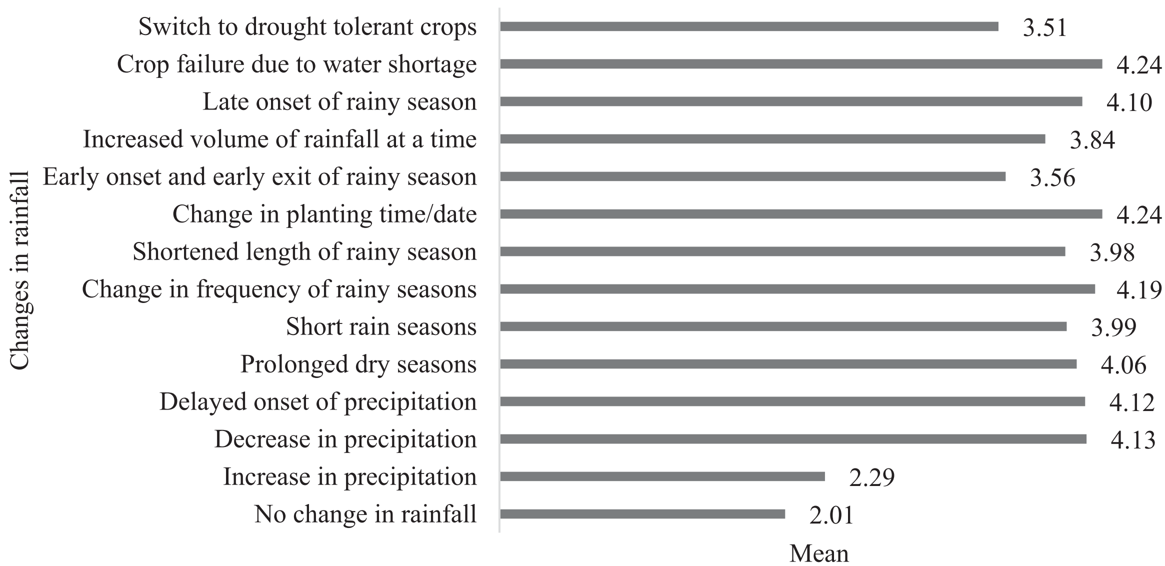

Figure 2. Farmers' perceptions of changes in rainfall. *Cut-off score = 3.0 (> 3.0 = important observation, < 3.0 = not important observation).*

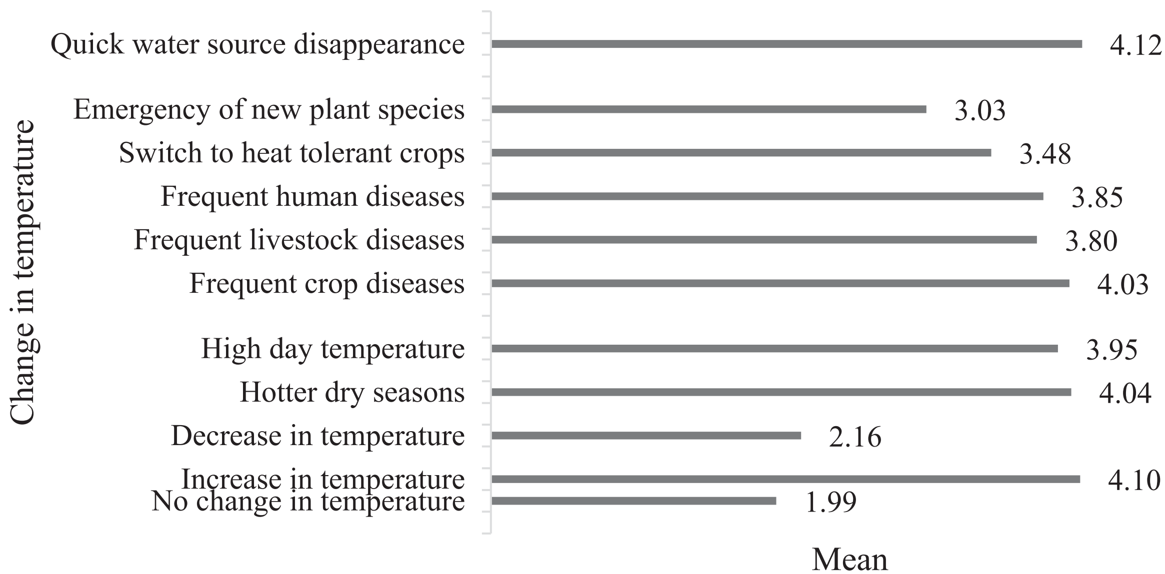

Figure 3. Farmers' perceptions of temperature changes. *Cut-off score = 3.0 (> 3.0 = important observation, < 3.0 = not important observation).*

national climate changes, especially in relation to the decline in rainfall and increase in temperature as presented in Figure A1. Our results corroborate prior studies that most farmers were aware of climate change over the past years, especially increased temperature and decreased rainfall (Atube, Malinga, et al., 2022; Fosu-Mensah et al., 2012; Mairura et al., 2021; Tesfahunegn et al., 2016). Farmers' awareness of climate variability determines the selection of appropriate adaptation options (Bryan et al., 2009).

4.3. Determinants of farmers' climate variability perceptions

Multivariate analysis was performed to further understand the relationship between farm and farmer characteristics and farmers' perception of climate

Table 3. Determinants of farmers' perceptions of climate variability.

	Determinants	Coef	Std. Error	*p*-value	Conf. Interval (95%)	
Change in temperature	Gender	0.39	0.63	0.54	−0.85	1.63
	Familiarity with CSA*	0.07	0.03	0.04	0.01	0.13
	Education years	−0.10	0.09	0.27	−0.29	0.08
	Agricultural experience*	0.05	0.03	0.00	0.01	0.07
	Access to climate info	0.01	0.77	0.99	0.00	1.51
	Extension agent interaction*	0.03	0.02	0.03	0.01	0.12
		Coef Std. Error *p*-value Conf. Interval (95%)				
Change in rainfall	Gender	0.70	0.74	0.35	−2.17	0.76
	Familiarity with CSA **	0.07	0.04	0.05	−0.01	0.14
	Education years	−0.10	0.11	0.30	−0.34	0.10
	Farming experience*	0.05	0.04	0.01	0.02	0.06
	Access to climate info	0.35	0.90	0.70	−1.43	2.14
	Extension agent interaction*	0.06	0.05	0.03	0.00	0.11

$n = 226$, $^{**}P < 0.1$, $^{*}P < 0.05$, $R^2 = (0.53, 0.52$ temp and rainfall resp), F statistic=(1.1, 0.9 temp and Rainfall resp).

variability. Table 3 shows that independent variables explain 53% and 52% of the farmers' perception of change in temperature and rainfall respectively. Both models fit the data well and show that; male farmers with fewer years of formal education, who were more familiar with CSA, who had high agricultural experience, who had interacted with an extension agent and had access to climate information were more perceptive to temperature and rainfall changes than their counterparts. Familiarity with CSA, agriculture experience and interaction with an extension agent were the only significant predictors of farmers' climate variability perceptions. Experienced farmers were more likely to notice temperature and rainfall changes than their counterparts (Mairura et al., 2021; Tesfahunegn et al., 2016). Farmers familiar with CSA have more realistic perceptions about climate variability than those unfamiliar (Gwambene et al., 2015). CSA awareness improves farmers' adaptive skills to anticipate, minimize, and manage climate risks (Gwambene et al., 2015). The farmers' interaction with an extension agent also enhanced farmers' climate variability perceptions (Zamasiya et al., 2017). Male-headed households acknowledge climate change more than female-headed households (Tesfahunegn et al., 2016). Surprisingly, farmers with more formal education were less likely to observe long-term climatic changes, which was also observed by Gbetibouo (2009). This means that most smallholder farmers in Luweero learn about climate change from informal channels other than formal education (Tesfahunegn et al., 2016). This relates to the access to climate information among farmers, for which the extension system is mainly mostly responsible (Ebenehi et al., 2018). Access to climate information can notify farmers of early warning systems, climate variability indicators, and climate adaptation options (Silvestri et al., 2012; Swaminathan & Kesavan, 2012). Disseminating climate information to farmers via trainings, radios, and extension agents is therefore crucial for supporting their climate change adaptation (Ebenehi et al., 2018; Tesfahunegn et al., 2016).

4.4. Farmers' adoption of CSATs

Farmers adopted mostly CSATs requiring unskilled labour (69%), followed by those requiring skilled labour (61%) and high financial investments (44%) (Figure A2). This affirms previous research (Akudugu et al., 2012; Kangogo et al., 2020; Kangogo et al., 2021; Nyasimi et al., 2017) and explains the low adoption of certain CSATs by smallholder farmers due to their resource constraints (Jassogne et al., 2017). It was observed that there was a relatively high rate of adoption of a number of technologies among the farmers that could be detrimental to health, nature, biodiversity and the environment including chemical weed management (53.54%), inorganic fertilizers (44.69%), and chemical pest and disease management with a relatively low adoption rate (29.65%). Other scholars also found a high rate of herbicide use (Kudsk & Streibig, 2003; Obiri et al., 2021), inorganic fertilizer application (Ketema & Kabete, 2017) and chemical pest and disease management (Banjo et al., 2010) among farmers. The high use of these yet detrimental technologies among farmers has been highly influenced by the high prevalence of notorious crop pests and rampant crop diseases, soils with highly leached nutrients and very low soil fertility, the producers and distributors of these technologies who operate in agricultural communities with a high motivation towards achieve substantial sales revenue from these technologies (Ngowi et al., 2007). Similarly, the extension programmes in many African nations promote the use of inorganic pesticides, herbicides, and fertilizers (Abate et al., 2000) making the farmers believe that these offer the best protection to crops and enhance productivity (Banjo et al., 2010) without considering their risks to health, biodiversity and the environment (Banjo et al., 2010; Ketema & Kabete, 2017). Therefore, smallholder farmers should be encouraged to adopt healthier, environmentally friendly and sustainable soil and environment technologies including the use of organic manure to boost soil fertility and crop yield (Verma et al., 2020), mechanical weed management (Hussain et al., 2018) and use of natural control of pests and diseases (Macfadyen et al., 2015), alternatives that better align to the goals of regenerative agriculture and CSA (Codur & Watson, 2018).

Also, from Table A3, the MVP regression models of the factors influencing farmers' adoption of different CSATs show that a few farm and farmer characteristics negatively and significantly influenced the adoption of some technologies. For example, farming experience negatively and significantly influenced mechanical weeding. This means that more experienced farmers are less likely to practice mechanical weeding and instead use other alternative weed management technologies like herbicide application (Alemu & Dufera, 2017). This informs us that although most of the CSATs are complementarity, a few can be substitutional (Alemu & Dufera, 2017). Also, farmers who did not have credit access were more likely to manage their shade trees than those with credit access. This could mean that the farmers with no credit access managed their shade trees using family labour (Cerda et al., 2014), and it is likely that farmers with credit access prefer to use the credit to adopt other credit-requiring technologies (Kangogo et al., 2020; Nyasimi) like buying mulch, pesticides and improved coffee varieties. Atube et al. (2021) also found that access to credit influences farmers' adoption of improved seeds. The farmers with smaller land sizes were more likely to plant cover crops compared to those with larger land sizes. This justifies the fact that farmers with small land sizes have no option but to intercrop in their coffee other crops like beans, as they don't have other pieces of land to grow other crops separate from their coffee fields (Jassogne et al., 2013b). Small-scale farmers are also usually subsistence farmers characterized by intercropping (Moore et al., 2014). Yet farmers with large land sizes can afford to grow a single crop alone and other crops separately (Himmelstein et al., 2017; Min et al., 2017). Intercropping cover crops in a farming system should be promoted as these have the potential to not only enhance climate change adaptation but also restore soil health and fertility (Lal, 2020).

All the remaining factors positively and significantly influenced the adoption of the following CSATs: Gender promotes the adoption of improved coffee varieties and chemical weeding. Education promotes the adoption of gap filling, mulching, cover crops, intercropping with bananas and fertilizer application. Household size promotes the adoption of gap filling, mulching, planting cover crops, intercropping with bananas and fertilizer application. The presence of household income promotes the adoption of gap filling, irrigation, intercropping with bananas and shade tree planting. Possession of a larger land size promotes the adoption of planting cover crops and irrigation. Farming experience promotes the adoption of mechanical weeding and irrigation. Credit access promotes managing shade trees, irrigation, mulching, planting improved coffee varieties, shade tree planting and chemical weed control. Access to climate information promotes managing shade trees, soil and water conservation, irrigation and planting improved coffee varieties. Farmers' perceptions of changes in rainfall promote managing shade trees, irrigation, mulching and chemical pest and disease control. Farmers' perceptions of changes in temperature promote the adoption of irrigation, intercropping with bananas and mulching. Farmers' familiarity with CSA promotes the adoption of mechanical weeding, chemical pest and disease control, irrigation, planting cover crops and mulching. The interaction with an extension agent promotes managing shade trees, gap filling, irrigation, cover crops, intercropping with bananas and chemical weed control. Finally, farmers' attendance to business skills training promotes the adoption of chemical pest and disease management and fertilizer application. Generally, the above evidence confirms that the adoption of different CSATs is influenced by somewhat different factors (Atube et al., 2021; Grazhdani, 2013; Zakaria et al., 2020), justifying the need to embrace different channels to enhance the uptake of multiple CSATs.

The table in Table A4 shows that all different combinations of CSATs have positive coefficients, except for mechanical weeding with herbicide application as well as for mechanical weeding and mulching.

This suggests that coffee farmers adopt different CSATs simultaneously, but herbicides and mulch are not used concurrently with mechanical weeding. This is because herbicides replace mechanical weeding for weed management, and are, as such, not complementary (Alemu & Dufera, 2017). Also, during mulching, mechanical weeding is unnecessary since mulches suppress weeds (Alemu & Dufera, 2017) and also enhance soil health and restore fertility (Lal, 2020). The majority of the estimated pair-wise correlation coefficients were statistically significant at 5%, showing a strong correlation between the error terms of the multiple decision equations. The hypothesis that the covariance of the error terms through equations is not correlated is rejected since the likelihood ratio test ($\chi^2 = 272.45$) is statistically significant at 5%. This validates the use of a Multivariate Probit model. Of the 171 CSAT correlation pairings, 108 were statistically significant and positively associated indicating that coffee farmers considered most CSATs to be complimentary rather than substitutional options. This matches the findings of other scholars who confirmed that farmers adopt a combination of multiple agricultural technologies (Aryal, Jat, et al., 2018). Therefore, this justifies the need to encourage farmers to adopt a combination of CSAs to enhance their adaptive capacity to multiple climatic risks and maximize CSATs' adaptation benefits (Aryal, Jat, et al., 2018; Kassie et al., 2015).

Table 4 shows that all farmers implement at least one CSAT. Most farmers (14%) adopted 4 technologies and 12% implemented 3 technologies while only 0.4% of the farmers adopted 17 and 18 technologies. The majority of the farmers adopted few CSATs (less than 10 CSATs) and were at either Step 1 or 2 of the CSIPs. Ony a few farmers adopted ≥10 CSATs, the acceptable number of CSATs that smallholder resource-constrained farmers should adopt as recommended in the CSIPs to attain higher yields and CSA benefits (Jassogne et al., 2017). Other scholars also found that the majority of farmers adopted few technologies while only a minority adopted many CSATs (Akudugu et al., 2012; Kangogo et al., 2020). This signifies limited CSAT acceptance among smallholder coffee farmers despite efforts and investments by development partners, policymakers, and scientists over the years. Since the number of adopted CSATs increases farmers' resilience to climate change and crop yield (Atube, Okello, et al., 2022), farmers' adoption of CSATs needs to be urgently boosted (Jassogne et al., 2017; Kolady et al., 2021; Vanlauwe et al., 2014). One major path is to

Table 4: Adoption intensity of CSATs.

Number of CSATs adopted	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	Total	Mean	SD	Median	Range
% of farmers	0	6.6	8	12	14	10	11	7.1	7.5	3.5	3.1	3.5	2.7	3.5	2.7	3.5	1.3	0.4	0.4	100	9	5.6	8	1–18

first understand farmers' perceptions of CSATs in order to identify factors that can be tackled to positively influence the uptake of more CSATs in the future.

4.5. Determinants of the adoption intensity of CSATs

4.5.1. Influence of farm and farmer characteristics on adoption intensity of CSATs

The results from the Poisson regression model shown in Table 5 reveal that farm and farmer characteristics positively influence the adoption intensity of CSATs, with household income, farming experience, familiarity with CSA, interaction with an extension agent, and access to climate information being significant. Increased household income was associated with increased CSAT adoption intensity, suggesting that farmers with higher incomes adopted more CSATs. Higher household income encourages investment in agricultural technologies and tolerance of adoption risks (Baiyegunhi, 2014). Likewise, farmers accessing credit adopted more CSATs than their peers, which corr","respondents with previous literature (Akudugu et al., 2012; Chiputwa et al., 2010; Zakaria et al., 2020). This proves that credit is a vital requirement for resource-constrained farmers to access and implement CSATs. Technologies like chemical pest and disease management, irrigation and fertilizer application require equipment (sprayers, sprinklers) and inputs (chemicals, fertilizers) which most farmers cannot afford, thus hindering adoption. Furthermore, the high perceived cost of CSATs reduces their adoption intensity. This is possibly because resource-constrained farmers are less likely to adopt expensive technologies since these require resources like money to procure pesticides and pruning equipment in order to carry out chemical pest control and pruning, for example. Therefore, farmers would benefit from assistance to procure and use more technologies (Akudugu et al., 2012; Chiputwa et al., 2010; Tesfahunegn et al., 2016).

Farming experience positively and significantly impacts the adoption intensity of CSATs. Experienced farmers adopt more CSATs than their peers. This means that the longer farmers practice farming, the more they appreciate CSATs' importance in improving production and the more likely they will adopt a combination of technologies, resulting in higher adoption intensities (Zakaria et al., 2020). The findings are consistent with Grazhdani (2013) and Zakaria et al. (2020), who found that farming experience positively and significantly influenced the adoption of resource-conserving agricultural technologies in Albania (Grazhdani, 2013) and CSATs in Ghana (Zakaria et al., 2020). Ainembabazi and Mugisha (2014) found a positive

Table 5. Poisson regression model of determinants of farmers' adoption intensity of CSATs.

Variables		Coefficient	Std. Err.	Marginal effect
	Gender	0.58	0.45	0.20
Farm and farmer characteristics	Education	0.06	0.07	0.37
	Household size	0.00	0.01	0.74
	Income (USD)	1.28	0.60	0.03*
	Land size	0.03	0.08	0.68
	Farming experience	0.06	0.02	0.01*
	Credit access	0.06	0.44	0.89
	Access to climate information	0.23	0.58	0.03*
	Familiarity with CSA	2.11	0.52	0.01*
	Extension agent interaction	0.21	0.32	0.02*
	Business skills training attendance	0.59	0.53	0.26
Climate variability perception	Perceived rainfall change	0.43	0.65	0.05*
	Perceived temperature change	0.93	0.62	0.13
	Constant	6.39	1.43	0.00
	Log-likelihood	−581.43		
	Model diagnostics			
	Number of obs	226		
	LR $\chi^2(20)$	94.06		
	Prob > χ^2	0.00		
	Pseudo R^2	0.08		
	Log-likelihood	−581.43		
	P-value	0.00		
	R-squared	0.34		
	Adj R-squared	0.28		
	Root MSE	3.11		

$^*P < 0.05$.

and significant relationship between farmers' agriculture experience and the adoption of agricultural technologies in Uganda. In this case, farmers with experience using particular technologies were more likely to have a higher adoption intensity. Therefore, continuous training of farmers is essential for the sustainable adoption or uptake of agricultural technologies in specific crops (Ainembabazi & Mugisha, 2014).

The farmers who were more familiar with CSA had a significantly higher adoption intensity than their counterparts. This reflects Wassmann et al. (2019) who found that farmers who were familiar with CSATs from previous project activities and experiences applying the technology were more likely to adopt more improved crop varieties than those who had only been informed through training and demonstration observations. This again aligns with previous research. Farmer's familiarity and understanding of CSA influences their knowledge, perceptions, and attitudes towards CSATs (Mmapatla et al., 2021), which, in turn, influences consumers' adoption. Also, Yameogo et al. (2017) reported that the lack of farmer familiarity with CSA was a barrier to the adoption of CSATs in Burkina Faso.

Like in other studies, the farmers who were interacting with extension agents had a significantly higher adoption intensity of CSATs than their counterparts (Deressa, Hassan, and Ringler, 2009; Ubisi et al., 2017). Since most farmers get CSA knowledge from extension agents, this explains why strengthening the farmer-extension agent relationship will be important in enhancing agriculture technology adoption intensity (Kolady et al., 2021).

4.5.2. Influence of farmers' perceptions of climate variability on the adoption intensity of CSATs

As shown in Table 5, farmers' perception of changes in rainfall positively and significantly affected their CSATs adoption intensity. Farmers who perceived decreased rainfall were 5% more likely to adopt more CSATs than their peers. Farmers' perception of changes in temperature also positively, though non-significantly, affected their adoption intensity of CSATs, in line with Zakaria et al. (2020) on rice farming in Ghana. The results of our study reveal that farmers' access to climate information had a significantly higher likelihood of increased CSATs adoption just as was revealed by other scholars (Ndamani & Watanabe, 2016; Partey et al., 2018). This is because timely climate information alerts farmers to upcoming climate variations, allowing them to plan strategically and implement appropriate (combinations of) agricultural technologies to strengthen their climate resilience (Ndamani & Watanabe, 2016; Partey et al., 2020). Therefore, giving farmers access to timely, accurate and reliable climate information should be prioritized by the government to foster the uptake of multiple agricultural technologies (Heitkemper et al., 2013; Staff, 2012). Uganda's public and private sectors should work together to diversify dissemination channels suitable for men and women, offer more farmer training, improve climate information interpretation, and recommend a combination of multiple CSATs to help farmers overcome multiple climate-related risks. The high and negative Log-likelihood shows that the model fits the data appropriately (Quinn et al., 2015). Other goodness-of-fit measures were also satisfactory (LR = 94, Pseudo E2 = 0.08 and R2 = 0.34).

5. Conclusion and recommendations

The study had some limitations. For example, since a cross-sectional study design was employed, this is considered a limitation of this research, as this does not allow the researcher to capture changes in farmer behaviour over time, since human behaviour is dynamic rather than static. To resolve this issue, we propose panel data for future studies to be able to more comprehensively explore the innovation adoption process within small-holder farmers while also embracing the knowledge of key sector experts. The study was conducted in a specific region of Uganda and may not be representative of the entire country. The sample size of 226 smallholder coffee farmers was also not large and diverse enough. Future studies could consider at least three locations, larger sample sizes, a longitudinal study design and a mix of different farmer holdings and farming systems to enhance the generalizability and replicability of the findings. The study exclusively relied on self-reported data from the farmers since it is only the farmers who could provide the information under study. Since this could subject the responses to Social Desirability Bias (SDB) due to self-reporting (Rosenman et al., 2011), we tried to minimize the bias through careful study design and data collection process. Simple language was used in framing questions, we ensured anonymous data collection and guaranteed total confidentiality during data collection (Durmaz et al., 2020).

Also, although the current study revealed that business skills have a likelihood to enhance technology adoption, this is not conclusive as it was not exclusively measured. Therefore, a more detailed, stronger theoretical analysis and foundation are necessary to provide clearer evidence on the business models smallholder farmers can follow and how this links to their entrepreneurial skills and the adoption and continued adoption of CSATs. The current study did not assess the age influence on farmers' climate variability due to the multicollinearity with farming experience. As such, future studies could consider assessing the potential influence of farmers' age on climate variability perceptions on the adoption of CSATs in cases where age has no relationship with farming experience. The economic feasibility of adopting CSATs can be considered in future studies. Future studies should also consider the potential role of market demand and consumer preferences in driving CSATs adoption. The results from this study should also be compared with other analogous studies to further validate the findings and analyse the variations and similarities with logical explanations.

The current study revealed that, firstly, the smallholder coffee farmers in Luweero adopted mostly CSATs requiring unskilled labour, followed by those requiring skilled labour and those CSATs that require high financial investments were the least adopted. Secondly, they adopt the majority of the CSATs simultaneously except weed management options like herbicide application and mechanical weeding that are substitutional. The adoption of different CSATs is influenced by somewhat different factors. Thirdly, it was also observed that socio-demographic factors such as farming experience, household size, household income, interaction with extension workers and familiarity with CSA positively and significantly influenced the adoption intensity of CSATs. This justifies the need to embrace different channels to enhance the uptake of multiple CSATs. Fourthly, the farmers were aware of key variations in the climate over the past 20 years. Their perceptions about the increase in temperature and decrease in rainfall aligned well with actual meteorological data. Lastly, farmers' perceptions of changes in rainfall and temperature and access to climate information positively influenced their adoption intensity of the CSATs. It can be concluded that efforts to enhance the adaptive capacity of smallholder coffee farmers should consider enhancing farmers' awareness of climate variability through the provision of climate information, strengthening extension service delivery and enhancing farmers' access to credit facilities to enable them access capital that they can use to procure and implement multiple healthy and environmentally friendly CSATs. This will enable farmers to comply with the urgent need to adopt multiple CSATs and increase their adaptive capacity against the diverse impacts of climate risks while at the same time contributing to the achievement of the goals of regenerative agriculture.

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Author contributions

CRediT: **Diana Kirungi:** Conceptualization, Data curation, Formal analysis, Methodology, Writing – original draft; **Joshua Wesana:** Conceptualization, Supervision, Writing – review & editing; **Haroon Sseguya:** Funding acquisition, Investigation, Project administration, Resources, Supervision, Writing – review & editing; **Xavier Gellynck:** Conceptualization, Investigation, Supervision, Validation, Writing – review & editing; **Hans De Steur:** Methodology, Supervision, Validation, Writing – review & editing.

Disclosure statement

The authors report there are no competing interests to declare.

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Ethical statement

All subjects gave their informed consent for inclusion before they participated in the study. The study was conducted in accordance with the Declaration of Helsinki, the protocol was approved and an ethical clearance certificate was obtained from the International Institute of Tropical Agriculture (IITA) Internal Review Board (IRB) per the Research Ethics Policy under the Reference number IRB/003/2022 on 13/05/2022.

Informed consent statement

Informed consent was obtained from all subjects involved in the study.

Institutional review board statement

The study was conducted according to the guidelines of the Declaration of Helsinki and approved by the Institutional Review Board of the International Institute of Tropical Agriculture (IITA) under the Reference number IRB/003/2022 on 13/05/2022.

Data availability statement

Data will be made publicly available when the article is accepted for publication. The data will then be available in a depository at Ghent University online and physical libraries and the Consultative Group for International Agricultural Research (CGIAR) website. The data set associated with the article can be found at Data-Farmer perceptions of climate variability and adoption intensity of CSATs in Uganda.

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Annex

Annex A1. Luweero district meteorological trends

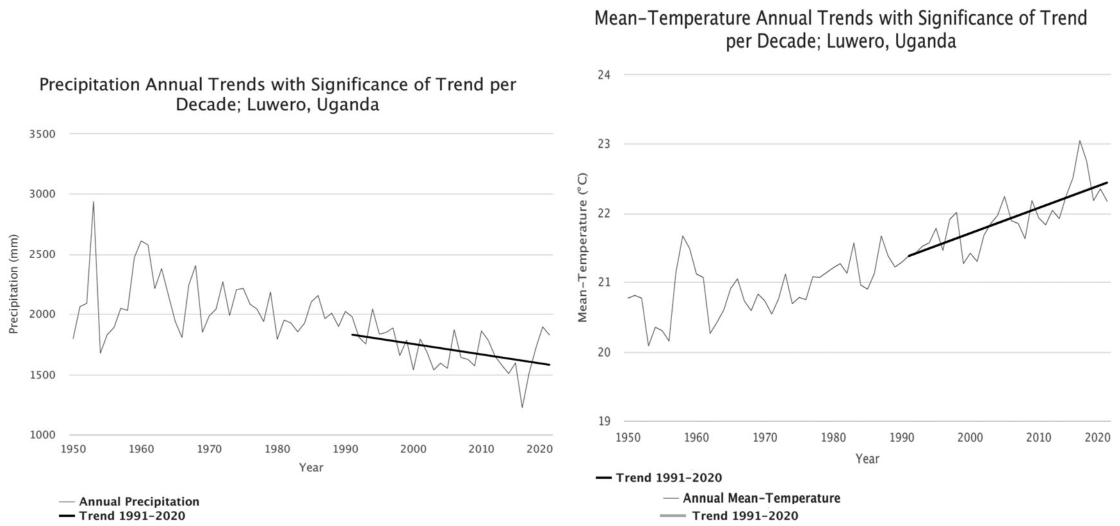

Figure A1. Rainfall (LHS) and temperature (RHS) trends Luweero for 19512020 (World Bank, 2020).

Annex A2. Adoption rate of different CSATs

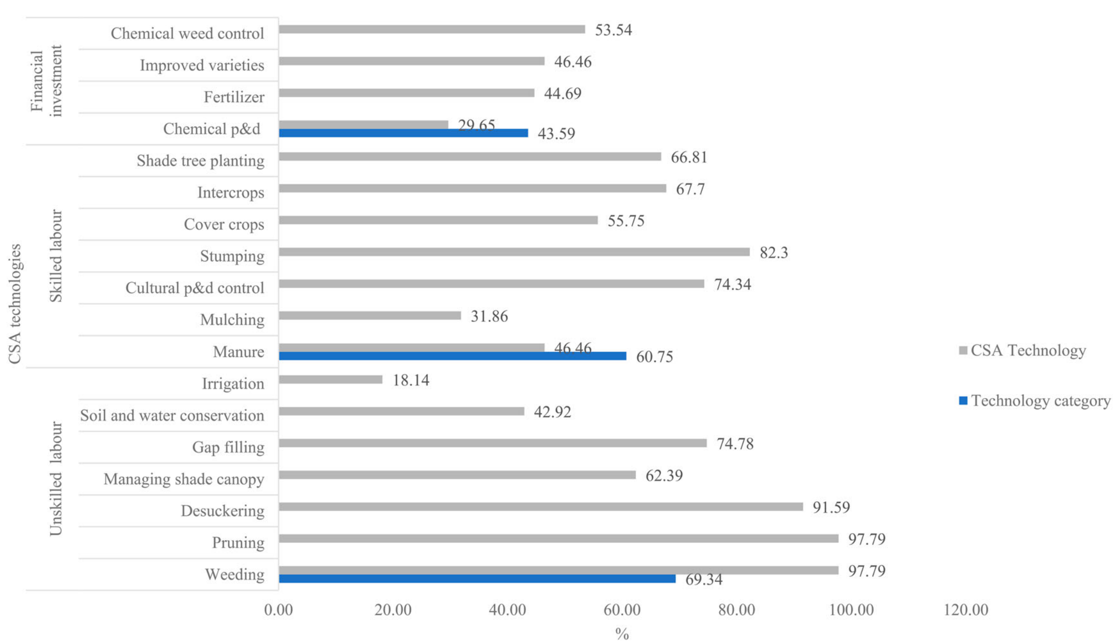

Figure A2. Adoption rate of multiple CSATs.

Annex A3. Factors influencing farmers' adoption of different CSATs

Table A3. MVP regression models of the factors influencing farmers' adoption of different CSATs.

CSA technology	Mechanical weeding		Prunning		De-suckering		Shadetree management		Gap filling		Soil and water conservation structures	
Influencing factors	Coef	p-value	coef	p-value	coef	p-value	coef	p-value	coef	p-value	coef	p-value
Gender	0.10	0.18	−2.72	1.00	0.05	1.00	−0.72	0.19	0.45	0.17	−3.68	1.00
Education	−0.36	0.67	0.36	1.00	0.02	1.00	0.04	0.49	−0.05	0.30	4.28	0.98
Household size	1.18	0.18	9.81	1.00	12.21	1.00	0.67	1.00	1.90	0.00*	169.24	0.99
Income	−0.30	0.75	8.47	1.00	12.35	1.00	8.78	0.99	1.87	0.00*	231.07	0.99
Land size	−0.23	0.24	0.45	1.00	−0.11	1.00	0.09	0.22	−0.03	0.58	6.67	0.98
Farming experience	−0.22	0.03*	−0.32	1.00	0.00	1.00	−0.02	0.53	0.01	0.64	−0.18	1.00
Credit access	−0.09	0.19	−4.50	1.00	−0.37	1.00	−1.14	0.04*	0.12	0.69	10.47	0.99
Climate information access	1.39	0.17	−2.87	1.00	0.46	1.00	0.99	0.07**	0.28	0.50	29.89	0.09**
Perceived rainfall changes	0.11	0.93	12.70	1.00	−0.81	1.00	0.84	0.06**	0.33	0.57	203.65	0.99
Perceived temperature changes	5.93	1.00	9.28	1.00	0.20	1.00	0.27	0.74	0.72	0.08	153.70	0.99
Familiarity with CSA	2.20	0.04*	5.37	1.00	0.45	1.00	0.70	0.16	0.43	0.21	122.50	0.98
Extension worker interaction	0.99	0.35	9.80	1.00	12.74	1.00	2.13	0.00*	1.31	0.00*	187.46	0.98
Business skills training attendance	0.64	0.62	2.16	1.00	0.03	1.00	−0.13	0.82	0.02	0.96	12.06	0.99

CSA technology	Irrigation		Manure application		Mulching		Culture p&d		Stumping		Cover crops	
Influencing factors	coef	p-value	coef	p-value	coef	p-value	coef	p-value	coef	p-value	coef	p-value
Gender	0.06	0.93	−6.46	1.00	0.62	0.10	4.52	1.00	-30.98	0.99	−0.09	0.65
Education	−0.07	0.53	−0.10	1.00	−0.10	0.20	−0.31	1.00	−0.63	1.00	0.01	0.76
Household size	−0.01	0.99	−0.63	1.00	7.68	0.00	24.14	1.00	102.95	0.99	−0.54	0.07**
Income	4.94	0.00*	15.60	1.00	3.42	1.00	38.54	1.00	124.30	0.98	0.30	0.18
Land size	0.42	0.04*	−0.88	1.00	0.03	0.22	−0.14	1.00	3.72	1.00	−0.08	0.03*
Farming experience	0.16	0.03*	0.11	1.00	0.08	0.77	0.82	1.00	0.60	0.99	0.00	0.91
Credit access	1.64	0.07**	0.10	1.00	0.10	0.02*	−8.73	1.00	9.65	0.99	0.08	0.68
Climate information access	3.54	0.09**	6.01	1.00	0.56	0.83	35.31	1.00	87.33	0.99	0.11	0.69

(Continued)

Table A3. Continued.

CSA technology	Irrigation		Manure application		Mulching		Culture p&d		Stumping		Cover crops	
Influencing factors	coef	p-value	coef	p-value	coef	p-value	coef	p-value	coef	p-value	coef	p-value
Perceived rainfall changes	0.87	0.03*	14.12	1.00	0.17	0.01*	3.80	1.00	72.87	0.99	0.02	0.94
Perceived temperature changes	2.45	0.07**	9.34	1.00	0.01	0.00*	9.44	1.00	46.75	0.98	0.03	0.91
Familiarity with CSA	2.10	0.01*	1.35	1.00	0.08	0.05**	9.93	1.00	74.25	0.98	0.09	0.00*
Extension worker interaction	2.66	0.02*	37.81	1.00	0.01	0.99	25.75	1.00	179.74	0.98	0.67	0.01*
Business skills training attendance	2.77	0.12	6.04	1.00	0.19	0.01*	14.14	1.00	62.45	0.98	0.66	0.01*

CSA technology	Intercropping bananas		Shade tree panting		Chemical p&d		Fertilizer application		mproved coffee varieties		Herbicide use	
Influencing factors	coef	p-value	coef	p-value	coef	p-value	coef	p-value	coef	p-value	coef	p-value
Gender	0.01	0.99	0.30	0.44	0.37	0.67	7.47	1.00	1.83	0.09**	1.04	0.05*
Education	0.00	0.98	0.04	0.43	0.04	0.41	0.13	1.00	0.52	0.03*	0.01	0.94
Household size	1.33	0.00	1.02	0.14	0.64	0.40	0.21	0.07**	−0.06	−0.20	−0.33	−0.47
Income	1.83	0.00*	2.62	0.00*	2.01	1.40	1.43	1.46	1.50	1.53	1.57	1.60
Land size	−0.04	0.60	0.02	0.79	0.09	0.55	0.52	1.00	0.21	0.22	0.05	0.49
Farming experience	0.04	0.05	0.03	0.20	0.03	0.21	0.02	1.00	0.16	0.04*	0.01	0.59
Credit access	0.09	0.79	1.27	0.01*	0.16	0.12	2.98	1.00	4.51	0.03*	0.91	0.07**
Climate information access	0.04	0.93	0.10	0.86	0.98	0.87	3.36	1.00	2.56	0.07**	0.64	0.19
Perceived rainfall changes	0.59	0.19	0.27	0.69	0.19	0.04*	0.01	1.00	0.95	0.52	0.34	0.62
Perceived temperature changes	0.91	0.07**	0.60	0.35	1.11	0.72	8.68	1.00	2.71	0.28	0.24	0.69
Familiarity with CSA	0.51	0.15	0.09	0.83	0.77	0.02*	4.69	1.00	14.81	0.99	0.03	0.95
Extension worker interaction	2.82	0.00*	1.53	0.01*	1.91	0.87	27.96	1.00	23.54	0.98	3.21	0.00*
Business skills training attendance	0.62	0.12	0.75	0.15	0.87	0.02*	4.87	0.1**	4.22	0.10	0.86	0.13

*$P < 0.05$, **$P < 0.1$.

Annex A4. Correlation of multiple CSATs

Table A4. Pairwise correlation of the multiple CSATs

CSATs	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Mechanical weeding (1)	1.00																	
Prunning (2)	0.02	1.00																
	0.74																	
De-suckering (3)	0.17*	0.17*	1.00															
	0.01	0.01																
Manure (4)	0.02	0.14*	0.25*	1.00														
	0.77	0.03	0.00															
Mulching (5)	−0.03	0.10	0.10	0.16*	1.00													
	0.69	0.12	0.12	0.01														
Cultural P&D control (6)	0.12	0.05	0.41*	0.16*	0.10	1.00												
	0.08	0.46	0.00	0.01	0.15													
Chemical pesticides (7)	0.03	0.10	0.16*	0.25*	0.16*	0.09	1.00											
	0.63	0.14	0.01	0.00	0.02	0.16												
Inorganic fertilizer (8)	0.01	0.01	0.24*	0.32*	0.13	0.16*	0.25*	1.00										
	0.83	0.83	0.00	0.00	0.05	0.02	0.00											
Shade tree planting (9)	0.15*	0.20*	0.36*	0.20*	0.22*	0.25*	0.25*	0.20*	1.00									
	0.02	0.01	0.00	0.00	0.00	0.00	0.00	0.00										
Shade management (10)	0.01	0.01	0.32*	0.23*	0.20*	0.28*	0.16*	0.22*	0.56*	1.00								
	0.91	0.91	0.00	0.00	0.00	0.00	0.01	0.00	0.00									
Cover crops (11)	0.18*	0.18*	0.24*	0.18*	0.03	0.23*	0.09	0.10	0.22*	0.15*	1.00							
	0.01	0.01	0.00	0.00	0.51	0.00	0.17	0.13	0.00	0.02								
Irrigation(12)	0.07	0.03	0.14*	0.25*	0.24*	0.09	0.35*	0.27*	0.23*	0.13	0.14	1.00						
	0.29	0.29	0.03	0.00	0.00	0.17	0.00	0.00	0.00	0.05	0.03							
Improved coffee varieties (13)	0.08	0.14*	0.22*	0.29*	0.20*	0.18*	0.21*	0.25*	0.30*	0.30*	0.06	0.25*	1.00					
	0.23	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.36	0.00						
Gap filling (14)	0.06*	0.06*	0.07*	0.11*	0.15	0.06*	0.20*	0.20*	0.15*	0.04*	0.00*	0.49*	0.22*	1.00				
	0.00	0.00	0.00	0.00	0.70	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00					
Banana intercropping (15)	0.15*	0.09	0.30*	0.19*	0.21*	0.24*	0.22*	0.30*	0.46*	0.40*	0.2*	0.18*	0.40*	0.06*	1.00			
	0.02	0.18	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00				
Soil and water conservation (16)	0.01	0.07	0.16*	0.19*	0.19*	0.18*	0.04	0.25*	0.08	0.11	0.19*	0.29*	0.18*	0.11	0.02	1.00		
	0.89	0.30	0.01	0.00	0.00	0.00	0.51	0.00	0.23	0.07	0.00	0.00	0.01	0.17	0.85			
Stumping (17)	0.01	0.17*	0.07	0.04	0.07	0.10	0.15*	0.02	0.19*	0.00	0.21*	0.01	0.06	0.23*	0.08	0.05	1.00	
	0.89	0.01	0.31	0.58	0.31	0.14	0.02	0.76	0.00	0.99	0.00	0.31	0.37	0.00	0.25	0.05		
Herbicides (18)	−0.01	0.05	0.23*	0.16*	0.02	0.06	0.42*	0.35*	0.24*	0.19*	0.09	0.14*	0.20*	0.26*	0.05	0.07	0.08	1.00
	0.77	0.54	0.00	0.02	0.68	0.35	0.00	0.00	0.00	0.00	0.14	0.03	0.00	0.00	0.41	0.23	0.45	

Likelihood ratio test = 0
χ^2 (171) = 272.45
Prob > χ^2 = 0.00