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Drivers of climate-smart agricultural technology uptake among smallholder coffee farmers in Kalehe Territory, Democratic Republic of Congo

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ABSTRACT

Climate-smart agricultural technologies (CSATs) are important for climate change adaptation and mitigation in developing countries. Therefore, it is crucial for farmers to have access to sustainable CSATs to cope with climate change. While coffee is an important commercial crop in Democratic Republic of Congo (DRC), farmers suffer from coffee fluctuation in production attributed to climate variability. Accordingly, various coffee-related CSATs, notably coffee cultivars, manure and intercropping have been introduced in Kalehe Territory of the DRC to build climate resilience and adapt to changing environmental conditions. However, coffee cultivars are not widely used. This study fitted a two-step Heckman model to correct for selection bias on a randomly selected cross-sectional sample of 442 smallholder coffee farmers to examine the drivers of CSATs uptake in Kalehe Territory. The model results showed that family labour, non-farm income, access to credit and extension services, and residing in Butumba Village were the major factors influencing the decision of coffee farmers to use CSATs. The results revealed that manure and new coffee cultivars, manure and intercropping combined with manure had the potential to be substitutes for each other. The study recommends that policy makers and other stakeholders in CSATs support the dissemination of CSATs, especially coffee cultivars, to facilitate access. There is need to promote extension services so that the combination of intercropping and manure can help to increase coffee farmers' welfare. The government should support farmers' use of CSATs through either the subsidization of coffee cultivars or the provision of cheap agricultural credit.

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1. Introduction

Smallholder farmers in Sub-Saharan Africa (SSA) are incessantly exposed to climate change risk due to their heavy reliance on rain-fed agriculture (Omotoso et al., 2023). Thus, their ability to achieve food security is severely compromised, which makes efforts to reduce poverty ever more difficult (Mbuli et al., 2021; Molotoks et al., 2021; Nyiwul, 2021). Studies indicate that climate change is expected to disproportionately affect resource-poor smallholder farmers in SSA through factors like erratic rainfall, rising temperatures, extreme weather events such as drought and floods (Ahmed & Eklund, 2021; Azadi et al., 2019; Lawson et al., 2020). According to Intergovernmental Panel on Climate Change (IPCC) (2022), the policy response to address these issues includes adaptation strategies, the promotion of renewable energy, sustainable agriculture and natural resource management.

While the Democratic Republic of the Congo (DRC) hosts a vast and fertile country with immense agricultural potential, over 90 percent of its agriculture is predominantly rain-fed and based on smallholder 'slush and burn' cultivation (Karume et al., 2022). Accordingly, the growth of agriculture fluctuates with rainfall (Amani et al., 2022; Balasha et al., 2023). Droughts cause major disruptions to the agricultural calendar, resulting in failure of both cash and food crops thereby intensifying food insecurity and poverty (Paul, 2019). According to United States Agency for International Development (USAID,)

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(2019), the DRC is the eighth most vulnerable country in the world to climate change after Bangladesh, Maymanar, and Pakistan (Busby at al., 2018).

According to Mushengezi et al. (2022), coffee growing has always been an important source of income for a large majority of agricultural producers in eastern DRC where it has been grown since the 1920s and accounted for up to 15% of GDP and 75% of export crops in the 1990s. The DRC has great potential in the development of the supply chain of coffee value and this cash crop demonstrates significant economic and social potential, making coffee a relevant product to develop (Manfroy, 2021). Axel (2022), further highlight the optimum range of temperatures for growing arabica coffee (Coffea arabica) is between 18 and 22 °C, while for robusta coffees (Coffea canephora) it is between 22 and 26 °C. Axel (2022), highlighted that the proper amount of rainfall for cultivation is between 1,500 and 2,000 millimeters per year, or about 125 millimeters per month and the recommended number of sunshine hours is 1,800 hours per year. This is because temperature, rainfall and sunshine conditions are considered to be the key factors affecting potential coffee yields of resource-poor smallholder coffee farmers (Egan et al., 2021; Kandegama et al., 2022; Ofori et al., 2021; Zerssa et al., 2021). These factors interfere with plant phenology and, therefore, affect the productivity and quality of the coffee (Axel, 2022). For example, Rwigema (2021) predicts significant rainfall decreases for large parts of DRC, which is likely to negatively affect coffee yield (Tegera, 2018).

Kalehe Territory is one of several coffee-growing areas in the DRC with significant potential for specialty coffee production (USAID, 2018). Although Kalehe presents, by its extent and its relief, a great diversity of agro-ecological zones favorable to agriculture, its agroecosystems with land specialized in the production of a diversity of cultivated plants are fragile and vulnerable to fluctuations in climatic factors such as rain and temperature because its agriculture is essentially rainfed (Bienda et al., 2019). This territory has been transformed by history and the evolution of farming practices that degrade the quality of its soil, especially in the most populated areas, consequently, there is damage of both crops (especially coffee which is mostly cultivated) and livestock, thereby increasing poverty, food insecurity and malnutrition in the region. In addition, its agricultural landscape has undergone several changes due to anthropogenic pressure on natural resources reinforced by the adverse effects of the climate (Bienda et al., 2019). According to International Monetary Fund (IMF) (2022), increased climate variability in Kalehe Territory, has exacerbated pre-existing food insecurity and poverty in the region.

Defined as a way of finding which production systems are best appropriate to answer to the problem of a changing-climate for a precise location, to protect and increase the capacity of agriculture, sustainably support food security in a sustainable way, climate-smart agricultural technologies (CSATs) are crucial to protect and increase agricultural capacity, ensuring sustainable support for food security in Kalehe Territory. On the other hand, CSATs are instruments, practices and techniques available to farmers for use in to cope or mitigate adverse climate-related effects (Neufeldt et al., 2015).

Understanding the drivers of adoption of CSATs in coffee production is important for enhancing productivity. The lack of information about the drivers of adoption of CSATs in coffee production can hinder efforts to enhance sustainability, resilience, and productivity in the coffee industry. This limitation affects farmers, policymakers and stakeholders involved in the coffee supply chain, as they may struggle to implement targeted strategies without a comprehensive understanding of the factors influencing the adoption of CSATs.

While numerous studies have evaluated the determinants of CSATs adoption in coffee production in Uganda, India, Ethiopia and Nicaragua (Bro et al., 2019; Diro et al., 2022; Eshetu et al., 2021), the assessment of key determinants in coffee farming in the DRC is critically missing, lacking not only a thorough evaluation of these factors but also any attempt to address potential selection bias that might skew the results which was the goal of this study. Doing that would be crucial for farmers' well-being, policy formulation, and research advancement.

2. Literature review

2.1. Trends of coffee production in the DRC

Since its introduction in 1920s (Tout savoir sur le café de la RDC, 2022), coffee production in the DRC has being fluctuating (Figure 1). The trend in coffee production in DRC shows that the production declined from year 2000–2016 and production decreased considerably from 2007 and 2009 due to

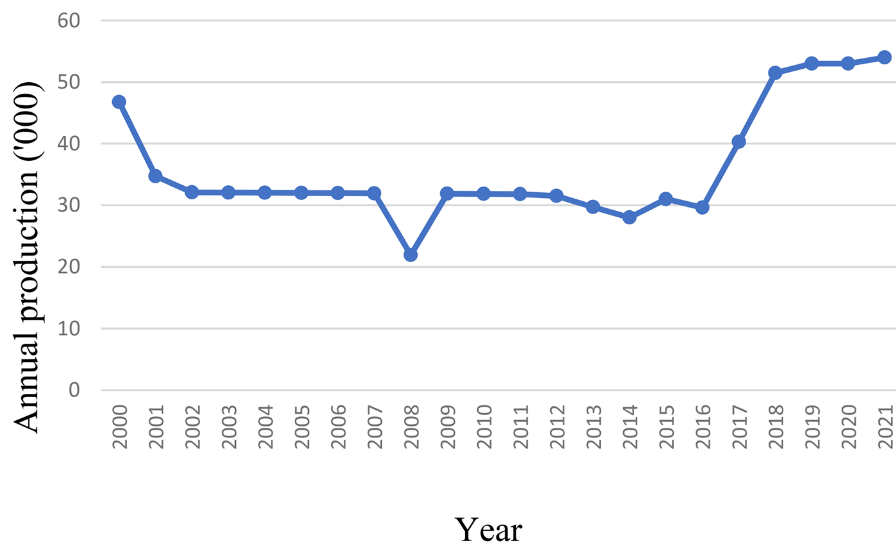

Figure 1. Trend in coffee production in DRC.
Source: FAOSTAT data (2023).

number of challenges; including the precipitous decline of infrastructure, the chronic absence of an agricultural credit system for smallholders (Tegera, 2018), and the increasingly unpredictable nature of the climate (Rwigema, 2021).

2.2. Explanatory factors for the deterioration of working conditions in the coffee sector in the DRC

When asked about the reasons that explain the deterioration of working conditions in the coffee sector in DRC, coffee farmers put forward several reasons including: lack of coffee buyers, lack of government support, not enough land for everyone, war, poor quality of production, as well as climate change (Tegera, 2018). According to Pombengo (2018), the Congolese government is looking for new strategies to revive the coffee sector by improving productivity, quality, marketing and the business climate and highlights that strategies for reviving the sector would be to increase the number of agricultural households to reach approximately 6 to 7 million people living directly or indirectly from this product. It is in this regard, in 2012, the government launched the National Coffee Sector Recovery Strategy document 2011–2015 with 100 million US$ earmarked for the province of South-Kivu Province (Atyi et al., 2020), where this study was conducted. In fact, for 5 years the DRC authorities have been talking about the relaunch of coffee but the progress is difficult to assess (Graine de café (GCD), 2018). In addition, adoption of CSATs is another strategy to improve coffee productivity.

In Kalehe Territory, eastern DRC, the government typically supports coffee production by regulating quality standards, providing research and extension services, developing infrastructure, facilitating market access, promoting sustainability, and addressing social issues. These efforts aim to enhance the coffee industry's quality, sustainability, and the livelihoods of smallholder farmers. The Université Evangélique en Afrique (UEA) with its partners initiated a series of projects dealing with CSA practices in coffee (Karume et al., 2022). These include soil restoration at the hill scale, adapted agroforestry tree selection, soil and water conservation techniques, land use and land cover assessment in wetlands, biofertilizer and biopesticide development, waste recycling, use of resilient crops. The impact of these initiatives on coffee production in the DRC remains an open question.

3. Methods and data

3.1. Theoretical framework

In this study, smallholder coffee farmers in Kalehe Territory were conceptualized as consumers of CSATs. According to the random utility theory, a CSAT adopter will select the technology that maximizes their utility from a set of available options (Greene, 2012; Greene & Hensher, 2010). In coffee production, utility is derived from the profits derived from the use of a specific CSAT. For example, if two CSATs are available, say, T_1 and T_2 with associated utilities U_1 and U_2 where $U_2 > U_1$, the farmer will adopt T_2 instead of T_1 if T_2 leads to higher utility than T_1 (Greene, 2003; MMcFadden, 1981). According to Greene (2003), the utility derived from use of a given CSAT can be expressed as a linear sum of two components: a deterministic part, V_{ij}, that captures the observable components of the utility function, and a random error term, ε_{ij}, that captures unobservable components of the function including measurement errors, i.e.

$$U_{ij} = V_{ij} + \varepsilon_{ij} \tag{1}$$

The Butler and Moffitt approach for this model has proved useful in numerous applications. But, the underlying assumption that $cov\left[\varepsilon_{it}, \varepsilon_{is}\right] = \rho$ is a substantive restriction. By treating this structure as a multivariate Probit model (*MVP*) with a restriction that the coefficient vector be the same in every period, one can obtain a model with free correlation (Greene, 2003). The *MVP* with *m* dependent variables and consequently *m* latent variables, I_m^*,

$$I_m^* = \beta_m^{'} X_m + \varepsilon_m, m = 1, \ldots, M \tag{2}$$

$$I_m^* = 1 \; if \; I_m^* > 0 \; and \; 0 \; otherwise \tag{3}$$

where, $\varepsilon_m \forall m = 1, \ldots, M$ are error terms distributed as multivariate normal, each with a mean of zero, and V is the variance-covariance matrix, with a value of 1 on the leading diagonal and correlation $\rho_{jk} = \rho_{kj}$ as off-diagonal elements as follows (Greene, 2003):

$$\begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_M \end{pmatrix} \sim N\left[\begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho_{12} & \rho_{1M} \\ \rho_{21} & 1 & \rho_{2M} \\ \rho_{M1} & \rho_{M2} & 1 \end{pmatrix}\right], \text{where } V = \begin{bmatrix} 1 & \rho_{12} & \rho_{1M} \\ \rho_{21} & 1 & \rho_{2M} \\ \rho_{M1} & \rho_{M2} & 1 \end{bmatrix} \tag{4}$$

With the exception of the dependent variables being binary indicators, this model's structure is similar to that of seemingly unrelated regression (SUR) model. Additionally, unlike SUR, this model does not require that all of the explanatory variables in the equations be precisely the same.

Assuming that there are *M* several options, there are multiple Probit models, the log-likelihood of which for *N* independent observations is given by:

$$L = \sum_{i=1}^{N} w_i \log \Phi_m\left(\mu_i; \Omega\right) \tag{5}$$

Where w_i is an optional weight for observation $i = 1, \ldots, N$ and $\Phi_m(.)$ is the multiple standard normal distribution with arguments μ_i and ' where

$$\mu_i = (K_{i1}\beta_1^{'} X_{i1}, K_{i2}\beta_2^{'} X_{i2,} K_{im}\beta_m^{'} X_{im}) \tag{6}$$

Eight joint probabilities for each of the eight possible outcomes-success ($Y_{im} = 1$) and failure ($Y_{im} = 0$) exist in the trivariate scenario. Assume that there are three successes, denoted by $Y_1 = 1; Y_2 = 1$ and $Y_m = 1$, which suggests that three decisions are taken at the same time. The joint probability that each outcome is successful is provided by:

$$\begin{aligned} \Pr(Y_1 = 1, Y_2 = 1, Y_m = 1) &= \Pr\left(\epsilon_1 \le \beta_1^{'} X_1, \epsilon_2 \le \beta_2^{'} X_2, \epsilon_m \le \beta_m^{'} X_m\right) \\ &= \Pr(\epsilon_m \le \beta_m^{'} X_m \mid \epsilon_2 < \beta_2^{'} X_2, \epsilon_1 < \beta_1^{'} X_1) \times \\ &\quad Pr(\epsilon_2 < \beta_2^{'} X_2 \mid \epsilon_1 \le \beta_1^{'} X_1) \times \Pr(\epsilon_1 < \beta_1^{'} X_1) \end{aligned} \tag{7}.$$

The technology adoption decision reflects an unobservable underlying motivation of potential adopters to belong to one group or the other. Although unobservable, this motivation could be shaped by the adopter's idiosyncratic factors including his/her initial endowment, risk attitude, exposure, and level of awareness of the benefits of the technology. Accordingly, the analysis of the adoption decision is often fraught with the problem of selection bias that underpins the unobserved tendency. In this study, selection bias was captured in a *MVP* using awareness in the selection equation and the conditional mixed process (CMP) procedure in STATA version WHAT?.

3.2. Empirical models

The multivariate probit estimation was used to evaluate factors influencing adoption of CSATs in this study. This model has been employed in a number of studies that assessed the factors that influence the adoption of agricultural technologies (Negera et al., 2022; Oyawole et al., 2021; Shahbaz et al., 2022; Teklu et al., 2023; Zakaria et al., 2020). The reason for this choice is that farmers make simultaneous decisions about what to adopt. Because unobserved characteristics simultaneously influence the adoption of each CSAT, the application of a *MVP* model is more appropriate (Zhang et al., 2020).

The Heckman two-stage approach was used to control for potential selection bias in the adoption decision. In the first stage, an assessment of the determinants influencing awareness of CSATs was conducted, with awareness serving as the dependent variable. The two stages were estimated simultaneously using CMP command in STATA to correct for self-selection bias.

$$Awareness_{ij} = \alpha_0 + \alpha_1 \text{Age} + \alpha_2 \text{Gender} + \alpha_3 \text{Education} + \alpha_4 \text{Extserv} + \alpha_5 \text{Location} + \mu_{ij} \quad (8)$$

where $Awareness_{ij}$ represents the ith farmer's awareness about the jth CSAT with $Awareness_{ij} = 1$ if the farmer was aware and 0 otherwise, α_k are unknown parameters to be estimated, and μ_{ij} is the error term assumed to be normally distributed with a mean of zero and constant variance. The second stage fitted the following *MVP* into the data:

$$Y_{ij} = \beta_0 + \beta_1 \text{Age} + \beta_2 \text{Gender} + \beta_3 \text{Education} + \beta_4 \text{Farmlab} + \beta_5 \text{Nonfarmincome} + \beta_6 \text{Extserv} + \beta_7 \text{Credit} + \beta_8 \text{Farmsize} + \beta_9 \text{InputDist} + \beta_{10} \text{Easeofuse} + \beta_{10} \text{Location} + \varepsilon_{ij} \quad (9)$$

where Y_{ij} represents the ith farmer's decision to adopt the jth CSAT, 1 = manure, 2 = new coffee cultivars, and 3 = manure and intercropping with $Y_{ij} = 1$ if a farmer adopted the CSAT and 0 otherwise. β_k are unknown parameters to be estimated, and μ_{ij} is the error term defined in equation (9) above. Table 1 describes the exogenous variables in Equation (9) and their expected signs.

Table 1. Description of exogenous variables in Equation (9) and their expected signs.

Variable	Description	Measurement	Expected sign
Age	Age of the head of farm household	Continuous	+/−
Gender	Gender of the head of the farm household	Dummy 1 = Male 0= Female	+
Education	Education of the head of the farm household	Number of years education completed	+
Farmlab	Number of family labour in a household	Number of family labour	+/−
Nonfarmincome	Non-farm income	Amount earned from household's non-farm activities	+
Extserv	Number of extensions visits over 1 year	Continuous	+
Credit	Access to credit over 1 year	Dummy 1= access to credit 0= otherwise	+
Farmsize	Farm size owed in hectares	Continuous	+
InputDist	Distance to input market	Distance in Km	−
Ease of use	Perceived ease of use	Dummy	+
Location	Village	1= Bulenga 2= Butumba 3= Kitembo 4= Muhanga	+

The choice of the explanatory variables used in this study was informed by previous studies. Studies show a positive or a negative relationship between age and technology adoption decision (Benimana et al., 2021; Eshetu et al., 2021). The gender of the household head is usually positively associated with technology adoption decision (e.g. see (Mutenje et al., 2019). The household head's education level has been shown to positively influence farmers' technology adoption decision due to the fact that educated farmers are more likely to adopt new agricultural technologies, innovate, and effectively access information, leading to more sustainable and resilient farming systems (Diro et al., 2022). The relationship between family labour and technology adoption in agriculture is context-dependent. It can be positive when additional family labor aids in technology implementation and management. Conversely, in case of limited resources, or when adoption requires significant investment, the impact may be negative (e.g. Kambanje et al., 2018). Off-farm income allows households to self-finance and therefore increases the likelihood of adopting new technology. The relationship between farm size and technology adoption is still unsettled in empirical literature. For example, Brown et al. (2020) and Dinh and Dung (2021) reported a positive relationship while Ntshangase et al. (2018) reported a negative one. The hypothesized sign on this variable was therefore indeterminate. Access to credit was hypothesized to be positive in keeping with Ntwiga (2020). Extension services have a crucial role in providing farmers with information, knowledge, and qualifications to exploit emerging opportunities (Darr et al., 2014). Therefore, the hypothesized sign was positive. Aggarwal et al. (2018) reported that villages with higher travel costs had lower adoption rates than those with larger travel cost in Tanzania. It was therefore expected to be negatively related to the adoption decision. Perceived ease-of-use of CSATs directly affects adoption behavior (Yuan et al., 2017). It was therefore expected to positively affect the adoption decision. Household location reflects its geographical context in terms of climate change impact (Intergovernmental Panel on Climate Change, 2023) and technological advancement (World Bank, 2023) and was therefore hypothesized to positively influence coffee farmers' CSAT adoption decision.

3.3. Data type and sources

3.3.1. Study area

This study was undertaken in Kalehe Territory, one of eight territories of South Kivu Province of the DRC. It borders Walikale and Masisi territories and Goma town to the North, Kabare Territory to the South, Lake Kivu to the East and Shabunda Territory to the West (Figure 2). According to the Office National de produits agricoles au Congo (ONAPAC) (2022), Kalehe Territory measures 5 057 km^2 with a population of 933 181 inhabitants in 2022. The Territory is divided into two Collectivity (Chiefdoms), with seven Groupments of Buzi, Kalima, Kalonge, North Mbinga, South Mbinga, Mubuku and Ziralo (Mugisho, 2010). Every Groupment comprises of several villages.

Kalehe Territory was selected for this study because it has the largest acreage of coffee relative to other territories with a mapping of coffee production areas is estimated at 1989 km^2 and of the estimated 4,000 tons produced by the South Kivu province, the Kalehe territory itself occupies 70% (ONAPAC, 2022)

The territory has a bimodal rainfall that ranges between 1,300 and 1,680 mm annually and annual temperature between 18 and 22 degrees Celcius (Cellule d'Analyse des indicateurs du Developpement, 2018). The main economic activities in the Territory include agriculture, livestock, fishing and artisanal mining (ibid.). The main food crops cultivated are maize, beans, cassava groundnuts and vegetables while the main cash crops are coffee and tea. The percentage of Arabica coffee grown in the Kalehe territory is 90% which is higher than the national average of 20% (Organisation internationale du café) (OIC) (2022). Cattle, sheep, pigs, goats are the main livestock kept. The poverty rate in the Kalehe territory is 94.6% which is higher than the national poverty rate of 70.8% (Programme des Nations Unies pour le développement (PNUD) (2017).

3.3.2. Research design and sampling procedure

A quasi-experimental quantitative research design was used in this study. To arrive to the sample households, a multistage sampling procedure was

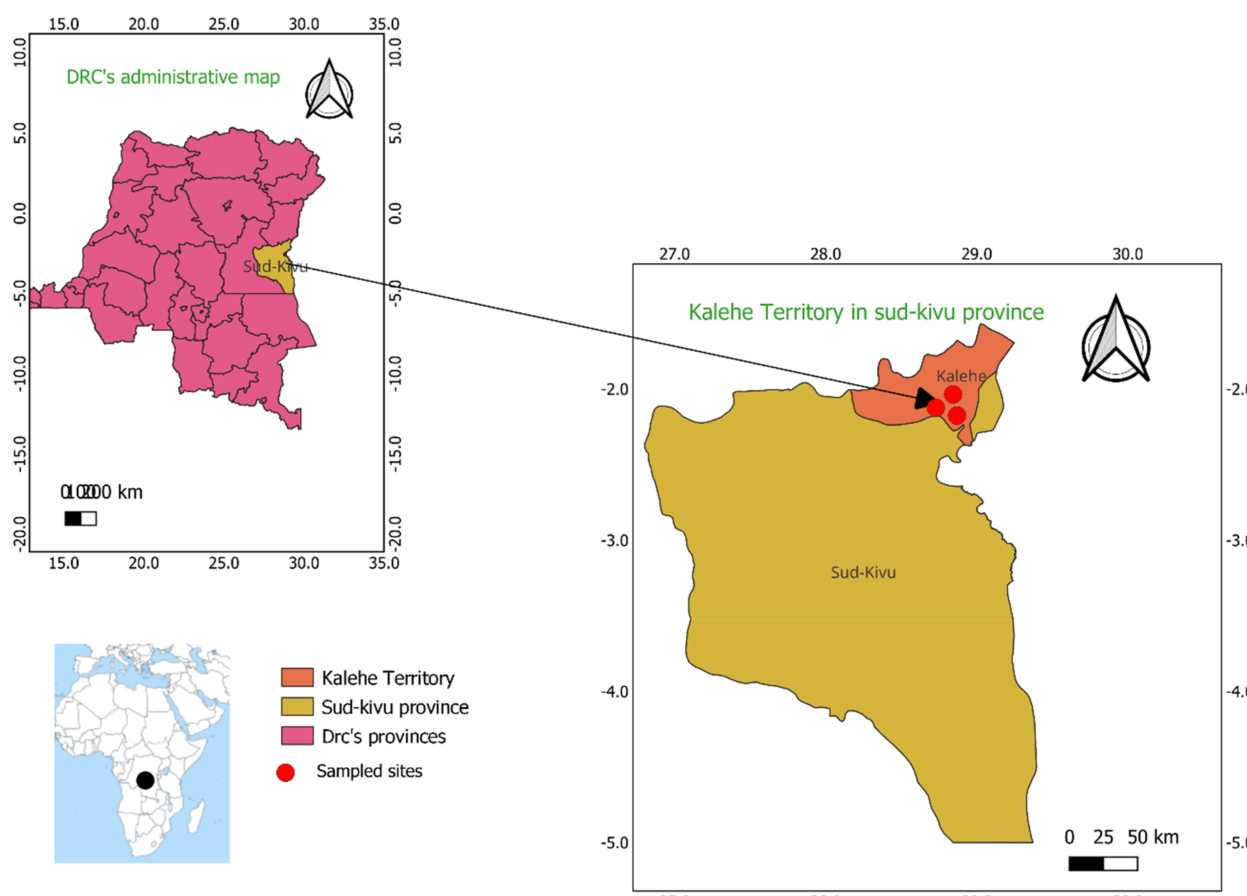

Figure 2. A map of DRC showing the location of Kalehe Territory in South Kivu Province.
Source: Author.

used. In the first stage, Kalehe Territory was purposively selected based on having the most smallholder coffee farmers in South Kivu Province (ONAPAC), 2022). In the second stage, Buzi Groupment was purposively selected based on significant level of coffee production (ONAPAC, 2022), accessibility and security. In the third stage, four villages, namely Bulenga, Kitembo, Muhanga, and Butumba, were purposefully selected from the Buzi Groupement based on their significant coffee production (ONAPACC, 2022) and security. In the last stage, a systematic random sampling procedure was used, where a random route was identified in every village and every fifth household on the right and on the left of the road was interviewed. A sample size of 600 households was determined using Cochran's (1977) formula for unknown population assuming 95% confidence level and a margin error of 0.04. However, the study ended up with 442 households due to non-response and missing data distributed as 25%, 22%, 25%, 26% in Bulenga, Butumba, Kitembo and Muhanga villages, respectively. The data were collected through administration of a pretested semi-structured questionnaire. The interviews were undertaken by trained enumerators using an Open Data Kit (ODK) app in 2021.

Before fitting the empirical models, multicollinearity was tested using the variance inflation factor (VIF) and Pearson correlation matrix. The results revealed no evidence of high correlation between explanatory variables as the correlation coefficient was less than 0.40. On the other hand, the hetprob command was used to test for heteroskedasticity. However, the null hypothesis of homoskedasticity could not be sustained (chi2(8) = 1.35, $p = 0.99$). Potential selection bias was controlled using awareness in the selection Equation (8) and incorporating that equation in Equation (9) using CMP command in STATA.

4. Results and discussion

4.1. Farmers' socio-demographic characteristics

As shown in Table 2, 85.5% of households were male-headed, reflecting the patriarchal societal structure in DRC where men hold primary authority in decision making. Of the 442 households surveyed, 84.8% had adopted at least one CSAT in coffee production while15.2% had not. The main CSATs adopted were, manure (54.1%), intercropping (5.4%), and different coffee cultivars (5.2%). The rest adopted a combination of these technologies, i.e. 35.29%.

At about 46 years, the respondents were relatively young with substantial experience in coffee farming. When considering all individuals engaged in agriculture across 13 SSA countries, the average age drops to 32 years old. On average, respondents had only 6 years of formal education with 23.1% reporting none. This compares poorly with the national average of 9 years of schooling in the DRC (World Bank, 2023). The average family size was 6.8 members,

Table 2. Summary statistics of socio-demographic characteristics of CSAT adopters and non-adopters in Kalehe Territory, DRC.

	Adopters	Non-adopters	Overall	2-tailed t-test
Variable	n= 375	n= 67	n= 442	
Means				
Age of household head (Years)	46.1 (14.5)	44.8 (14.0)	45.8 (14.4)	1.2
Experience (Years)	23.5 (15.3)	25.1 (14.5)	23.7 (15.2)	1.6
Schooling of household (Years)	6.0 (4.1)	4.8 (4.5)	5.8 (4.1)	1.1**
Household size (Number)	6.9 (2.8)	6.3 (2.7)	6.8 (2.7)	0.5*
Family labor (Number)	3.2 (1.6)	2.6 (1.5)	3.1 (1.6)	0.5**
Farm income (US$)	92.9 (52.5)	77.5 (53.4)	90.5 (52.9)	15.4**
Non-farm income (US$)	2.5 (5.3)	4.8 (8.5)	2.8 (6.0)	2.3***
Total annual income (US$)	102.0 (55.2)	80.3 (58.4)	98.7 (56.2)	21.7***
Farm size (Ha)	3.0 (13.6)	2.4 (7.4)	2.9 (12.9)	0.5
Farm transportation (Number)	0.2 (0.8)	0.1 (0.4)	0.1 (0.8)	0.0
Distance to input market (Km)	9.6 (12.0)	8.4 (6.3)	9.4 (11.4)	1.2
Frequencies	Percentage	Percentage	Percentage	χ^2-value
Gender (1 = Male)	12.8	87.2	85.5	5.6**
Group-membership (1 = Yes)	65.3	34.6	33.4	1.5
Access to credit (1 = Yes)	79.7	20.2	21.9	4.0**
Access to subsidy (1 = Yes)	90.9	9.0	9.0	0.0009***
Access to extension services (1 = Yes)	55.4	44.5	42.9	2.4
Bulenga village (1 = Yes)	75.7	24.2	25.3	1.5
Butumba village (1 = Yes)	76.8	23.2	22.4	0.9
Kitembo village (1 = Yes)	74.9	25.0	25.3	0.09
Muhanga village (1 = Yes)	72.5	27.4	26.9	0.3
Awareness (1 = Yes)	58.1		40.2	2.6
Ease-of-use (1 = Yes)	81.0		81.0	0.008***
Usefulness (1 = Yes)	93.8		92.3	8.4
Satisfaction (1 = Yes)	26.1		29.19	11.1

*, **, *** significant at 10%, 5% and 1% respectively. Standard deviations are in parentheses.

which is slightly higher than the DRC national average of 5.3 (MPSMRM, 2014). The average farm size of 2.9 ha was above the national average of 2,5 hectares (FAO, 2017). Based on the respondents' average income, 100% of the respondents lived below the poverty line of US$1.90 per person per day. The amount was US$0.27 compared with the national average of US$1.3 (Fonds monétaire international, 2023). About 33% of farmers belonged to farmer groups while 21.9%, 9% and 42.9% had access to credit, subsidy and extension services respectively.

4.2. Determinants of CSATs among smallholder coffee farmers in Kalehe Territory of DRC

4.2.1. Model validation

Table 3 presents the results of the MVP. The Wald Chi^2 of 154.67 ($p = 0.0000$) indicates that model fitted the data well. Additionally, the likelihood ratio test rejects the null hypothesis of uncorrelated errors in the underlying SURs thereby validating the use of the MVP. The significant values of all the atanhrhos were significant providing evidence of the presence of selection bias in the adoption of CSATs. Emphasizing the need for corrective measures, employing the MVP corrected for self-selection bias was essential. Out of the 11 variables considered for adopters of manure, four were statistically significant. Among the adopters of new coffee cultivars and intercropping combined with manure, only two out of 11 variables were statistically significant in each case.

The following sections discuss the results of the MVP using intercropping as the reference CSAT.

4.2.2. Factors influencing adoption of manure

Non-farm income was positively correlated with the probability of a farmer adopting manure relative to intercropping at 10% level of significant. A positive correlation between non-farm income and adopting manure use suggests that as households earn more income from sources outside of farming, they are more likely to adopt the practice of using manure. As such, a 1% increase in non-farm income would increase the probability of adopting manure by 7%. This could be explained by the fact that higher non-farm income provides households with greater financial resources. This allows them to invest in labour needed for manure collection, storage, and application, such as purchasing equipment, hiring

Table 3. Factors influencing CSAT adoption among smallholder coffee farmers in Kalehe Territory, DRC.

	CSAT						Selection equation	
	Manure (n = 239)		New coffee cultivars (n = 23)		Intercrop & Manure (n = 75)		Awareness (n= 375)	
Variable	dy/dx	Z	dy/dx	Z	dy/dx	z	dy/dx	Z
Household characteristics								
Age (Years)	0.0003 (0.001)	0.17	0.0006 (0.006)	0.10	0.008 (0.005)	1.46	0.01 (0.004)	2.86***
Gender (1 = Male)	0.06 (0.06)	0.99	0.01 (0.26)	0.07	0.01 (0.19)	0.03	−0.07 (0.18)	−0.39
Schooling of household (Years)	−0.002 (0.006)	−0.35	−0.01 (0.02)	−0.51	0.006 (0.01)	0.38	0.01 (0.01)	1.09
Household size (Number)								
Family labour (Number)	−0.006 (0.01)	−0.52	−0.15 (0.08)	−1.80*	0.08 (0.03)	2.35*		
Log Non-farm income (US$)	0.07 (0.04)	1.82*	−0.58 (0.12)	−4.65***	0.10 (0.10)	1.02		
Institutional characteristics								
Access to extension (1 = Yes)	−0.12 (0.06)	−1.96*	0.001 (0.18)	0.01	0.65 (0.14)	4.51***	0.50 (0.12)	3.96***
Access to credit (1 = Yes)	0.11 (0.06)	1.91*	0.18 (0.20)	0.93	−0.11 (0.15)	−0.73		
Farm and technology characteristics								
Farm size (Ha)	−0.002 (0.001)	−1.36	0.002 (0.004)	0.66	−0.004 (0.003)	−1.17		
Distance to input market (Km)	0.001 (0.002)	0.52	0.009 (0.009)	1.05	0.001 (0.002)	0.41		
Ease of use (1 = Yes)	0.015(0.07)	0.23	0.10(0.21)	0.48	−0.10(0.15)	−0.69		
Location (Villages)								
Butumba	−0.11 (0.06)	−1.70*	−0.34 (0.28)	−1.23	0.08 (0.21)	0.41	−0.20 (0.18)	−1.11
Kitembo	−0.04 (0.07)	−0.60	0.21 (0.23)	0.92	−0.18 (0.19)	−0.93	0.18 (0.17)	1.05
Muhanga	0.05 (0.07)	0.70	−0.32 (0.23)	−1.37	−0.01 (0.20)	−0.08	−0.21 (0.17)	−1.22

*, **, *** denote significance at 10%, 5% and 1% respectively. Robust standard errors are in parentheses. Wald Chi^2 (46) = 148.80***; Log pseudo-likelihood = -542.55; $n = 442$; $p = 0.0000$. Note: Intercropping and Bulenga Village were used as reference categories.

labour, or building storage facilities. This result is consistent with the study that has shown how non-farm income increase the probability of adopting two or more sustainable agricultural technologies including manure in Ethiopia (Mutyasira et al., 2018).

It had been hypothesized extension services positively influence adoption of manure; however, results show that the variable was negatively correlated with the probability of manure adoption over intercropping at 10% level of significant. Accordingly, having access to extension services would decrease the probability of adopting manure by 12%. Farmers might already have access to alternative manure sources or traditional knowledge about manure use, rendering formal extension services less relevant or unnecessary. This could even create resistance to new recommendations if perceived as conflicting with existing practices. The result contradicts Diro et al. (2022) who reported that the application of manure in Ethiopia is positively affected by access to natural resource management extension.

Credit access refers to the availability of financial resources, through loans, grants, or other means, that individuals or communities can utilize to acquire and implement new technologies (International Development Research Centre (IDRC), 2015). Based on a priori expectation, access to credit was positively associated with the likelihood of a farmer adopting manure relative to intercropping. Credit access would increase the probability of adopting manure by 11% at 10% level of significant. It means that farmers who have access to credit are 11% more likely to adopt manure. This is because credit can help farmers overcome financial constraints that may prevent them from purchasing manure. For example, manure can be expensive to transport, and farmers may not have the cash on hand to cover the cost. Credit can also help farmers invest in equipment or infrastructure that is needed to use manure effectively, such as manure spreaders or storage facilities. The positive role of credit access to technology adoption observed in this study is consistent with Mwaura et al. (2021) who found that credit access influenced the adoption of manure in the Central Highlands of Kenya.

Location represents a specific physical place such as village. This geographical context influences access to technology infrastructure, resources, and knowledge, impacting adoption rates. The results revealed that residing in Butumba rather than Bulenga village would decrease the probability of adopting manure instead of intercropping by 11% at 10% significant level. This could be due to a number of factors, such as differences in knowledge about the benefits of manure as the data show that many respondents knew about manure in Bulenga village (112 respondent) rather than in Butumba village (99 respondents).

4.2.3. Factors influencing adoption of new coffee cultivars

Coffee production is a labour-intensive income-generating activity. Family labour serves as lower adoption costs i.e family labour can reduce the initial investment needed for new technologies, making them more accessible (Ango et al., 2022). This can be particularly beneficial for small-scale coffee farms with limited resources. However, in this study, an additional unit of family labour would reduce the probability of adoption of new coffee cultivars by 15% at the 10% significance level. This could be due to investment costs where new coffee cultivars might require additional inputs, which families with more labour might not have readily available, making adoption financially less attractive. The finding confirms Kambanje et al. (2018) who reported a negative correlation between labour and adoption of maize varieties in South-Africa.

Whereas non-agriculture income has been shown to positively correlate with technology adoption (e.g. see Bernard et al., 2019), this study found a negative relationship. This could be explained that new coffee cultivars might be at an earlier stage of adoption. Early-stage technologies often face challenges like limited functionality, high cost, or lack of awareness, leading to initial resistance and a negative correlation with revenue. As such, a 1% increase in non-farm income would decrease the probability of adopting new coffee varieties by 58%, *ceteris paribus*. This is not in line with (Hailu & Mezegebo, 2021) who found that access to non-farm income positively influenced technology adoption in Tigray, Ethiopia.

4.2.4. Factors influencing adoption of intercropping/manure combination

An additional unit of family labour would increase the probability of adopting intercropping combined with manure by 8% at 10% significant level. This could be explained by the fact that with more family members available to contribute labour, farmers might be less constrained by labour shortages, making it easier to manage the additional tasks involved in intercropping and manure application, such as planting, weeding, and composting. This finding is consistent with that of Daadi and Latacz-Lohmann

(2021) who reported a positive association between the adoption of organic fertilizer and family labour use in Northern Ghana.

Extension services are essential in addressing challenges related to weak market infrastructure and limited credit access in adopting 'lump inputs'. They build trust, facilitate collective action, and advocate for policy changes, addressing these limitations (Hoang & Long, 2016). Crawford and Jayne (2008) highlight the effectiveness of extension services in providing information, demonstrating benefits, and facilitating credit access, contributing to increased adoption of lumpy inputs. The results of this study showed that at 1% significance level, access to extension services would increase probability of intercropping combined with manure by 65% in Kalehe Territory. Extension services play a crucial role in informing farmers about innovative agricultural practices like intercropping and manure use. This could be extension services are essential for educating farmers about agricultural practices, including intercropping and manure use. They provide technical knowledge, highlight potential benefits, such as improved soil fertility and pest control, and offer best practices for local adaptation. The result is in line with Abebe and Debebe (2019), who found that access to extension services positively influenced the application of manure in Northwestern Ethiopia.

4.3. Potential substitutability between alternative CSATs in Kalehe Territory

The results in Table 4 were generated using in Stata. The negative and statistically significant correlation between manure and new coffee cultivars suggest potential substitutability between the two technologies. That between manure and coffee cultivars also manure only and intercropping combined with manure. These findings suggest that promoting the use of manure could lead to a decrease in the adoption of new crop cultivars, given the presence of favorable conditions such as affordability, availability, and pricing. Additionally, the promotion of manure is likely to result in reduced adoption of new intercropping combined with manure.

Table 4. Potential substitutability between the three CSATs used in coffee production in Kalehe Territory, DRC.

CSAT	Manure	New coffee cultivars	Intercropping and manure
Manure	1		
New coffee cultivars	−0.63***(0.00)	1	
Intercropping and manure	−1.21***(0.00)	0.12(0.25)	1

*, **, ***significant at 10%, 5% and 1% respectively.

5. Conclusion and implications

The existing research on key determinants of coffee farming suffers from a significant gap. Previous studies haven't conducted a thorough evaluation of these factors in DRC and leaving a critical need for a more nuanced and comprehensive analysis. This includes addressing potential selection bias, which has been largely overlooked in past research and can severely skew results. To ensure a representative sample of 442 smallholder coffee farmers in Kalehe Territory, a multistage sampling process employed purposive selection for high coffee production areas and secure villages, followed by systematic random sampling within villages, utilizing pretested questionnaires administered by trained enumerators via the ODK app in 2021. A multivariate Probit model corrected for selection bias was employed to assess the drivers of CSATs uptake among smallholder coffee farmers in Kalehe Territory, DRC. The results show that intercropping, manure, and new coffee cultivars were the most common CSATs used by coffee farmers in the study area.

The probability of farmers choosing to use manure increased with non-farm income and access to credit but decreased with access to extension services and residing in Butumba Village. This suggests supporting local non-farm economic development by invest in creating local job opportunities within the agricultural value chain, such as processing facilities, logistics networks, or rural service businesses to avoid farmers getting out of agriculture. In addition, providing credit facilities specifically targeted towards manure acquisition or transportation to make it more accessible to farmers with limited financial resources. This can be possible by regularly monitor and evaluate the effectiveness of credit programs such as track loan uptake, repayment rates, and impact on manure adoption and farm productivity. This feedback can inform adjustments to lending practices and ensure efficient use of resources.

Surprisingly, the adoption of new coffee cultivars was negatively influenced increase in family labour and non-farm income. This was unexpected because traditionally, one would expect more labour availability to facilitate the adoption of new cultivars, which might require additional care or specific management practices. With more hands on deck, farmers can potentially handle the increased workload associated with coffee cultivars.

The adoption of a manure/crop intercrop by farmers was been positively influenced by family labour and access to extension services. Unlike monoculture systems, intercropping requires more diverse tasks spread throughout the season. Therefore, with increased family labour, farmers can efficiently manage these tasks like planting multiple crops, weeding different intermingled species, and harvesting varied produce. This labour distribution makes intercropping a feasible undertaking. Extension services play a crucial role in educating farmers about the benefits of intercropping and manure use. They can provide technical guidance on specific practices, suitable crop combinations, and efficient manure application methods. This empowers farmers to make informed decisions and adopt intercropping with confidence. Promote extension services should be enhanced for empowering farmers to make informed decisions about their practices, leading to improved productivity, resilience, and environmental sustainability by providing training programs on best practice and facilitating information access through various channels. This would motivate farmers to more adopt these technologies, which would in turn secure their welfare.

Manure, new coffee cultivars and intercropping combined with manure had the potential to be substitutes for each other, meaning that the promotion of manure could lead to a decrease in the use of new crop varieties among coffee farmers. However, this would only happen if the right conditions, such as pricing, affordability, and availability, were met. This substitution is important because manure is often readily available and free or inexpensive for farmers, while coffee cultivars can require purchasing seeds and potentially adapting existing practices. This makes manure a potentially more efficient and cost-effective option, especially for resource-constrained farmers.

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Declarations

Author contribution statement

Florence Bwiza: Conceived, analyzed and interpreted the data; wrote the paper.

Patrick Irungu; John Mburu; Alisher Mirzabaev: Conceived; analyzed and interpreted the data.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Data availability statement

Data will be made available on request.

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