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Evaluating the Influence of Carbon Credit Payments on Coffee Farmers' in Uganda and Kenya

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Abstract

Carbon payments offer smallholder farmers a potential additional source of income that will encourage participation in the sustainable carbon projects. This study will aim to investigate how the impact of carbon payments affects farmers' practices, particular focusing on the changes in farm investment, productivity, and land management. Using a regression analysis on data from Kenya and Uganda, from the existing literature and the findings these suggest that when carbon payments are perceived by the farmers as a reliable source of income, these are more likely to increase on-farm investment, improve yields, and adopt more sustainable land-management practices. These results highlight the importance of trust and consistency in payment schemes to ensure both environmental and economic benefits.

Keywords:

Sustainable carbon projects , carbon payments, Smallholder farmers , Farm investment, Agricultural productivity, Land management

Contents

1 Introduction

1.1 Brief Problem Description

In East Africa, the coffee sector is a leading export commodity as well as a powerful tool for restoring degraded land and improving the life's of smallholder farmers [Partnerships for Forests, 2024]. Over the past 20 years, coffee has contributed to an average of 16% of Uganda's national foreign exchange revenue, in which small farms have accounted for roughly about 85% of the overall production [Uganda Coffee Development Authority, 2023]. Furthermore in Kenya, coffee cultivation for nearly 800,000 rural households it's their main source of income, and even though the productivity has decreased by 40% since 1980, the coffee sector still accounts for around 10% of the national agricultural export earnings [Nyambane et al., 2022].

Despite the economical importance coffee has in both countries, the sector has faced numerous challenges, among which are included high volatile markets, fluctuating prices and intensifying effects of climate change causing more frequent droughts, shorter growing seasons, and accelerated soil erosion, that have reduced farmers yields and degraded crop quality over time [Nyambane et al., 2022]. Across Kenya and Uganda, the implementation of sustainable carbon sequestration projects have demonstrated average yield gains of up to 30% and income increases that averaged 62% compared to more traditional farming methods [Farmonaut, n.d.]. However, high transaction, and MRV (measurement, reporting, and verification) costs and unclear land tenure arrangements continue to limit the participation of the farmers and scalability of the programs [Wollenberg et al., 2023]. Therefore, it's essential to evaluate whether these sustainable carbon sequestration projects are delivering meaningful socio-economic benefits to smallholder farmers and ensure that these interventions actually improve farmers' livelihoods.

1.2 Research Objectives

This study aims to evaluate in what ways do yield, agricultural investment, and land use decisions differ between smallholder coffee farmers in Uganda and Kenya who have participated in carbon credit payment schemes and those who have not?. By capturing these real-world impacts, the research also will assesses the project schemes' to potentially also foster a more resilient and sustainable coffee landscapes and whether sustainable carbon-credit projects enhance smallholder farmer livelihoods and deliver their intended environmental benefits in East Africa.

By testing three core hypotheses:

Yield: Participating farmers in sustainable carbon-credit projects is associated with having significantly higher yields than those that have not participated.

Agricultural Investment: Participants of the sustainable carbon-credit projects invest more in farm inputs and infrastructure than non-participants.

Adoption of sustainable land use: Participation increases the likelihood that farmers will adopt sustainable land-use practices.

Together, these three hypotheses will help guide the methodology investigation to determine whether and how carbon-credit interventions can boost productivity, investment, and increase sustainable land practice adoption among smallholder coffee farmers in Uganda and Kenya.

1.3 Literature Search Strategy and Selection Criteria

In order to find and evaluate the relevant research papers on the influence of carbon credit incentives on coffee in Uganda and Kenya, the literature review adopted a thematic-narrative review design. The search strategy was conducted on discovery web tools such as Elicit, Paper Digest, Google Scholar and Scite, additionally to direct the search by key words such as "yield impact," "agricultural investment," "land-use decisions," "carbon payment/finance," and "farmers involvement in carbon initiatives/payment for ecosystem services," were used to narrow the results and find the most useful papers.

Initially the results were filtered to Uganda and Kenya to maximize the contextual relevance, then systematically widened to other coffee-producing regions to temper regional bias and introduce new contrasting viewpoints. However, the assessment encountered a few difficulties in the literature exploration. Since limited research has been done on carbon farming in Uganda and Kenya, the narrowness of the subject made it complicated to find applicable and related studies. Additionally, only English-language articles were included in order to preserve the review's credibility and applicability, which may have cause a language bias barrier by excluding important contributions from other non-English sources in this research. Finally to guarantee the validity and scholarly rigor of the review, papers that were not published in respectable journals or that lacked enough citations were disqualified from being further investigated. The review aimed to balance specificity and diversity by including insights from other similar contexts.

2 Literature Review

2.1 Coffee Sector in east Africa

In East Africa, coffee farming for many families is a one of the main sources of income and a key earner for the national economies of the countries [Partnerships for Forests, 2024], but focusing in Uganda and Kenya we see that they have taken very different routes to success.

Uganda is one of the largest coffee exports in the world and the second largest in Africa just behind Ethiopia. In 2023, Uganda produced 6.85 million 60 kg bags of Robusta coffee and exported 6.5 million bags worth nearly 1 billion US dollars [Partnerships for Forests, 2024]. This large production comes supported from farmers being able to join carbon credit projects, using loans to buy fertilizer and letting private buyers compete for the bean, keeping prices competitive. However, over the recent years coffee has seen a drop in its productivity [International Coffee Organization, 2023]. For example in the year 2022/23, after a second consecutive drought in Uganda, the yield fell by almost 6.8 percent.

Kenya on the contrary is not such a massive producer but it is better known for its quality beans. Were farmers harvest only about 750 000 to 800 000 bags, but of well known bean varieties such as SL 28 and Batian which are some of the worlds highest bean coffee prices. However due to most farmers relaying on traditional farming techniques with limited adoption of modern inputs this result in lower yields per hectare [Hussain et al., 2020].

Even though in terms of the importance they give to the farming industry both countries are very similar, their differences in structure influence how the carbon credit programs integrate shade trees, enrich soil or reduce deforestation. Uganda for example has a large network of enrolled farmers however they are very dispersed across the country [Uganda Coffee Development Authority, 2023]. In Kenya there are already formation of natural groups for carbon tracking and certification, yet funding gaps and regulatory obstacles are delaying advancements [Hussain et al., 2020].

Kenya and Uganda are facing very similar climate change consequences such as hotter nights, erratic rain, longer dry seasons and hotter climate causing crops to struggle to survive reducing productivity and causing pests to propagate faster. In addition the farmland in both countries is under constant pressure as in Kenya its being turned into housing and in Uganda other crops are starting to gain popularity [Hussain et al., 2020] [Uganda Coffee Development Authority, 2023]. Due to all these challenges faced by the farmers carbon payment projects are an attractive yet complicated solution; governments and organizations are trying to help, for example in Uganda the "Coffee Roadmap" pays for seedlings, rural processing equipment and training in climate-smart agronomy alongside agroforestry practices. On the other hand Kenya's new Coffee Act promises growers payment within a week of the auction, also funds low-interest harvest, and has even launched a "carbon-neutral" label for premium beans headed to Europe [International Coffee Organization, 2023].

Knowing these sector basics is vital before judging whether carbon projects will really have an impact on the farmers, because this will depend on each country's unique market structures, policies, and climate challenges.

2.2 Carbon Payment Schemes in Uganda and Kenya

In the recent years, carbon-sequestration projects have gained more popularity as a climate-mitigation strategy, by promoting the use of sustainable agricultural methods and providing an extra source of income to the farmers.

These projects relay on providing farmers with incentives, which are often in the form of tradable carbon credits or dedicated funds, allocated to offset the upfront costs faced when joining these projects and moreover these incentives also foster a prolonged commitment and drive an increase in engagement and participation in the sustainable projects [Murali K. V. & C., 2015].

The carbon market works by enabling the farmers to earn tradable credits by using climate-smart methods, like agroforestry (The intentional placement of trees or bushes alongside crops and/or cattle on the same plot in order to improve soil health, biodiversity, and production), to sequester carbon emissions. These reductions are then verified by an independent third-party auditor to measure the amount of carbon sequestered in biomass and soil. Once verified, these credits are then sold by project developers through the voluntary or compliance markets [Murali K. V. & C., 2015]. The Voluntary market allows any type of buyer to purchase the verified credits independently, to offset emissions at their own will. On the other hand, the compliance market is established by the law or government requiring firms to purchase credits to match their emission gap [Eastern Africa Carbon Markets, 2022]. Farmers then receive a percentage of the revenue from these credit sales.

One notable example is international support through the Dream Fund of the Dutch Postcode Lottery, which invested €12.7 million to help 100 000 farmers, including those in Uganda and Kenya to integrate agroforestry systems for sequestering carbon; this program enables farmers to earn additional revenue via carbon markets on top of the already existing local incentives [Network, 2025].

The voluntary market in Eastern Africa surpasses the compliance market, with a total of 73.6 million VCM units issued compared to 31.9 million CERs as of 2022 [Eastern Africa Carbon Markets, 2022]. This dominance can be attributed to robust net-zero commitments from corporations and NGOs that boost demand for voluntary offsets, as well as the greater flexibility the voluntary market offers under standards such as VCS, which encounters fewer regulatory and administrative hurdles [Eastern Africa Carbon Markets, 2022].

The Vi Agroforestry and ECOTRUST initiatives analyzed by BioMed Central [Shames et al., 2016] although not representative of all project models, they do conform to the basic institutional structure typical of smallholder carbon projects. In Kenya, the Western Kenya Agricultural Carbon Project (Vi Agroforestry) combines CDM and VCS, engaging over 60 000 farmers through 30 different intermediary communities; participants receive on average 200–300 USD per half-hectare over a 10 year contract, all supported by county-level extension services for agroforestry training and payment management. In contrast, Uganda's ECOTRUST scheme operates solely under VCS with just 17 intermediaries and pays individual households for generated credits in annual installments over 10 years, averaging USD 2.50 per hectare per year, while farmers also report improved farm productivity; however, low and delayed payments, high upfront development and seedling procurement costs, and land-tenure restrictions have resulted in low participation and retention despite clear gains in agroforestry knowledge.

2.3 Farm-Level Impacts of Carbon Payments

This segment will examine the empirical evidence found on how carbon payments can yield tangible, enduring advantages for smallholder coffee farmers.

Evidence found by Kenya agricultural carbon project (KACP) indicated that integrating carbon payments alongside with sustainable agricultural land management (SLAM) practices can improve the coffee productivity by strengthening the soil and creating microclimate conditions throughout the farmland [Nyberg et al., 2020]. In addition SALM practices such as crop residue management, agroforestry, and composting are intended to trap carbon, strengthening the ecosystem services that support coffee yields.

According to Schultz's theory, first presented by Theodore W. Schultz in his seminal work Transforming Traditional Agriculture, in 1964 and then later became known as the "poor-but-efficient" hypothesis, states that smallholder farmers allocate inputs optimally and react strongly to price incentives despite having limited resources. This suggests that by directly linking payments to performance, it is possible to capitalize on this associated efficiency and generate significant yield gains [Duflo, 2002].

A case study by [TechnoServe, 2022] which aim was to examine how sustainable carbon programs can encourage the adoption of agroforestry and enhance productivity among smallholder Robusta coffee growers in Tanzania. Found that coffee growers that received carbon-backed financing for establishing and maintaining shading trees saw that their average yields rose by 15 %, causing an increase from about 420 kg/ha to 483 kg/ha within the three years examined. The extra income received enabled them to purchase better seedlings and apply targeted agrochemicals moreover offsetting the costs of agroforestry integration and improving on-farm management .

TechnoServe also reported that carbon payments led to a notable shift towards farmers' attitudes on long-term investments decision making, knowing that revenues would arrive reliably, growers felt more confident and committed to labor and tree maintenance and were more likely to seek out for complementary credit and technical advice. On the other hand, [Shames et al., 2016] warns that when carbon payments are too low, farmers end up assuming most of the upfront costs themselves, discouraging them from even beginning tree-planting activities. Because the payments fail to cover expenses or provide a meaningful income stream, participation rates fall drastically as farmers loss the trust in the programs, and yields remain unchanged, unless carbon payments are significantly increased to meet with farmers expectations.

Moreover a 2024 study in Kenya, involving 207 smallholder farmers, showed that 86% of participants experienced increased household income, and 68% saw higher consumption expenditure, indicating a greater capacity for farm investment [Nkatha et al., 2024]. Similarly, a 2023 case study in Ghana's Eastern Region on cocoa agroforests revealed that integrating carbon payments significantly boosted key profitability indicators for farmers. For instance, the modified internal rate of return (MIRR),which accounts for both the cost of financing outflows and the realistic reinvestment of inflows, for participating farmers, notably increased from 19.3% to 29.8% with carbon payments, demonstrating a clear incentive for further investment with the extra money they receive [Gockowski et al., 2023]. These studies show that carbon payments reduce income volatility and also provide an additional farm-level investments and incentives for sustainable agricultural practices.

Carbon payments have positively influenced investment decisions by providing farmers with an extra source of income, reducing the short-term financial pressure [Jayachandran et al., 2017]. Moreover helping support the maintenance and planting of trees, allowing the farmers to allocate resources towards long-term productivity improvements like purchasing better seeds, applying more fertilizer, hiring extra labor or investing in soil management.

An analysis in Uganda which aim was to investigate how the design of carbon-payment schemes can affect smallholder farmers' with on-farm investment choices [Rode et al., 2023], showed that when payments are:

1) Large enough to fully cover the upfront and ongoing costs associated with joining these programs

2) Payments scheduled to match with planting/harvest calendars

3) Delivered directly to farmer groups with minimal to no delay on payments

Households will shift land previously used to low-yield annual crops into agroforestry systems, purchase improved seedlings, and invest in soil-conservation structures. Across the Ugandan sites, 90 % of participants reallocated at least 25 % of their land into tree plots, 85 % purchased higher-quality seedling and moreover the average tree survival rates rose from 45 % to 95 % when payments met the criteria mentioned above. On the other hand, when payments covered less than 50 % of true costs or were delayed by more than two months, fewer than 30 % of farmers made any new investments, instead farmers diverted the funds to immediate household needs instead of on-farm investment once the extra income of the carbon payments was received.

In practice, this suggests that trust and predictability and actually receiving the carbon payments are more important than simply the promise of the extra income when it comes to driving farmers' decisions to invest in long-term assets. When farmers have confidence in receiving the right amount at the right moment, they view carbon payments as a stable source of capital rather than a temporary source. This stability allows them to plan and secure finance for higher-quality inputs and ultimately integrating climate-smart practices into the farming strategies. If farmers can't count on getting the right money at the right time, they'll ignore carbon payments and use any extra cash to cover immediate needs instead of improving their farms [Rode et al., 2023] and moreover if payments are not what the farmers were promised by the sustainable carbon projects this will cause farmers to loss trust and interest in the them reducing drastically engagement and participation [Shames et al., 2016].

It has been found that farmers will shift from their familiar monoculture cropping systems to agroforestry only when carbon payments both cover all upfront establishment costs (seedlings, labor and maintenance) and are structured to reward them at clear stages of tree growth, giving them the confidence to invest in on-farm land use [Jayachandran et al., 2017]. With payments secured, farmers are able to expand on-farm tree cover enhancing soil health and biodiversity. Whereas, in the absence of such incentives, they generally remain committed to traditional methods and miss out on both environmental and income gains [Murali K. V. & C., 2015]. In the Cash for Carbon program analyzed by [Jayachandran et al., 2017], from the benefits scheme only 32 % of eligible landowners chose to enroll, whereas in control villages (which received no payment offer) there was effectively no voluntary adoption of new tree-based practices over the same period. Since the adoption of tree-based practices is almost nonexistent without money, this demonstrates the importance of the carbon payments incentives in promoting their adoption.

However on the contrary a study shown by [Goncalves et al., 2021] in Brazil, came to the conclusion the provision of carbon payments alone may not be enough to induce significant behavioral change. In their study of coffee agroforestry systems, receiving payments for carbon credits did not alter how farmers managed shade-tree cover, fertilization, or soil practices. In other words, the study found that farmers valued more having other additional incentives directly linked to tangible on-farm benefits, such as improved soil health or better microclimate buffering, rather than carbon payments, showing that in some cases the extra financial incentive showed to be too weak to drive of practice changes.

2.4 Literature Gap

The existing reviewed literature, presents valuable insights into the potential of carbon payments to incentivize sustainable land use, increase yield and incentives on-farm investment, improving farmers livelihoods. However, it has numerous limitations. Most studies tend to focus on the environmental outcomes or emission reduction, putting limited focus to how the carbon payments actually influence farm-level decisions. Additionally, while some of the research explores the economic incentives under carbon schemes they often overlook the complexity of post-payment decision-making and very few studies actually compare the differences between Uganda and Kenya.

Adding to these restrictions, there is still a significant gap in the literature, very little studies have evaluated the effects of carbon payments at the smallholder farm level in Kenya or Uganda, when it comes to analyzing how farmers change there attitude when they receive carbon payment and fully understand there decision making, it is still unclear on how they react to each scenario. Therefore, by comparing the on-farm investment decisions, yield results, and land-use changes under carbon payment systems in Kenya and Uganda, this study seeks to close that gap.

3 Data Analysis

For the investigation the choice of data was not selected but more of what could be found to be most relevant due to the limited public data that was available online. For the analysis two datasets were selected one for Uganda and another for Kenya.

3.1 Kenya Analysis

The dataset on Kenya was analyzed by three researchers from the Jomo Kenyatta University of Agriculture and Technology, College of Agriculture and Natural Resources found on Mendeley data. Which was gathered from smallholder coffee farmers in the county of Kiambu Kenya, who either participated and received carbon credit payments or did not participate and hence not received payments from the Commodity Fund credit program. The dataset contains 16 variables, including each farmer's unique identifier and key demographic characteristics such as age, gender and education level. It also captures agronomic details such as coffee yield and major input metrics such as: fertilizer use, agrochemical expenditures, labor inputs (man-hours), farm size, and other relevant measures. Moreover, for the data preparation procedure, the variables labor-cost, fertilizer, and agrochemical variables were standardized before fitting them into the data analysis and models. The scaling of predictors was done to ensure that the coefficients are directly comparable and that the model and analysis would be less sensitive to differences in variable magnitudes.

Furthermore a descriptive analysis was done to better understand the Kenya dataset and identify patterns to be able to observe more in-depth insights:

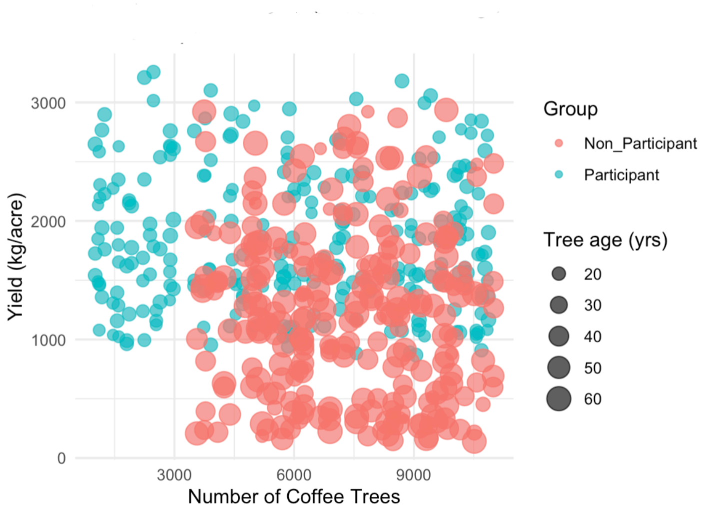

Figure 3.1: Yield vs Number of Trees and Tree Age by Participation

Figure 3.1 suggests credit-receiving farmers in color turquoise tend to achieve a higher yields per acre even though having a lower tree density compared to non-recipients in color red, implying that access to credit may support more intensive management rather than simply expanding tree numbers, also is seen how non-participant farmers tend to have older tree suggesting that credit might be used by the farmers to finance maintenance activities and replanting of newer and fresher tress. These patterns motivate our hypothesis that the carbon payment could improve technical and yield efficiency.

Figure 3.2: Age Distribution of Farmers by Credit Participation

Figure 3.2 is Kernel density plot which shows farmers age by payment receiving status (participation). The graph shows that non-participants (red) have a age distribution that is shifted to the right, with a peak around 55 years old. On the other hand participants (turquoise) cluster more tightly around 50 years. The age distribution of the dataset shows significant overlap between both groups and it can be seen that younger farmers (<45) are disproportionately represented. Moreover the non-participant group tends to be conformed of older farmers. This suggests that age might influence credit adoption, with middle-aged farmers more likely to participate in carbon project initiatives.

3.2 Uganda Analysis

On the other hand for Uganda, the MISACI data (provided by Sidi Amar) was analyzed. This dataset composed of a 36 question survey, which contained information on demographics of the farmers, some data on carbon payments, data on annual income and perceptions of farmers in different aspects such as willingness to continue using agroforestry practices, and expectations of future yields. Additionally, it also captures farmers' attitudes toward climate change and their perceived role in addressing it through tree planting, among other key variables.

For this dataset, the data cleaning procedure was a bit more extensive than the one done previously on Kenya, as it involved handling missing values and standardizing variable formats to ensure consistency. Categorical responses such as ”Yes” were recoded into binary values (0 for ”Yes”, 1 for ”No”) to simplify their interpretation and facilitate their use in the statistical models and descriptive analysis. Additionally, income-related variables such as Income and Income from main crop (which in all cases was coffee), were converted from Ugandan Shillings to Euros using the current exchange rate of 4172.52 Uganda Shilling : 1 euro, enabling for a more meaningful financial comparisons in an international context. Furthermore, income from main crop (coffee) was divided by total cultivated land to compute earnings per hectare, providing a standardized measure of agricultural productivity. These transformations helped prepare the dataset for a reliable analysis.

Again an exploratory assessment was carried out on the Uganda dataset to uncover trends and gain a clearer understanding of the data :

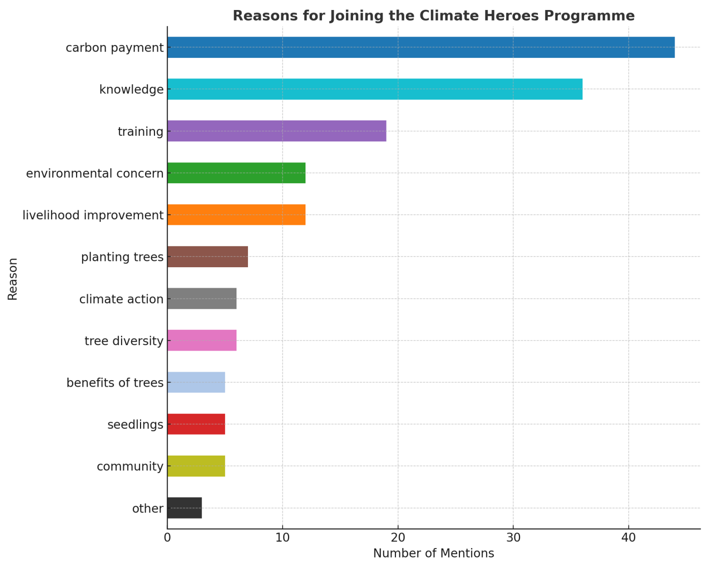

Figure 3.3: Reasons for joining the Sustainable Program

Figure 3.3 shows the most common reasons the farmers gave for joining the program. From graph it can be appreciated how the carbon payment was the primary incentive for joining the program, closely followed by knowledge and training. These results indicate that monetary rewards and availability of information are the main factors influencing participation. Environmental and other social aspects such as livelihood enhancement were cited less often, suggesting they might be perceived as additional advantages instead of primary incentive.

On the other hand figure 3.4 illustrates the anticipated challenges farmers feel they will face once they have joined the projects. Interestingly, the most prominent concern identified was payment related issues, which appear more frequently than any other issue such as pest

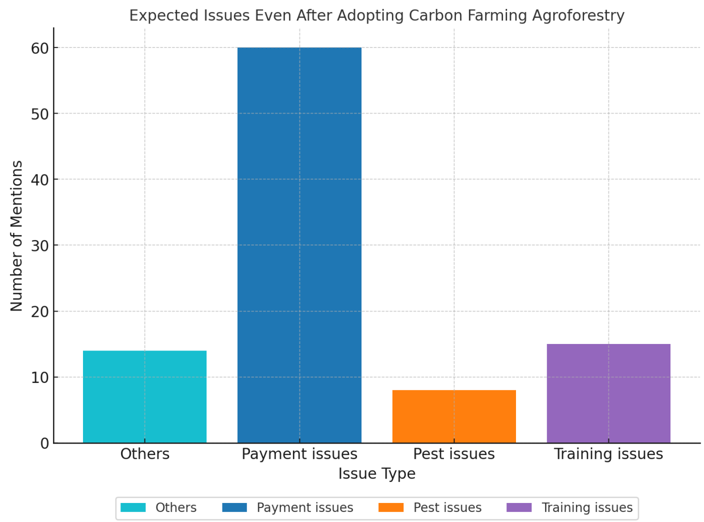

Figure 3.4: Expected complications after joining the Sustainable Program

problems, training gaps, or other types of concerns. Indicating technical and environmental issues are perceived as less urgent and important compared to payment issues.

The findings from Uganda reveal that while farmers view carbon payments as the main incentive for joining climate-focused programs, they also see payment issues as the most likely challenge they will face once they have enrolled in the program. This contrast highlights a critical tension on how farmers are motivated by the promise of financial support, but uncertainty around payment delivery can undermine their trust and commitment.

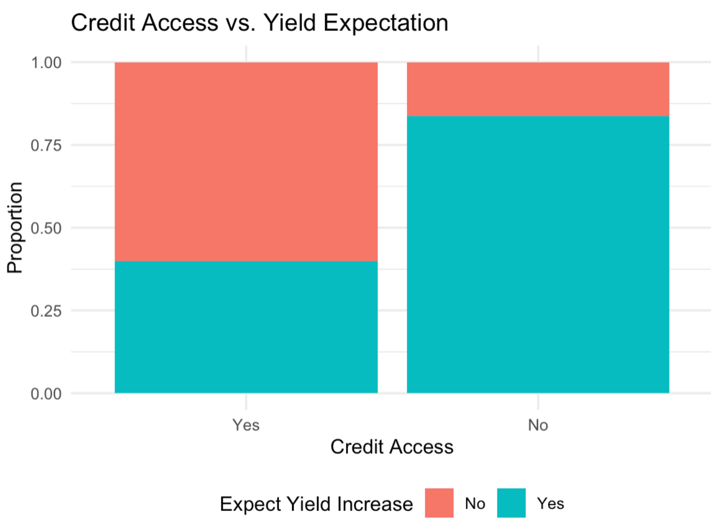

Figure 3.5: Credit access Vs Expected yield growth

Figure 3.5, surprisingly shows that farmers that have not applied to loans are more likely to expect yield increases compared to those who have not applied. This finding is unexpected, as normally access to credit is associated with having a greater ability to invest. Further analysis is needed to explore and determine what can cause these differing expectations and determine whether the observed pattern is statistically significant.

4 Methodology

The current literature review presents numerous strategies and methodologies. When it came to choosing the most appropriate method, an in-depth analysis was performed to assess the advantages and drawbacks of each option, and to align the results with the existing data and research context.

Taking into account the complex nature of the topic, between the different types of methodologies used to explore literature (Quantitative, Qualitative and Mixed Methodology), this last one, a mixed methodology, was found to be the most suitable, as it combines both the qualitative and quantitative elements, helping ensure more robust and generalizable insights and moreover help provide deeper connections [Kiptot & Franzel, 2015]. Mixed methodology also better fits the available data found as it is flexible and can be modeled to fit different analysis techniques, providing a broader perspective.

Moreover, the methodology choice was also influenced by the contradictory top-down and bottom-up perspectives. Top-down strategies adopt a theory-oriented route, thoroughly examining hypotheses based on policy structures and financial motivations [Murali et al., 2025], whereas bottom-up strategies move gradually, revealing insights from farmers' life experiences and local dynamics [Kiptot & Franzel, 2015] Given the goal of quantifying how carbon-credit participation affects farmers, a top-down design was chosen, as it enables a more accurate hypothesis testing and actionable insights.

From the methodologies studied, the most promising were Regression Modeling, and SEM, which have already demonstrated a strong efficiency. [d'Albertas et al., 2024] used an MLR to examine when do carbon payments and improved pollination together boost coffee yields enough to offset forest restoration costs, evidencing its reliability for assessing incentive effects. [Camarillo et al., 2025] aimed to find how carbon payments influence coffee farmers' participation and investment decisions in agroforestry conservation scheme by using a binary logistic regression model. Moreover, SEM was used by [Hou & Hou, 2019] whose objective was to pinpoint factors like carbon payment awareness and contract farming that drive rice farmers' adoption of low-carbon practices in Jiangsu, China.

All three approaches have their distinct strengths and weakness. SEM works best with large survey data as it can capture the ideas you care about and see how those ideas influence one another, all while filtering out measurement noise. On the contrary, small sample sizes can give shaky results or ignored assumptions. [Hou & Hou, 2019]

Multiple Linear Regression even though sometimes can overfit and struggles to capture behavioral aspects, it's very useful when it comes to analyze the direct relationship between the observed variables [d'Albertas et al., 2024]. Additionally, Multiple Regression is more suited to top-down approaches which focus more on the aspect of incentives as it takes advantage of the model's strengths.(Anderson, J. R., Feder, G. (2007))

Binary logistic regression mirrors MLR but predicts a binary outcome by modeling log-odds with a logistic curve instead of a continuous value, being able to handle variance and heterogeneity and generate odds ratios that are simple to understand. However, with small sample sizes, the model's accuracy may degrade, and it can obscure undetected individual preference variations [Camarillo et al., 2025].

Considering the nature of the dataset the Regression (MLR and Binary logistic regression) were found to be the most suitable models for the research as they will enable to measure how much each variable will affect the farmers while keeping other factors constant.

Before running the regression models it was verified that key assumptions were met:

1) Linearity: a correlation analysis showed moderate positive relationships between dependent variables and our main predictors, confirming approximate linearity.

2) Multicollinearity:. Variance inflation factors (VIFs) for all variables were below 5, indicating that collinearity was not a concern and that we could retain every predictor.

3) Homoscedasticity: A scale–location plot of the residuals exhibited a roughly flat trend and evenly scattered points, confirming constant variance.

Moreover, when deciding which variables to include in the different regressions models, a variety of combinations were used, such as only including the carbon payment to analyze the effect individually. However, even though this gave a raw estimate of the expected results, it was too simple a model and would leave out other key variables that could bias the participation effect and weaken the credibility of the findings. When deciding which other variables such as demographics or other potential relevant variables to include different variations were used and finally the ones that delivered the strongest predictive power or best helped explain the model were included.

When analyzing the data, no strong explanatory model emerged to predict land use based on the variable indicating how many additional agroforestry trees farmers would plant next year, as shown in Table 6.1 of the appendix. Although no variables were statistically significant enough to explain the variation in this outcome, valuable insights can still be drawn from the other models in the study and from the existing literature, to help explain land use systems and carbon payments relationship.

5 Result

5.1 Kenya Results

Table 5.1: MLR Regression Results: Predicting Yield

Variable	Coefficient	Std. Error	p-value
Intercept	987.71	83.35	< 0.001 ***
Participant Dummy	270.80	72.99	< 0.001 ***
Fertilizer (std)	48.13	26.56	0.071 ·
Agrochemicals (std)	119.57	31.17	< 0.001 ***
Labor Cost (std)	134.76	28.83	< 0.001 ***
Hectares	63.36	14.40	< 0.001 ***
Gender (Male = 1)	81.49	43.07	0.059 ·
Observations		522	
R-squared		0.340	
Adjusted R-squared		0.333	
Residual Std. Error		581.4 (df = 515)	
F Statistic		44.3 (p < 0.001)	

Table 5.1 shows the result of the Multiple linear regression analysis which aimed to investigate how carbon payments and other variables affect yield, it can be seen how the coefficient on participant (receiving carbon payment) implies that, if we hold all other variables constant, participation is associated with an average increase of about 271 units of yield and the p value indicating the statistical significance of this finding. Among the inputs, agrochemical, labor-cost intensity and farm size have a highly significant positive effects, while fertilizer use and gender show a weaker evidence of an effect. Moreover the model explains roughly 34% of the variation in yields, indicating a moderate fit and a F statistic of 44.2 (p-value < 0.001) meaning the model is highly statistically significant and the predictors which were included collectively improve the model's explanatory power.

These results demonstrate that receiving the carbon payment from participating in the program, can contribute to improving farmers total yield, independently of input application rates and farm size, implying that aspects such as the extra income farmers received and sustainable practice adoption from joining the program, play a significant role in boosting productivity. Additionally, the strong positive impacts of agrochemical and labor investments underscore how participation's knowledge enhancements work hand in hand with the extra revenue received by the farmers to drive higher output.

The second regression analyses the effect participation has on the investment intensity. As there were many different variables that could be interpreted as indicators of investment behavior, a PCA investment index was chosen rather than just analyzing each input individually. This was done because the single index can capture the common "investment intensity" latent factor while avoiding the multicollinearity and over-parameterization that would be caused from including the variable separately [Abson et al., 2012]. The PCA index takes the five variables and computes a new single variable by projecting each farmers data onto the direction that explains the greatest shared variance among them (First Principal Component). This new variable represents each farmers overall investment intensity. A continuous index that summarizes how heavily they invest across all five dimensions is in a single measure [Abson et al., 2012].

Table 5.2: MLR Regression Results: Predicting Investment Index (PCA)

Variable	**Coefficient**	**Std. Error**	**p-value**
Intercept	-0.363	0.274	0.186
Participant Dummy	0.899	0.149	< 0.001 ***
Gender (Male = 1)	0.067	0.069	0.335
Education	-0.075	0.056	0.182
Age of Trees	-0.0055	0.0044	0.206
Applicant's Age	0.0031	0.0050	0.540
Observations	522		
R-squared	0.310		
Adjusted R-squared	0.303		
Residual Std. Error	0.835 (df = 516)		
F Statistic	46.29 (p < 0.001)		

The multiple linear regression analyzing participation and other variables on the effect they have on investment index shown in table 5.2, it can be seen that participant dummy coefficient shows that receiving payments from participation, causes a raise in the overall investment intensity from the farmers by nearly 0.9 units in the investment index, with a highly statical significant effect. Moreover, none of the other covariates in the model reach the significance level, indicating that once participation level is accounted for, gender, education, tree age, and farmer age do not help predict the investment index.

The model explains about 31% of the variation in the investment index and yields a residual standard error of 0.835 index units, meaning predicted scores typically deviate from observed values by less than one standard deviation unit. The F-statistic confirms that the set of predictors, driven almost entirely by participation variable, offer a highly significant explanation of the investment behavior.

These findings indicate that involvement in the program and hence receiving the carbon payments is one of the primary factors in enhancing farmers overall investment choices. Surpassing variations in demographic factors or plot attributes. From the model it can be observed that participating in the program significantly alters the way in which farmers distribute there resources among labor, agrochemicals, and various inputs, leading to a distinct and substantial rise in their investment intensity, some factors that might initially seem important for determining investment, such as education, which is often associated with greater and more informed investment decisions, were not statistically significant. Overall this suggests that when farmers receive the extra income, they are likely to increase their investment in on-farm inputs that they might be perceived as future investments.

5.2 Uganda Results

Table 5.3: MLR Results: Effects of Carbon Payment and Expectations on Outcome

Variable	**Coefficient**	**Std. Error**	**p-value**
Intercept	818.39	147.97	< 0.001 ***
Carbon Payment (Yes = 1)	-368.96	100.67	< 0.001 ***
Gender (Male = 1)	-65.56	56.64	0.250
Age	-2.94	2.00	0.146
Expect Payment for Agroforestry	159.64	74.29	0.034 *
Expect Yield Increase from Agroforestry	-236.06	60.07	< 0.001 ***
Observations		104	
R-squared		0.288	
Adjusted R-squared		0.252	
Residual Std. Error		269.8 (df = 98)	
F Statistic		7.93 (p < 0.001)	

Table 5.3 shows a multiple linear regression model that assess how in Uganda on the MISACI project do the carbon payments and related factors influence yield productivity, which is measured as income from coffee per hectare. The model shows statistically significant and it can explain about 25% of the variation in productivity (Adjusted $R^2 = 0.25$). With a residual standard error of 269.8 and no major signs of multicollinearity, the model can be considered statistically valid for the analysis.

The model shows that carbon payments were significantly associated with lower productivity, precisely the coefficient shows payments are associated with a negative income per hectare of -368.96 euros, suggesting potential short-term trade-offs from adopting carbon-focused practices. This could be because as carbon payment schemes often come with rules or compliance costs like only being able to use certain fertilizer, this might have negativity impacted farmers practices or farmers could need more time to adapt to the new practices and hence reducing the overall income per hectare. Moreover the model also shows that farmers that expect higher payment for agroforestry had higher income per hectare possibly reflecting increased motivation or investment. Interestingly, expecting higher yield gains from agroforestry was negatively linked to productivity with -236.06 income per hectare when farmers expected yield gains, perhaps due to unrealized or overestimated benefits. Gender and age were not significant predictors.

The results show, that even though carbon payments are designed and aim to incentivize sustainable practices, initially they may cause a reduction in farm productivity, highlighting a potential short-term cost of participation. Overall, this shows that in order for farmers to benefit from the carbon payments, this must align with farmers' expectations to contribute both to environmental and economical goals.

Table 5.4: Logistic Regression Results: Predicting Access to Credit

Variable	**Estimate**	**Std. Error**	**p-value**
Intercept	-3.590	1.431	0.012 *
Carbon Payment (Yes = 1)	1.409	0.914	0.123
Gender (Male = 1)	0.519	0.544	0.339
Age	0.034	0.020	0.092 ·
Expected Trees Planted (Next Year)	0.001	0.004	0.774
Expect Yield Increase from Agroforestry	1.906	0.570	< 0.001 ***
Income Gain	-0.184	0.797	0.817
Residual Deviance	92.12 (df = 92)		
Null Deviance	116.02 (df = 98)		
AIC	106.12		

Table 5.4 presents a binary logistic regression model examining factors influencing whether farmers apply for bank credit, an indicator of their intention to invest. The model's residual deviance (92.12) and AIC (106.12) indicate a reasonable fit, though some variation remains unexplained. The only statistically significant predictor is the belief that agroforestry will increase yields, suggesting that perceived productivity gains strongly influence credit-seeking behavior Although carbon payments show a positive association with credit application, the effect is not statistically significant once other variables are controlled for. Other factors, including gender, income gain, and planting intentions, show no significant influence. Age shows a marginal effect, possibly reflecting experience or reputation.

The results indicate that farmers' decisions to seek credit are driven more by their expectations of yield increases than by the carbon payments. This could be due to the fact that the carbon payments in this project were seen by the farmers as unreliable, possibly because of delayed or lower payments than expected. Hence farmers don't view them as a dependable income source. In contrast, believing in higher future returns, such as from increased coffee income, likely encourages farmers to apply for loans.

5.3 Comparative Results

The findings from Uganda and Kenya across the different models show a mix of results, especially when it came to comparing both countries, this is likely influenced by differences in project design or regional context. In Kenya, farmers that participated in sustainable practices and hence received the carbon payments were more likely to increase their total yield outcome and invest more in their farms. This suggests that when the payments are perceived as reliable source of income and are accompanied by knowledge or support, farmers are motivated to adopt better practices and invest in on-farm practices which are viewed as future investment. In contrast, the results from Uganda indicate a very different pattern. Farmers who received carbon payments experienced a decrease in income per hectare, and the payments were not a significant factor in predicting whether they applied for bank loans, which are a signal of investment intent. This may be due to initial challenges in project implementation or farmers viewing the payments as unstable or insufficient. Instead, expectations of yield increases were a stronger driver of credit-seeking behavior, highlighting the importance of perceived returns over promised incentives.

The contrasting effects of carbon payments in each country underscore their varied influence, in Kenya, they acted as a catalyst for higher yields and investment, while in Uganda, they had limited or even negative economic impact. At this point further context and research is needed to fully understand this differences and see if this is the case for all project.

5.4 Research Limitations and Improvements

This study faces several limitations that should be taken into account when analyzing the results. A significant constraint that should be considered was the limited public available data. Moreover the Kenyan dataset, focused only on Kiambu region, this adds the risk of location bias. Furthermore, because projects might differ greatly in terms of design and payment structure, it is challenging to generalize results to country level, because both datasets only include a single project from each nation. Future studies could include data from multiple carbon projects from each country, allowing for a more comparative evaluation. Additionally, the lack of detailed information on the actual amounts of payment received by farmers in both countries, it was difficult to separate the impact of merely participating in a carbon project from the actual financial benefit received. Knowing how much farmers received and additionally how consistently, would have enabled the study to better distinguish between the effects.

The analysis could have benefited from adding a different range of farm related investments variables to be able understand a different perspective in farmers investment behavior. This would have helped capture the complexity of how farmers allocate resources under different conditions. Additionally, while the study had as an initial aim to also assess how carbon payments change land use, the limited data made it difficult to reach clear conclusions on this hypothesis. Future research should explore this in more depth, as land use changes are a key component of sustainable farming outcomes. Finally as the data was cross-sectional,it only captured farmer behavior at a single point in time. Future studies should also investigate how the effects of carbon payments evolve over time by using longitudinal data.

6 Conclusion

Carbon payments have the potential to significantly benefit smallholders farmers in the regions of Uganda and Kenya, by offering an additional source of income they help improve yields [TechnoServe, 2022] and encourage a greater investment in farmland activities [Nkatha et al., 2024]. The extra financial support offered by the payments can additionally encourage farmers to adopt a more sustainable land management practice, such as agroforestry, which can lead to a more stable and long-term income compared to more traditional farming methods [Farmonaut, n.d.] .

As discussed in the literature review, carbon payments are aim to motivate farmers to join and engage in the sustainable projects. However, for these payments to be seen as an effective measurement, they have to be both sufficient and reliable [Rode et al., 2023]. When they are viewed in this way, farmers will be more likely to use the additional income to improve their agricultural practices and invest in the farm land. The study analysis revealed a mixed picture when it came to interpreting the results. In Kenya, carbon payments were associated with producing higher yields and a greater investment intensity, suggesting that the payments positively influenced these factors. On the contrary, the findings from Uganda indicated a decrease in income per hectare when farmers received the carbon payments and no significant relationship between carbon payments and loan-seeking behavior (associated with intention of investing). This suggests that, in some contexts, the payments may not be meaningfully enough to influence farmers' financial decisions.

Despite some contradiction in the results, analysis of the data and current studies indicates that carbon payments can positively impact farmers, when these are seen as reliable and sufficient; allowing farmers to gain higher yields and invest more in farm productivity. However due to the mix of results and limitations further investigation is needed to fully comprehend the effect that payments have on farmers in Uganda and Kenya.

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Appendix

Equation for model 1:

$$\text{yield}_i = \beta_0 + \beta_1\,\text{participant\_dummy}_i + \beta_2\,\text{fertilizer\_std}_i + \beta_3\,\text{agrochem\_std}_i + \beta_4\,\text{labcost\_std}_i + \beta_5\,\text{hectare}_i + \beta_6\,\text{gender}_i + \varepsilon_i.$$

Equation for model 2:

$$\text{investment\_index\_pcai}_i = \beta_0 + \beta_1\,\text{participant\_dummy}_i + \beta_2\,\text{gender}_i + \beta_3\,\text{education}_i + \beta_4\,\text{age\_trees}_i + \beta_5\,\text{appage}_i + \varepsilon_i.$$

Equation for model 3:

$$\text{income\_per\_hectare}_i = \beta_0 + \beta_1\,\text{carbon\_paid}_i + \beta_2\,\text{gendermale}_i + \beta_3\,\text{age}_i + \beta_4\,\text{expect\_payment}_i + \beta_5\,\text{expect\_yield\_increase}_i + \varepsilon_i.$$

Equation for model 4:

$$\log(\Pr(\text{credit}_i = 1)1 - \Pr(\text{credit}_i = 1)) = \alpha_0 + \alpha_1\,\text{carbon\_paid}_i + \alpha_2\,\text{gendermale}_i + \alpha_3\,\text{age}_i + \alpha_4\,\text{nextyear\_expected\_trees\_planted}_i + \alpha_5\,\text{expect\_yield\_increase\_for\_agroforestry}_i + \alpha_6\,\text{income\_gain}_i.$$

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	80.5947	41.5992	1.937	0.0557*
carbon_paid	9.6373	35.9662	0.268	0.7893
income_gain	8.7719	29.0874	0.302	0.7637
gendermale	9.9707	18.8654	0.529	0.5984
income_per_hectare	-0.0377	0.0301	-1.253	0.2135
farm_size	-2.5534	2.1505	-1.187	0.2381
Residual Std. Error	87.33 on 93 DF			
Multiple R^2	0.0421			
Adjusted R^2	-0.0094			
F-statistic (5, 93 DF)	0.8165 (p = 0.5409)			

Table 6.1: MLR on Next-Year Expected Trees Planted

Appendix:

Official statement of original thesis

By signing this statement, I hereby acknowledge the submitted thesis (hereafter mentioned as “product”), titled:

Evaluating the Influence of Carbon Credit Payments on Coffee Farmers’ in Uganda and Kenya
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