Bachelor Thesis – Business Analytics

Effect of carbon farming incentives on the use of agroforestry on smallholder coffee farms in Uganda and their income

Maastricht University

School of Business and Economics

April 2025

Author:

Mate Balogh

Student ID: i6321242

Supervisor:

Amar Sidi

Second Reader:

Chandra Tamang

Bachelor of Science in Business Analytics

Academic Year 2024–2025

Contents

Acknowledgments

I would like to acknowledge and express gratitude towards my supervisor, Amar Sidi, for providing guidance throughout the process.

I would also like to thank the coordinator of the thesis course, Ioannis Diamantis, for his understanding behavior towards students, management of the course, and academic support.

Abstract

This paper investigates the economic effect of Payments for Ecosystem Services (PES) on smallholder farmer's household income in Uganda. As climate change poses an increasing threat to traditional farming practices, agroforestry and PES projects have been a recent topic of discussion. Agroforestry offers a way to fight climate change and help farmsteads, while PES projects offer financial aid to farmers. However, evidence on direct financial benefit remains limited. This research uses a mixed-method approach, using Double Machine Learning (DML) and Causal Forest to estimate Average Treatment Effect (ATE) and provide a Cost-Benefit analysis of PES project participation. The study samples a 168 farmers, the results showed that the mean cost per farmer is 1,214,208 UGX, with mean net benefit of -2,200,170 UGX and mean cost efficiency of -0.81UGX. These results contradict general assumptions that agroforestry provides both economic and ecological benefit. The study concludes that PES projects do not provide financial benefits to farmers' household income in the short term.

1 Introduction

Globally, the farming industry is suffering from soil degradation and biodiversity loss Thorn et al., 2020. Conventional farming practices being a significant driver of soil degradation, as they often lead to nutrient depletion, erosion, loss of soil organic matter, and affect the biodiversity of the land Sollen-Norrlin et al., 2020. In Uganda where coffee farming represents a critical part of the economy, soil degradation can have devastating impacts, causing yield instability, reducing household incomes, and increasing financial insecurity, with smallholder farmers being heavily impacted. Castro et al., 2013 There is an urgency to address these climate change effects, especially in Uganda, as they experience an increasing vulnerability to climate shocks and biodiversity loss through land degradation.

Agroforestry is the implementation of trees among grown crops and offers a viable solution to battle these changes. It offers both ecological and economic benefits to the farmers through enhancing soil fertility, providing an additional source of income and providing a potential source of food. However, implementation of this practice comes with high initial labour cost as well as delayed yield, making it difficult for smallholder coffee farmers to adapt.

In order to make agroforestry and climate friendly farming practices more accessible, incentives such as carbon farming and Payment for Ecosystem Services (PES) were introduced in recent years. PES projects offer the farmers financial aid, in return for them to implement eco-friendly farming, such as planting trees for carbon sequestration. Based on the retained carbon in the soil, PES projects such as REDD+ and Trees for Global Benefits, offer ways for farmers to access international carbon markets.

Although these projects attempt to address poverty alleviation while battling climate change, empirical evidence on the actual impact remains limited, especially regarding household income of smallholder coffee farmers. Many studies provide insights on the positive impacts of PES projects regarding social and environmental aspects, however, a gap still remains in quantifying monetary gains specific to Uganda. The motivation of the study is to address this gap and examine and quantify the economic impact of PES participation while focusing on household income for smallholder coffee farmers in Uganda, and provide policy recommendations based on past data.

The paper is based around the research question of “How participation in Payment of Ecosystem Services influences income of smallholder coffee farmers in Uganda” while proposing the hypothesis that "Participation in PES projects provide a positive increase on the household income of smallholder coffee farmers in Uganda".

2 Literature Review

2.1 Methodology

The literature review began with scoping the general literature related to the topic of Uganda coffee farmers. Websites like Elicit and Google Scholar were used to search for scientific papers. General information regarding the topic was collected from papers regarding farming practices, agroforestry and adaptation barriers. Keywords and phrases used for finding these scientific papers included: coffee farmers, smallholder farmers, Uganda, agroforestry, carbon farming, carbon sequestration, sustainability, knowledge transfer, incentives. After screening initial search results, a snowballing technique was used to search for additional literature. In addition to the general research, a more concentrated search was carried out for the specific research question. Scientific papers were collected using additional keywords in combination with the previous keywords: farmer income, farmer costs, farmer expenditure, PES payments, PES projects, payment services and carbon payments. Snowballing technique were again applied to extend research.

2.2 Relevant literature

Uganda is one of Africa's largest coffee producers and a major global exporter. Uganda's coffee sector has over 1.7 million smallholder coffee farmers cultivating various coffee types with mixed cropping systems. These systems are often characterized by low yields, poor soil fertility, and labor constraints HereWeGrow, 2024. While some farmers practice intercropping with bananas or cassava Haneishi et al., 2013, the adaptation of such practices is not easy. Many farmers face challenges relating to financial barriers, lack of knowledge and market volatility. Ellis and Bahiigwa, 2003 talks about Uganda's poverty reduction attempts such as the plan for Modernization of Agriculture. Which aims to link smallholder farmers to international markets, although many of such attempts fail or have limited impact due to a decentralised government and high rural taxation. Other issues such as technical, environmental, socio-economic, policy, and regulatory factors make it hard for smallholder coffee farmers to manage their land and have a sufficient household income.

Climate change is another external factor affecting coffee farmers. Recent climate changes had had a significant impact on soil quality and coffee yields. Studies such as Jassogne et al., 2013 show that temperature rise and erratic rainfall are affecting the land and reducing the suitability of traditional growing areas, such as the Rwenzori Mountains. Uganda Bureau of Statistics, 2020 reports yield stagnation at approximately 0.6 metric tons per hectare for both Arabica and Robusta coffee, with increased weather-related crop failures.

For these reasons farmers have to look from alternative means to continue their practices. One method to adapt to these changes is to implement agroforestry. Although this requires extra labour and expenditure for the farmers, it also comes with several benefits. According to Sanchez et al., 1997, tree-based systems improve soil fertility and buffer microclimates. Fahad et al., 2022 further assert that agroforestry reduces erosion, enhances biodiversity, and improves water retention.

Besides environmental benefits, agroforestry can also be used for carbon sequestration. Through agroforestry, farmers can also participate in carbon markets as a complementary income source. Migadde, 2020 and Cacho et al., 2003 highlight that cooperatives can facilitate access to carbon credit schemes through pooled monitoring and verification. Jayachandran et al., 2017 found that PES schemes can also reduce deforestation cost-effectively in Uganda. On the other hand, Fisher, 2012 raises ethical concerns about incentivising eco-friendliness, through the promise of financial gain.

While the promises of agroforestry show favorable outcomes for both the farmers and for battling climate change, adaptation of this technique is limited. Aganyira et al., 2020 find that barriers such as high entry costs, weak trust in institutions, and lack of technical knowledge persist. Many rural coffee farmers lack the funding, technical knowledge and manpower to start agroforestry and care for the trees, while some are not even aware of this technique. This shows that there is a need for a theoretical framework to spread awareness and educate farmers.

Another critical point is that, even if the farmer is able to implement agroforestry, without certain return farmers would still not implement it. Hence market access and financial incentives are just as critical for agroforestry development which is emphasised by Murali et al., 2025.

This reviewed body of literature provides context for the implementation of agroforestry; the advantages it brings for individual farmers; the limitations surrounding these techniques and how PES projects could be used to address these limitations. Carbon payments and agroforestry can be a promising pathway for poverty alleviation if implemented with farmer centered policies that ensure a positive impact for household livelihood.

2.3 Literature Gap

Even though literature assessing PES projects for smallholder coffee farmers provide a strong theoretical framework, studies assessing Uganda's coffee farmers income remain limited. Studies assessing PES scheme impacts tend to be limited when it comes to financial analysis. This includes the lack of assessment for longitudinal or immediate financial impact, evaluation of cooperative originated PES models tailored to Uganda specifically, and assessment of the knowledge transfer needed to start agroforestry practices.

The purpose of this research is to address the gap surrounding the financial effect of farmers household income, and to assess how PES projects influence this with the extra incurred costs for farmers.

3 Methodology

This section details the implemented methodology used to analyze the provided data and to evaluate the effect of PES project participation on household income for smallholder coffee farmers. The methodology includes supervised machine learning and advanced causal inference techniques.

3.1 Data

The datasets collected includes data from the MISACI Project in collaboration with Solidaridad and Rabobank, data from Ecosystem Services Evaluation Database (ESVD), data from the Annual Agricultural Data Survey 2019 Report by the Uganda Bureau of Statistics, and data from the Farm Diary of Coffee Farmers In Kalungu and Ibanda Districts, Uganda by Athari Lulu Consults Limited. These datasets were found through the provision of the thesis supervisor, and through online databases as well as official reports. The compiled dataset consists of 168 smallholder coffee farmers in Uganda and includes data on site location (by Uganda districts), land use (sites area), annual income, household expenditures and PES project payments. Additionally a pilot and control group was introduced based on the MISACI dataset, as the provided data contained it.

The merged dataset had all numerical values converted into uniform units, such as the site area to hectares, and all monetary values to Ugandan shillings (UGX).

3.2 Models

In order to get a working merged dataset, a Multivariate Imputation by Chained Equation (MICE) algorithm was used. This statistical method filled in the missing numerical variables by targeting the missing variables and using the other variables as predictors. Using a regression model, here specifically a Bayesian Ridge, the missing values get filled in, over the course of multiple iterations, until the imputed values converge.

Since the MICE algorithm was only used for predicting numerical variables, in order to split the rest of the dataset into pilot and control group a Propensity Score Matching (PSM) algorithm was implemented. This was necessary for the later causal impact evaluation. The model was trained on the MISACI dataset (n=120) and was later used on the rest of the observations to assign them into the pilot and control group. Three features were used for estimation: Int$ Per Hectare Per Year which is equivalent to how much monetary compensation the farmers would get from PES payments, Site Area In Hectares, and based on the reported income. The PSM algorithm was configured to use random forest classification for robustness and for its ability to capture non-linear relationships. A number of 100 trees, 5 cross-validation folds, 0.7 confidence threshold and a random seed was set for the prediction. The model achieved a mean cross validation Area Under the Curve (AUC) of 0.654 with a standard deviation of ±0.089. The performance metrics on the label set produced 73% accuracy, 0.71 precision and 0.96 recall. This suggests a medium to strong classification.

After completing the dataset Double Machine Learning (DML) and Causal Forest algorithms were applied to test for the Average Treatment Effect (ATE) of the PES participants' household income. ATE is a widely used and well suited model for high-dimensional confounding and complex treatment selection. The variables were set as follows: The outcome variable was set to annual household income, the treatment group was assigned to the pilot group, a cost variable was assigned and the covariates were set to Sites Area in Hectare, Small Producer Mean and Int$ Per Hectare Per Year. The model used a Linear DML composed of Random Forest and Logistic Regression and a Causal Forest for heterogeneous treatment effects. Upon the results a cost benefit analysis was done.

Notably, the previously described methodology does encounter some limitations. Upon classifying the missing pilot and control group labels, the remaining 49 observations were all assigned into the pilot group which may reflect model bias or sample imbalance. Furthermore the cost variable was a constant value that lacked variation which may have limited the models heterogeneity analysis and skewed the cost-efficiency metrics.

4 Data Analysis and Results

This section presents the results of the analysis. It covers the output of the label assignment using machine learning and the causal impact estimation on farmers household income, which was achieved by using DML and Causal Forest models.

4.1 Descriptive Statistics and Label Assignment

Out of the 168 total observations, 119 had group labeling and 49 did not. Out of the 119, 75 farmers belonged to the pilot group and 44 farmers were assigned to the control group. In the algorithm this was translated to binary classification, with the treatment group being the pilot group, assigned label 1, and the control group was assigned label 0. The remaining 49 observations were classified using the following covariates: Site Area in Hectares, Small Producer Mean Income (UGX), and International Dollar per Hectare per Year. After classification the observations were split up as following:

- Pilot: 124 farmers
- Control: 44 farmers

The accuracy was tested and yielded the following metrics:

- Mean cross-validation AUC: 0.654
- Final AUC on labeled data: 0.798
- Recall for pilot group: 96%

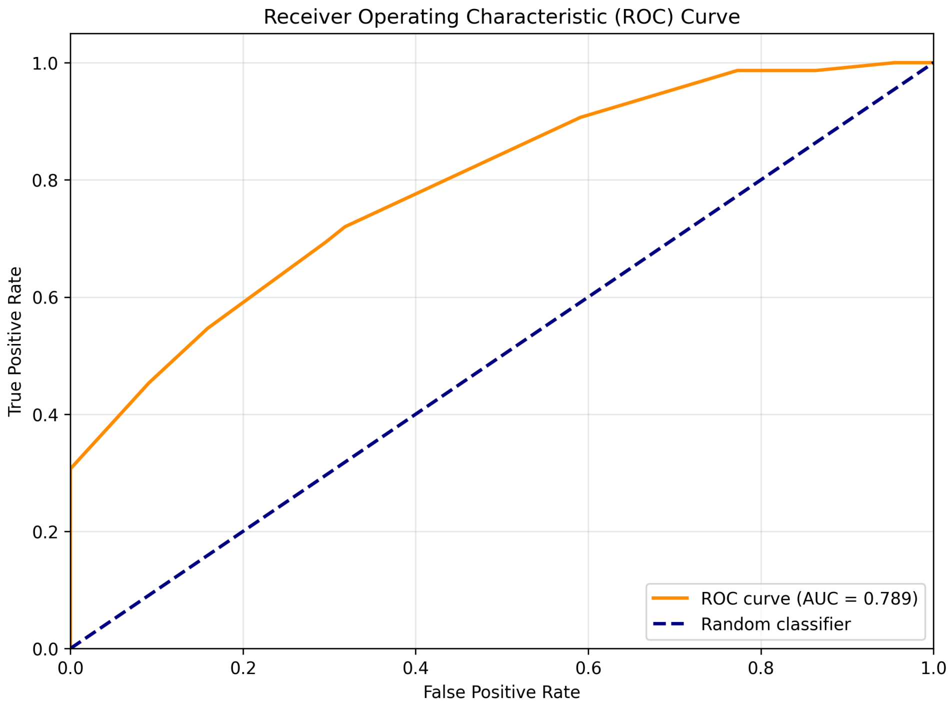

Figure 1: ROC Curve for Label Assignment

4.2 Causal Analysis Outcome

The causal analysis used household income as the outcome variable while treating participation in PES projects as the treatment variable and was tested for ATE. Table 1 summarises the findings:

Table 1: Average Treatment Effect (ATE) and Confidence Intervals for different methods

Method	ATE (UGX)	95% Confidence Interval
Linear DML (without household cost)	-75,211	(-1,450,170, 1,299,748)
Linear DML (with household costs)	-1,429,092	(-2,950,813, 92,629)
Causal Forest DML (with household costs)	-985,962	(-2,751,894, 779,969)

The three methods presented give more insight into the average treatment effect and presents the 95% confidence interval. The Linear DML without household costs shows that on average the ones who participate in PES projects have an annual income of 75,211 UGX less than those who do not. If we incorporate the household costs into the analysis this number jumps up to -1,429,092 UGX. This shows that the costs that come with participating in PES projects raise the already negative annual income up to 19 times more. The Causal Forest DML shows that on average farmers have an annual income of -985,962 UGX. The 95% confidence interval of each method shows that despite the average of these models presenting a negative income, there are farmers within this range whose turnover is positive, and there are farmers whose loss is even greater than the average. This variation can be due to farmer specific characteristics.

4.3 Cost-Benefit Analysis

After the implementation of previously mentioned machine learning models the cost-benefit analysis show the following:

- Mean Cost per Farmer: 1,214,208 UGX
- Mean Net Benefit: -2,200,170 UGX
- Participants with Positive Net Benefit: 0
- Mean Cost Efficiency (Effect/Cost): -0.81

The mean costs for farmers for annual expenditure and PES projects participation is 1,214,208 UGX and the mean net benefit of participation in PES projects is computed to be -2,200,170 UGX. Although the models show a confidence interval with a range that provided a plausible negative and positive outcome, the net benefit analysis showed that the percent of participants with positive net benefit is 0%. The mean cost efficiency ratio of participation in PES projects calculated by effects divided by costs showed a -0.81 UGX loss for every 1 UGX spent on implementation. This shows that PES project participation may not be financially beneficial and can even be counterproductive in the short term based on the analysis.

It should be noted, that since the cost of the study was a constant averaged from the Farm Diary of Coffee Farmers in Kalungu and Ibanda Districts, Uganda dataset, no cost heterogeneity could be analyzed.

Overall these results suggest that, on average, PES participation does not lead to a positive income increase for the farmers household income levels in the short term.

5 Discussion

This section discusses the results of the analysis in relation to the research question and hypothesis, while critically analyzing the results and their implication for real life practices. It also further addresses the limitations and maps out potential future research areas building on this paper.

5.1 Result interpretation and implications

The research paper was built around the question of how participation in PES projects influence income of smallholder coffee farmers in Uganda. The hypothesis was set up to answer this question while also assuming that participation in PES projects provide a positive increase on household income for smallholder coffee farmers in Uganda. Following the analysis, the hypothesis was rejected for this sample of data. Hence the null hypothesis is accepted stating that participation in PES projects does not provide a positive increase for household income for smallholder coffee farmers in Uganda.

This contradicts current findings, which suggest that there is an economic benefit to agroforestry and PES projects. The analysis showed that there is a negative average income impact for those participating in PES projects and there is a zero percent positive net benefit when accounting for individual implementation and costs. This conclusion challenges the assumption that PES projects are financially feasible for smallholder farmers.

While there are undoubtedly a lot of benefits with regards to agroforestry, it does not necessarily improve the livelihood of the farmers. This might impact long term adaptation of current PES projects, and demoralize the farmers. Policy makers should closely observe PES projects and how it influences the farmers, and should implement frameworks to integrate predictive analytics and to identify possible improvements, while monitoring external factors that affect participants. These findings contribute towards the idea that the design and contextual implementation of PES projects have to be tailored around the participants.

One thing to consider regarding the results is that its scope is only short term. The startup costs of implementing agroforestry are heavily front-loaded, meaning that the cost will appear almost entirely in the first year. Subsequent years will have reduced costs as maintenance would be fairly inexpensive and be partially combined with that of the crops. Furthermore, the benefits will not appear in the first year. The trees and shrubs require time to grow which will take time. As a result, the negative values for household income may be a poor representation of the sum net benefit.

5.2 Limitations

Several limitations regarding these results should be acknowledged. The data available for the research is very limited. Several sources were used to combine them into the working dataset. While monetary and other numerical values were matched to the same metrics, due to the different nature of the data sources, many missing variables were estimated using the MICE algorithm. While this approach is robust and makes sure to provide plausible data, it should be noted that these are just estimations based on machine learning. It is not guaranteed that these numbers match reality. Furthermore the MISACI dataset is based on self-reported questionnaires, which can be subject to recall and social desirability biases. Label assignment is exposed to the same limitation. There is a risk of misclassifications, as all 49 unlabeled observations were predicted to be part of the pilot group which could reflect that the sample is imbalanced, or that the model is introduced to a bias. Furthermore the dataset is relatively small, with a sample size of only 168 observations. This limits the treatment effect estimations for DML and Causal Forests. Lastly the cost variable is a constant which limits both heterogeneity testing and the cost-effectiveness across the different farmers.

In the analysis, only three predictors were used to estimate the causal analysis. This limited feature can omit real reasons for the difference between farmers. With more predictors such as age, education level, etc. the analysis could have produced a more insightful causal analysis. As a result the treatment model may have a reduced accuracy of the causal estimates and the treatment effect may be confounded by these variables that are not present and not controlled in the models, but are present in real life. Since DML is a flexible approach, Random Forest and Logistic Regressions may have trouble capturing the most complex interactions especially with the limited predictors.

Since the implemented practice is a single-pass, batch analysis long term effects cannot be observed. This is due to no time series modeling or feedback loops being incorporated to update values. Since agroforestry and the PES projects are of dynamic nature that can span over years, income effects may change over time and hence can limit the model's relevance.

5.3 Future research

With future research the limitations of this research could be addressed. Incorporating time series data, to see the long term effect of PES projects and agroforestry for farmers. Updating income and expenditure data from real reported sources, could produce a more in depth analysis that captures the long term effects of PES projects. Further increasing the sample size could provide more context for the causal analysis as the data would be further diversified, hence allowing machine learning to discover complex and more in depth patterns. In addition to increasing sample size, incorporating more variables that describe the observation such as age, education level, and type of crops grown could result in a more accurate analysis thereby strengthening the study.

6 Conclusion

The aim of this study was to analyse the effect of PES projects on smallholder coffee farmers in Uganda and to see whether it provides them with a positive increase to their household income. The research was motivated by the existing gap in analyzing the economic effects of participation in PES projects as a means to promote environmental sustainability while providing financial aid.

In order to address this gap, the research implemented a mixed-method approach, combining multiple datasets, estimating missing variables, and utilising machine learning, and causal inference modeling. The analysis contained data on 168 farmers: their income, expenditures, land site areas, and PES payments.

The findings of this research challenges the standard assumption that PES projects provide purely upsides. The results showed that there was a negative ATE on household income among the farmers present in the analysis. Furthermore, there was a zero percent positive net benefit on an individual level while accounting for costs surrounding the everyday expenditure of farmers and costs related to PES schemes. While there was a 95% confidence interval that did contain positive ATE, on an individual level the mean cost-efficiency was -0.81UGX, meaning that on average farmers lost an additional 0.81 UGX for every 1 UGX spent.

These results led to rejecting the null hypothesis that participation in PES projects does provide a positive increase in household income for smallholder coffee farmers in Uganda. Hence, we accept the null hypothesis that states that participation does not provide a positive increase in household income.

While the methodology incorporated multiple approaches for both data estimation and analysis, there are critical limitations. These include limited sample size, imputed data, self reported data, class imbalance, use of constant cost variables, and limited features used for causal analysis. Interpretation of the results should be done taking these factors into careful consideration.

Nevertheless, this research shows that data analysis integration for real world policy making can be an essential part for designing viable PES schemes. Currently, the results suggest, PES projects may not be economically viable for smallholder coffee farmers without further optimization targeting costs and returns. Detailed cost benefit analysis should be performed for PES projects to monitor their feasibility. Monetary compensation should be more closely monitored to ensure that the needs of each farmer are met. Data driven assessments and supporting continuous data collection for future analysis and evaluation could improve future PES project designs.

Possible future research based on these findings could incorporate a time series analysis to map out the long term effect of PES project participation with extended sample size and additional features to test causal inference on, allowing for better modeling and insight into the economic effect.

In conclusion this study provides insight into the short term economic effects of PES projects on smallholder coffee farmers in Uganda. The analysis concludes that the monetary impact of PES projects in the short term is negative. The study also acknowledges certain limitations which have an impact on this result.

7 Appendix

Official statement of original thesis

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

Effect of carbon farming incentives on the use of agroforestry on smallholder coffee farms in Uganda and their income

to be produced independently by me, without external help.

Wherever I paraphrase or cite literally, a reference to the original source (journal, book, report, internet, etc.) is given.

By signing this statement, I explicitly declare that I am aware of the fraud sanctions as stated in the Education and Examination Regulations (EERs) of the SBE.

Place: Maastricht University

Date: 29-06-2025

First and last name: Máté Balogh

Study programme: Business Analytics

EBT Code: 0017

ID number: i6321242

Signature:

Appendix 1: Mate Balogh – Official statement of original thesis

ZARDI	% Small Holders	Small producer Mean (UGX)	Small Producer - Confidance Interval	Small holder - Confidance Interval	Large producer Mean (UGX)	Large Producer - Confidance Interval	Large Producer - Confidance Interval2	Total Producer - Mean (UGX)	Total Producer - Confidance Interval	Total Producer - Confidance Interval2
Abi	73	671730	597694	745765	1901070	1524474	2277665	1008564	879245	1137883
Buginyanya	62	628617	578921	678313	2089321	1854341	2324302	1178929	1077518	1280340
Bulindi	49	1289655	1152021	1427289	2955786	2604023	3307550	2144566	1938686	2350447
Kachwekano	84	1142732	1018963	1266501	4309924	3400099	5219749	1657888	1429271	1886505
Mukono	37	710106	636356	783855	2807069	2611608	3002529	2023398	1877217	2169579
Ngetta	43	923309	844095	1002522	2013984	1814986	2212982	1539593	1415395	1663791
Nabuin	69	1086110	430851	1741368	2107221	180275	4034167	1405624	599023	2212226
Serere	55	616501	516298	716703	1788877	1509574	2068181	1142425	991894	1292957
Mbarara	54	1184051	1107425	1260677	3050951	2780592	3321310	2050719	1906164	2195274
Rwebitaba	54	1210259	1120888	1299630	3277827	2930608	3625047	2154349	1964227	2344472

Appendix 2: Data from the Annual Agricultural Data Survey 2019 Report by the Uganda Bureau of Statistics

ZARDI	Study Location	Site Area In Hectares	Int$ Per Hectare Per Year
	Kampala city and Nakivubo wetland	529	709,2997
Buginyanya	Mount Elgon region	50200	2,486
Buginyanya	Mount Elgon region	50200	0,627
Buginyanya	Mount Elgon region	50200	6,5341
Buginyanya	Mount Elgon region	50200	8,7121
Buginyanya	Mount Elgon region	50200	6,1821
Buginyanya	Mount Elgon region	50200	14,6192
Mukono	Mabira Forest Reserve	30000	0,9706
Buginyanya	Pallisa district Wetlands	71100	5754,9043
Kachwekano	Bunyonyi Lake	65	868,1127
Buginyanya	Pallisa District wetlands	71100	111,7919
Buginyanya	Namatala, within the Pallisa District wetlands	14400	3474,9914
Buginyanya	Pallisa District wetlands	71100	35,5621
Buginyanya	Pallisa District wetlands	71100	133,7814
Buginyanya	Pallisa District wetlands	71100	37,6313
	Kyoga plains	68932	45,8252
Kachwekano/Mbarara	Southwestern farmlands	746	648,8974
Kachwekano/Mbarara	Southwestern farmlands	746	721,5661
Kachwekano/Mbarara	Southwestern farmlands	12713	78,837
Kachwekano/Mbarara	Southwestern farmlands	29110	96,0415
Kachwekano/Mbarara	Southwestern farmlands	29110	38,4166
Kachwekano/Mbarara	Southwestern farmlands	29110	172,6086
Kachwekano/Mbarara	Southwestern farmlands	123686	81,1555
Mukono(/Buginyanya)	Lake Victoria crescent	2425	1582,5718
Mukono(/Buginyanya)	Lake Victoria crescent	2425	177,9927
Mukono(/Buginyanya)	Lake Victoria crescent	137125	14,0357
Mukono(/Buginyanya)	Lake Victoria crescent	137125	7,0836
Mukono(/Buginyanya)	Lake Victoria crescent	137125	2,8334
Mukono(/Buginyanya)	Lake Victoria crescent	137125	58,0494
	Kyoga plains	13068	2225,9846
	Kyoga plains	13068	32,3821
	Kyoga plains	68932	34,5476
	Kyoga plains	68932	16,7255
	Kyoga plains	68932	6,6902
Mukono	Nakivubo	529	667,3572
Mukono	Nakivubo	529	299,4381
Mukono	Nakivubo	529	36,7859
Mukono	Nakivubo	529	9683,5881
	Dohu Rice Irrigation system	1012	52,2788

Appendix 3: Data from the Ecosystem Services Evaluation Database (ESVD)

A62 Table 36: Monthly expenditures per households (Small-scale households)

	A	B	C	D	E	F	G	H	I	J	K	L	M	N
62	Table 36: Monthly expend	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Total
63	Kalungu													
64	Food	81000,00	125000,00	71000,00	197000,00	107000,00	152000,00	154000,00	89000,00	85000,00	175000,00	100000,00	65000,00	1401000,00
65	Education	135000,00	214000,00	257000,00	327000,00	155000,00	162000,00	277000,00	204000,00	150000,00	9000,00	254000,00	199000,00	2343000,00
66	Health	47000,00	30000,00	79000,00	76000,00	52000,00	67000,00	21000,00	23000,00	36000,00	39000,00	63000,00	39000,00	572000,00
67	Water & Sanitation	4000,00	15000,00	6000,00	16000,00	18000,00	17000,00	7000,00	3000,00	3000,00	3000,00	8000,00	3000,00	103000,00
68	Hard Energy (Fuel wood, para	12000,00	9000,00	8000,00	10000,00	3000,00	8000,00	7000,00	1000,00	8000,00	3000,00	3000,00	4000,00	76000,00
69	Soft Energy (Electricity)	5000,00	9000,00	11000,00	26000,00	11000,00	8000,00	10000,00	4000,00	18000,00	22000,00	12000,00	8000,00	144000,00
70	Home sundries	61000,00	92000,00	69000,00	100000,00	88000,00	100000,00	62000,00	68000,00	83000,00	112000,00	90000,00	81000,00	1006000,00
71	House and Repairs	11000,00	3000,00	12000,00	15000,00	9000,00	4000,00	16000,00	2000,00	2000,00	19000,00	10000,00	17000,00	120000,00
72	Land access	107000,00	98000,00	278000,00	475000,00	183000,00	169000,00	8000,00	0	14000,00	138000,00	33000,00	41000,00	1544000,00
73	Debt repayment	94000,00	43000,00	96000,00	515000,00	121000,00	180000,00	24000,00	15000,00	45000,00	81000,00	54000,00	34000,00	1302000,00
74	Other non-agricultural invest	37000,00	70000,00	109000,00	1622000,00	381000,00	332000,00	195000,00	90000,00	185000,00	670000,00	259000,00	155000,00	4105000,00
75	Social contributions	8000,00	49000,00	67000,00	115000,00	60000,00	105000,00	44000,00	55000,00	53000,00	67000,00	64000,00	47000,00	734000,00
76	Total	602000,00	757000,00	1063000,00	3494000,00	1188000,00	1304000,00	825000,00	554000,00	682000,00	1338000,00	950000,00	693000,00	1120833,33
77	Ibanda													
78	Food	102000,00	198000,00	151000,00	134000,00	95000,00	114000,00	127000,00	104000,00	133000,00	266000,00	108000,00	86000,00	1618000,00
79	Education	363000,00	269000,00	406000,00	637000,00	146000,00	170000,00	749000,00	442000,00	224000,00	34000,00	633000,00	626000,00	4699000,00
80	Health	28000,00	39000,00	63000,00	71000,00	56000,00	85000,00	79000,00	82000,00	89000,00	71000,00	80000,00	180000,00	923000,00
81	Water & Sanitation	4000,00	3000,00	25000,00	16000,00	1000,00	11000,00	2000,00	2000,00	0	2000,00	2000,00	2000,00	70000,00
82	Hard Energy (Fuel wood, para	0	3000,00	1000,00	0	0	1000,00	4000,00	1000,00	1000,00	8000,00	5000,00	1000,00	25000,00
83	Soft Energy (Electricity)	0	1000,00	1000,00	1000,00	0	4000,00	0	5000,00	1000,00	14000,00	13000,00	4000,00	44000,00
84	Home sundries	25000,00	33000,00	46000,00	40000,00	40000,00	56000,00	45000,00	39000,00	44000,00	43000,00	47000,00	38000,00	496000,00
85	House and Repairs	1000,00	2000,00	2000,00	0	3000,00	13000,00	1000,00	2000,00	3000,00	10000,00	8000,00	4000,00	49000,00
86	Land access	20000,00	78000,00	60000,00	40000,00	44000,00	136000,00	44000,00	160000,00	23000,00	52000,00	206000,00	406000,00	1269000,00
87	Debt repayment	83000,00	153000,00	235000,00	496000,00	150000,00	349000,00	169000,00	211000,00	314000,00	282000,00	237000,00	319000,00	2998000,00
88	Other non-agricultural invest	42000,00	5000,00	25000,00	225000,00	114000,00	210000,00	467000,00	183000,00	174000,00	280000,00	305000,00	159000,00	2189000,00
89	Social contributions	15000,00	68000,00	203000,00	226000,00	45000,00	55000,00	98000,00	119000,00	158000,00	150000,00	115000,00	59000,00	1311000,00
90	Total	683000,00	852000,00	1218000,00	1886000,00	694000,00	1204000,00	1785000,00	1350000,00	1164000,00	1212000,00	1759000,00	1884000,00	1307583,33

Appendix 4: Data from the Farm Diary of Coffee Farmers In Kalungu and Ibanda Districts, Uganda by Athari Lulu Consults Limited

feature_importance

feature	importance
Site Area In Hectares	0.4625999837530624
Small producer Mean (UGX)	0.33099062181328087
Int$ Per Hectare Per Year	0.20640939443365672

Appendix 5: Feature Importance for Label Assignment

References

Aganyira, K., Kabumbuli, R., Muwanika, V. B., Tabuti, J. R. S., & Sheil, D. (2020). Determinants of participation in state and private pes projects in uganda. *Scientific African*, *8*, e00370.

Brander, L. M., de Groot, R., Guisado Goñi, V., van 't Hoff, V., Schägner, P., Solomonides, S., McVittie, A., Eppink, F., Sposato, M., Do, L., Ghermandi, A., & Sinclair, M. (2024). Ecosystem services valuation database (esvd) [Database Version APR2024V1.1. Foundation for Sustainable Development and Brander Environmental Economics]. https://esvd.net

Cacho, O. J., Marshall, G. R., & Milne, M. (2003). *Smallholder agroforestry projects: Potential for carbon sequestration and poverty alleviation* (ESA Working Paper No. 03-06). FAO.

Castro, L. M., Calvas, B., Hildebrandt, P., & Knoke, T. (2013). Avoiding the loss of shade coffee plantations: How to derive conservation payments for risk-averse land-users. *Agroforestry Systems*, *87*, 331–347.

Ellis, F., & Bahiigwa, G. (2003). Livelihoods and rural poverty reduction in uganda. *World Development*, *31*(6), 997–1013.

Fahad, S., Chavan, S. B., Chichaghare, A. R., Uthappa, A. R., Kumar, M., et al. (2022). Agroforestry systems for soil health improvement and maintenance. *Sustainability*, *14*(22), 14877.

Fisher, B. (2012). No pay, no care? a case study exploring motivations for participation in payments for ecosystem services in uganda. *Oryx*, *46*(1), 45–54.

Haneishi, Y., Maruyama, A., Miyamoto, K., Matsumoto, S., Okello, S., et al. (2013). Introduction of nerica into an upland farming system and its impacts on farmers' income: A case study of namulonge in central uganda. *Tropical Agriculture and Development*, *57*(2), 61–73.

HereWeGrow. (2024). *Farm diary of coffee farmers in kalungu and ibanda districts, uganda: Endline report* (tech. rep.). HereWeGrow.

Jassogne, L., Laderach, P., & van Asten, P. (2013). *The impact of climate change on coffee in uganda: Lessons from a case study in the rwenzori mountains* (tech. rep.). CIAT.

Jayachandran, S., de Laat, J., Lambin, E. F., Stanton, C. Y., Audy, R., & Thomas, N. E. (2017). Cash for carbon: A randomized trial of payments for ecosystem services to reduce deforestation. *Science*, *357*(6348), 267–273.

Migadde, A. (2020). *Carbon farming opportunities for crop cooperatives in uganda: Practices, impacts and credit schemes* [Master's thesis, Van Hall Larenstein University of Applied Sciences] [
urlhttps://doi.org/10.13140/RG.2.2.21792.71683].

Murali, K. V., Rathod, C. B., & Karthik, K. C. (2025). Policy and financial support for agroforestry development: Incentives, programs, and market opportunities. In *Agroforestry systems* (pp. 152–155). Kerala Agricultural University.

Sanchez, P. A., Buresh, R. J., & Leakey, R. R. B. (1997). Trees, soils, and food security. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *352*(1356), 949–961.

Sollen-Norrlin, M., Ghaley, B. B., & Rintoul, N. L. J. (2020). Agroforestry benefits and challenges for adoption in europe and beyond. *Sustainability*, *12*(17), 7001.

Thorn, S., Seibold, S., Leverkus, A. B., Michler, T., Müller, J., Noss, R. F., Stork, N., Vogel, S., & Lindenmayer, D. B. (2020). The living dead: Acknowledging life after tree death to stop forest degradation. *Frontiers in Ecology and the Environment*, *18*(9), 505–512.

Uganda Bureau of Statistics. (2020). *Uganda annual agricultural survey 2018* (tech. rep.). Uganda Bureau of Statistics.