ASSESSING THE EFFECT OF PARTICIPATORY TRAINING ON THE ADOPTION OF CLIMATE-SMART AGRICULTURE (CSA) AMONG FARMERS: A CASE STUDY OF ERUTE COUNTY SOUTH, LIRA DISTRICT, UGANDA

BY

ATIM MERCY CAROLINE BU/UP/2023/1457

THIS DISSERTATION IS SUBMITTED TO THE DEPARTMENT OF MATHEMATICS IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE AWARD OF THE DEGREE OF BACHELOR OF SCIENCE IN STATISTICS OF BUSITEMA UNIVERSITY

JULY 2026

DECLARATION

I, ATIM MERCY CAROLINE, do hereby declare that this dissertation is my own original work and that it has not been presented and will not be presented to any other University for a similar or any other degree award.

Signature

Date

31st August 2026

APPROVAL

This dissertation titled "ASSESSING THE EFFECT OF PARTICIPATORY TRAINING ON THE ADOPTION OF CLIMATE-SMART AGRICULTURE (CSA) AMONG FARMERS: A CASE STUDY OF ERUTE COUNTY SOUTH, LIRA DISTRICT, UGANDA" has been submitted for examination with my approval as university supervisor, partial fulfillment of the requirements for the Bachelors of Science in Statistics

NAME: Wemakula Laurence DATE 31/8/2026

SIGN: ....

DEDICATION

First and foremost, I dedicate this work to Almighty God, whose grace and strength carried me through every challenging moment of this academic journey. To my parents, Mr. Alip Patrick and Mrs. Abalo Collins. this milestone is as much yours as it is mine. Thank you for the countless sacrifices, the endless prayers, and for believing in my potential even when the workload was overwhelming, your support has been my foundation. Finally, to my lecturers, the mathematics department, friends and classmates who shared the late nights, the stress, and the encouragement along the way, thank you for sharing the knowledge and keeping me grounded and pushing me to cross the finish line.

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LIST OF ABBREVIATION

Abbreviation	Full word
CSA	Climate-Smart Agriculture
PDM	Parish Development Model
MAAIF	Ministry of Agriculture, Animal Industry and Fisheries
FAO	Food and Agriculture Organization
PBC	Perceived Behavioral Control
TPB	Theory of Planned Behavior
NGO	Non-Governmental Organization
NDC	Nationally Determined Contributions
CBPR	Community-Based Participatory Research
EPRC	Economic Policy Research Centre
ACODE	Advocates Coalition for Development and Environment
OPM	Office of the Prime Minister
IDS	Institute of Development Studies
UNFCCC	United Nations Framework Convention on Climate Change
DLG	District Local Government

ABSTRACT

Climate-smart agriculture (CSA) is critical for building the resilience of smallholder farmers to the adverse effects of climate change; however, its adoption among farmers remains low, particularly in post-conflict regions. This study assessed the effect of participatory training on the adoption of climate-smart agriculture among Parish Development Model (PDM) farmers in Erute County South, Lira District, Uganda. Specifically, the study examined the influence of participatory training attributes, demographic factors, and socio-economic factors on the adoption of CSA. A comparative cross-sectional research design was employed, drawing on secondary data from 274 smallholder farmers affiliated with PDM groups. Univariate, bivariate, and multivariate analytical techniques were used, with binary logistic regression employed to determine the predictors of sustainable CSA adoption. The results revealed that gender representation was balanced, with males comprising 50.0% and females 49.6% of the respondents. Most respondents had only primary education (47.8%), while 79.2% held land under customary tenure. Bivariate analysis established that land tenure ($\chi^2 = 10.885$, df = 3, p = 0.012) and credit access ($\chi^2 = 4.221$, df = 1, p = 0.040) were significantly associated with sustainability status. Multivariate logistic regression identified training frequency as the single statistically significant predictor of sustainable CSA adoption ($\beta = 2.000$), showing that each additional training session substantially increased a farmer's odds of sustaining CSA practices. Demographic and socio-economic factors were largely non-significant in the model. The study concludes that regular, hands-on participatory training is the most powerful driver of sustained CSA adoption and can help farmers overcome structural barriers such as poverty, low education, and insecure land tenure. It is recommended that the Ministry of Agriculture, Animal Industry and Fisheries (MAAIF), extension agents, and PDM implementers adopt season-long training cycles with regular field follow-ups instead of one-off workshops, and that policy frameworks define minimum training frequency standard

CHAPTER1

Introduction

1.1Background of the study

Climate-smart agriculture (CSA) is an approach that guides farmers' actions to transform agrifood systems towards building the agricultural sector's resilience to climate change based on three pillars: increasing farm productivity and incomes, enhancing the resilience of livelihoods and ecosystems, and reducing and removing greenhouse gas emissions from the atmosphere ((FAO), 2013). Within this landscape, Participatory Development Methodology (PDM) farmer groups, organized cooperatives that prioritize peer learning, shared decision-making, and communitydriven problem-solving represent a promising yet underexplored vehicle for scaling CSA practices (Kansiime, 2022)

Climate change reduces agricultural productivity and leads to greater instability in crop production, disrupting the global food supply and resulting in food and nutritional insecurity. In particular, climate change adversely affects food production through water shortages, pest outbreaks, and soil degradation, leading to significant crop yield losses and posing significant challenges to global food security ((Mirón, 2023). United Nations reported that the human population will reach 9.7 billion by 2050. In response, food-calorie production will have to expand by 70% to meet the food demand of the growing population (United Nations, 2021). A transformation of the agricultural sector towards climate-resilient practices can help tackle food security and climate change challenges successfully. Promoting the adoption of CSA practices is crucial to improve smallholder farmers' capacity to adapt to climate change, mitigate its impact, and help achieve the United Nations Sustainable Development Goals

Recognizing the urgency of the climate crisis, the Ugandan government has formally embraced CSA through key policy instruments, including the National Climate Change Policy (Government of Uganda, 2015) and the Climate-Smart Agriculture Guidelines issued by the Ministry of Agriculture, Animal Industry and Fisheries (Ministry of Agriculture, 2019). These frameworks articulate a vision for transforming the agricultural sector into a climate resilient engine of inclusive growth. Despite this strong policy commitment, empirical evidence reveals that CSA adoption among smallholder farmers remains low, fragmented, and spatially uneven (nakimuli, 2021). However, structural barriers such as credit access and weak extension services impede uptake.

While a growing body of literature in Uganda has documented the multifaceted barriers to CSA adoption including financial constraints, insecure land tenure, and gender-based inequities in access to resources and information (Naluwairo, 2014) few studies have systematically investigated the role of training quality and modality as mediating factors. This gap is especially consequential in regions like northern Uganda, where the legacy of conflict has created unique institutional and psychosocial dynamics that shape how farmers interact with development interventions. Theoretical frameworks suggest adoption is shaped by attitudes and social norms. Evidence from neighboring east African countries such as Kenya and Ethiopia demonstrates that participatory extension approaches can significantly enhance the uptake and sustained use of agricultural innovations (Mwongera, 2017); (Tesfahunegn, 2022). However, the applicability of these findings to post-conflict settings like northern Uganda where decades of insurgency have eroded social capital, disrupted public institutions, and weakened agricultural extension infrastructure remains largely unexamined.

Current studies over look variations in training quality. A notable exception is the study by (Omoding, 2020)in eastern Uganda, which found that on-farm demonstration plots improved CSA adoption rates. Yet, this research did not isolate the specific contribution of participatory elements nor assess whether gains in adoption were maintained over time, leaving a significant gap in understanding the mechanisms through which training translates into sustained practice change.

The timeliness of this inquiry is further amplified by Uganda's renewed climate commitments under its updated Nationally Determined Contributions (Government of Uganda, Updated Nationally Determined Contributions (NDCs) 2022, 2022)and its active participation in continental initiatives such as the Scaling Up Climate Smart Agriculture in Africa Program. Therefore, this study directly responds to a critical knowledge gap by rigorously examining the relationship between participatory training and CSA adoption among PDM affiliated smallholder farmers in northern Uganda specifically in Lira District. Erute County South.

It goes beyond documenting whether training occurs to investigate how specific attributes of training such as interactivity, duration, and frequency, the depth (intensity of practice use), breadth (diversity of CSA adopted), and sustainability (long term retention) of adoption. By comparing trained and untrained farmer cohorts within the same communities and integrating both quantitative and qualitative data, the research will generate actionable insights for policymakers, NGOs, and extension agencies. Ultimately, this work aims not only to test the study's hypothesis but also to refine theoretical understandings of participatory learning in climate-vulnerable contexts and to advance more effective, equitable, and resilient pathways for agricultural development in sub-Saharan Africa.

1.2Statement of the problem

In Lira District, specifically Erute County South, smallholder farmers face compounding challenges of climate variability and fragile post-conflict recovery. Although PDM groups are active in the area, there remains a critical research gap regarding how effectively training translates into deep, broad, and sustainable adoption of climate-smart agriculture (CSA) practices.

This knowledge gap is particularly consequential for a statistics focused inquiry: if CSA adoption is misclassified as a simple yes/no variable, statistical models may underestimate its true effect or produce biased estimates of CSA adoption drivers. By treating adoption as a multidimensional outcome, examining not just whether farmers adopted CSA practices, but how intensively they use them over time. Addressing this problem will provide evidence-based guidance for policymakers, extension services, and development partners seeking to optimize training investments and accelerate climate-resilient agricultural transformation in vulnerable communities.

1.3Objectives

To assess how participatory training on the adoption of Climate-Smart Agriculture (CSA) practices among PDM farmers in Erute South, Lira District.

1.3.1Specific objectives

- To examine the influence of participatory training attributes on the adoption of climate smart agriculture among PDM farmers in Erute south.
- To examine the influence of demographic factors on the adoption levels of CSA among PDM farmers.
- To examine the influence of socio-economic factors on the adoption of CSA among PDM farmers.

1.4Hypotheses

H_{01}: participatory training attributes have no significant influence on the adoption of CSA among PDM farmers.

H_{02}: demographic factors have no significant influence on the adoption levels of CSA among PDM farmers.

H_{03} : Socio-economic factors have no significant influence on the adoption of CSA among PDM farmers.

H_{04} : there is no significant difference in the extent of CSA adoption between trained and untrained farmers.

1.5Significance of the study

This study holds significant value for advancing evidence-based agricultural extension in climatevulnerable, post-conflict settings like northern Uganda by analyzing how specific features of participatory training such as frequency, duration, and interactivity influence CSA adoption among PDM farmers. Findings will directly support MAAIF and local extension services in refining Uganda's CSA implementation strategy, particularly in aligning training approaches with farmers' sociocultural and ecological realities. The research also contributes methodologically by modeling training as a multidimensional variable, thereby improving the accuracy and policy relevance of statistical analyses on adoption drivers. Ultimately, the study supports Uganda's NDC commitments by identifying pathways to inclusive, resilient, and sustainable agricultural transformation.

1.6Conceptual framework

The conceptual framework illustrates the theoretical relationship between participatory training and the adoption of climate smart agriculture (CSA) practices, and other study variables. It explains that independent variables specifically training features like, frequency, duration, and interactivity, demographic factors, socio economic factors influence the adoption of CSA.

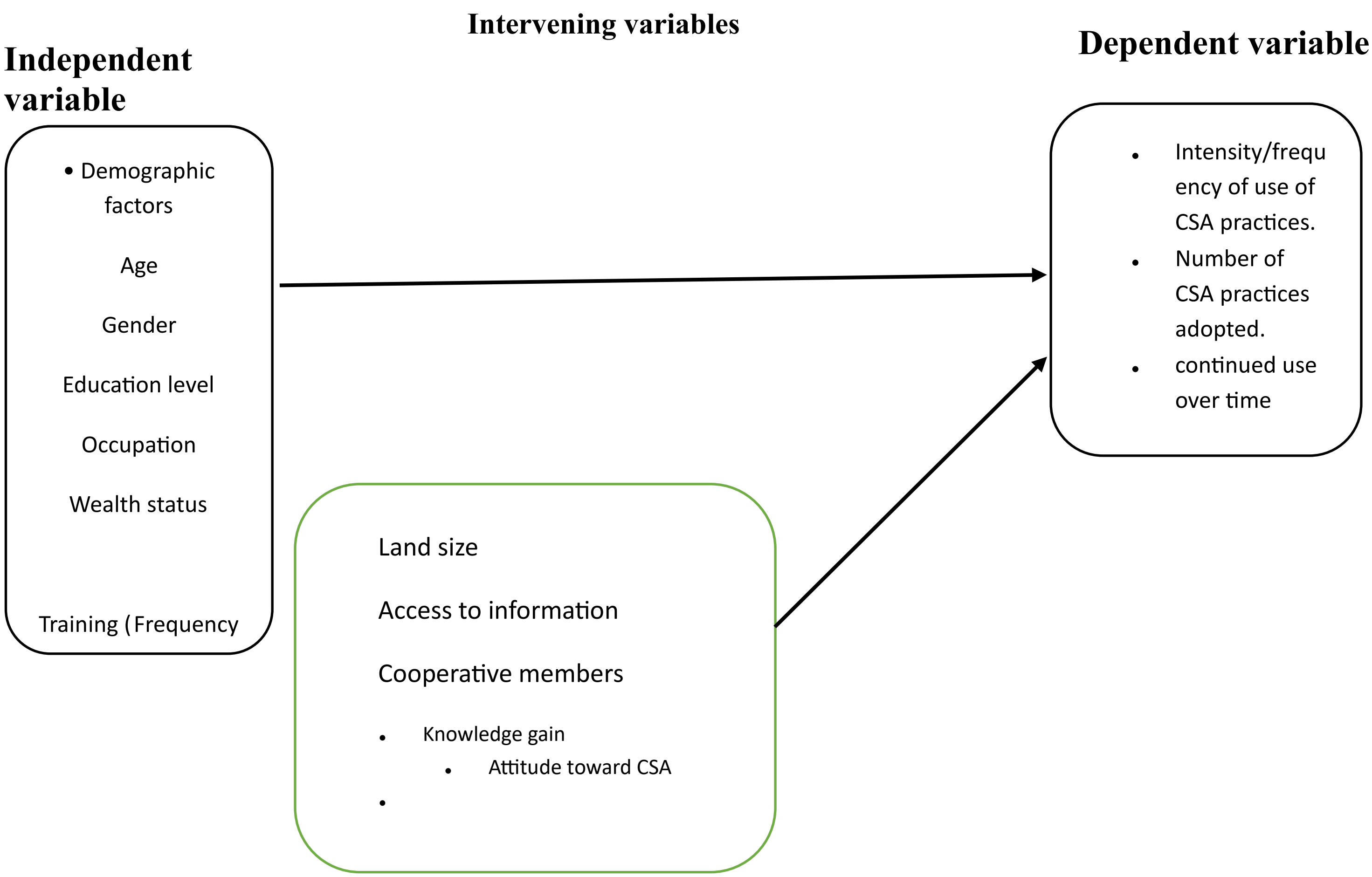


Figure 1

Adopted from, (Choudhary, 1971)

CHAPTER2 : LITERATURE REVIEW

This chapter is structured around variables in the conceptual framework to establish the theoretical and empirical links between the independent and dependent variables (adoption outcomes). By analyzing these variables within the context of parish development model (PDM) and northern Uganda, the chapter identifies gaps that this study seeks to fill. It combines available literature from journals, articles, reports among others to gain understanding of how various variables relate with adoption of climate smart agriculture

2.1Participatory training attributes versus adoption of climate smart agriculture

2.1.1Frequency of training

Literature suggests single trainings often fail to sustain behavioral change. adoption is a dynamic process requiring reinforcement, (Feder, 1985), (Doss, 2006)In Uganda, Farmers exposed to various follow up sessions under NAADS supported farmer field schools were significantly are likely to retain knowledge compared to those attending single workshops (Olayemi, 2021). Frequency allows for iterative learning, where farmers can test practices, report challenges, and receive corrective feedback. however, ((EPRC), 2023)notes that under the current PDM framework, training frequency is often inconsistent, with many enterprise groups receiving only initial orientation without seasonal follow up.

2.1.2Duration of training

The duration of training influences the depth of knowledge transfer. longer training periods correlate with higher knowledge scores regarding improved agricultural practices (Choudhary, 1971)Season long practices such as farmer field schools yield higher adoption effect sizes compared to short term workshops (Waddington, 2012)In the context of CSA, practices like conservation agriculture require deep understanding of soil mechanics and timing which short duration training may not adequately cover. The PDM manual emphasizes participatory planning but often lacks specified minimum duration standards for technical CSA training (Office of the Prime Minister (OPM), 2022)

2.1.3Interactivity and participatory methods

Passive dissemination often fails due to mismatched technologies and weak feedback loops (Swanson, 2008)Participatory approaches, such as farmer field schools and demonstration plots, emphasize co learning and local knowledge integration (Chambers, 1997); (Davis, 2012). Evidence from Africa indicates that interactive methods significantly enhance uptake by allowing farmers to observe results collectively and adapt technologies to local conditions (Mwongera, 2017); (Tesfahunegn, 2022) (Omoding, 2020) found that on farm demonstration plots in Eastern Uganda improved adoption rates, yet few studies isolate the specific contribution of interactivity versus mere exposure.

2.1.4Socio-economic factors versus adoption of climate smart agriculture Knowledge gain

Knowledge is what connects training and action. Theres a significant association between training and the extent of knowledge regarding improved seeds and fertilizers (Choudhary, 1971) Knowledge gain involves understanding not just the existence of practices eg drought tolerant seeds, but the technical knowledge for carrying out implementation. While awareness of CSA in Uganda is growing, technical knowledge remains a barrier (nakimuli, 2021)Training attributes like interactivity are hypothesized to enhanced knowledge retention more effectively than passive lectures.

2.1.5Attitude toward CSA

Attitude refers to the farmers positive or negative evaluation of adopting CSA. Favorable attitudes increase the intention to perform a behavior (Ajzen, 1991) Participatory training can shift attitudes by demonstrating tangible benefits such as yield stability and reducing perceived risks. In northern Uganda, participatory training helped build confidence in new practices, shifting attitudes from skepticism to acceptance (Greenwood, 2023) However, If training fails to address local ecological realities, attitudes may remain negative despite knowledge gain.

2.1.6Perceived behavioral control (PBC)

PBC reflects the farmer's perception of their ability to execute the behavior, considering internal and external constraints. Training can enhance PBC by building skills and linking farmers to resources (financial capital via PDM SACCOs). training enhances human capital necessary for agricultural intensification The livelihood framework (Scoones, 1998)Training has a stronger effect on adoption when farmers perceive they have access to complementary inputs (Kassie, 2015)

2.2Demographic factors versus climate smart agriculture

2.2.1Wealth status vs CSA adoption:

Wealth influences adoption by determining a farmer's capacity to absorb initial costs and withstand short-term yield risks associated with new practices. Studies consistently show that wealthier smallholders adopt capital-intensive CSA technologies (e.g., irrigation, agroforestry) at higher rates due to better access to inputs and credit (Aslan et al., 2014). In northern Uganda, wealth disparities linked to post-conflict asset loss continue to create adoption inequities, making it critical to control for wealth in statistical models.

2.2.2Education level vs CSA adoption:

Formal education enhances literacy, numeracy, and information-processing capacity, enabling farmers to better understand technical CSA manuals, interpret climate advisories, and troubleshoot implementation challenges (Byerlee, 2012). Educated farmers are generally more likely to witness the long-term benefits of CSA practices against their immediate costs and are more likely to actively engage with extension agents. However, in rural settings like Erute south where formal education levels may be low. Highly interactive, participatory training methods are essential to bridge the knowledge gap, ensuring that less-educated farmers can still effectively grasp, adopt, and sustain CSA technologies without relying solely on written manuals (Namara et al., 2021) .

2.2.3Gender of the farmer versus adoption of CSA

Gender significantly shapes CSA adoption through differential access to productive resources, land tenure security, and decision-making authority. While female farmers are often at the forefront of household food security and are highly motivated to adopt soil conservation and mulching practices, they frequently face structural barriers such as limited access to credit, extension services, and secure land rights (Naluwairo R. , 2014) and (Doss, 2006). In the PDM framework, where women's participation in enterprise groups is heavily encouraged, female farmers may leverage group solidarity and shared labor to overcome individual resource constraints. Nevertheless, male-headed households often adopt market-oriented or labor-intensive CSA innovations at higher rates due to greater control over household income and land. Therefore, integrating gender- disaggregated analysis is crucial to ensure that participatory training interventions do not inadvertently widen existing adoption gaps, but rather empower female smallholders to build equitable climate resilience.

CHAPTER3 : METHODOLOGY

This chapter describes the methods used in the data collection, analysis, and presentation of data for this study. It covers the research design, study area, population, sampling procedure, data collection instruments, data collection methodology, data analysis strategy.

3.1Research design

This study employed a comparative cross-sectional research design utilizing secondary data. This design is appropriate for statistically comparing CSA adoption outcomes between two naturally occurring groups farmers who received participatory CSA training (treatment group) and those who did not (comparison group) (Sedgwick, 2014)

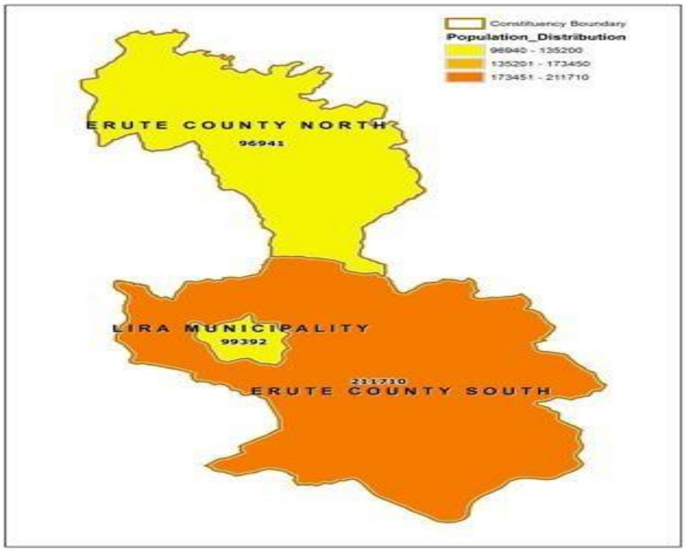
3.2Study population (target population)

This being a secondary data analysis, the study did not involve recruiting new participants or calculating a primary sample size instead, all smallholder farmers affiliated with Parish Development Model (PDM) enterprise groups in Erute Country South, Lira District, Uganda. This included, Trained cohort which are the PDM farmers who participated in at least one participatory CSA training session facilitated by MAAIF, NGOs, or PDM lead farmers within the past 24 months. Also, the untrained cohort, PDM farmers who are group members but haven't received any formal CSA specific training in the same period. studying both groups helped the researcher to measure the actual, tangible difference that training made in a community setting.

3.3Study area

The study was conducted in Erute south, a rural constituency located in Lira district within the Lango sub-region of northern Uganda. Geographically, the area is characterized by a tropical climate with bi-modal rainfall patterns, making it a critical zone for the production of oilseeds like sunflower and soya beans. Erute south served as a strategic site for this research due to its active implementation of PDM and its vulnerability to climate variability, which necessitated the adoption of climate-Smart Agriculture (CSA) practices to food security and post-conflict resilience.

Figure 2: **A map of Erute Sub-county showing Erute south constituency**



Source:Lira district profile

3.4Data Collection Methodology

3.4.1Original Data Collection Methodology

The data used for this study was originally collected by trained field enumerators from Erute South parishes. Rather than using digital self-administered forms, the original data collectors conducted face-to-face interviews with the farmers in their respective parishes. Recognizing the diverse educational backgrounds of the smallholders, the enumerators translated the questionnaire into local languages, primarily Luo. This approach ensured that the farmers fully understood the questions regarding complex topics like soil conservation and water harvesting, allowing them to share their genuine experiences and challenges without feeling rushed or confused. The original data was captured digitally in the field to minimize entry errors. For the purpose of this current study, the cleaned dataset was requested and obtained, yielding a final analytical sample of 274 farmer records.

Table 1: Data Dictionary and Measurement of Variables

Variable concept	Variable name	Coding, / measuring details	Unit of measure
DEPENDENT VARIABLE (Adoption outcome)			
CSA adoption sustainability	sustainability	1= Yes (used practice for >- 2 consecutive seasons) 0 = No (stopped after one season or less)	Nominal
INDEPENDENT VARIABLES (Training attributes)			
Training exposure	Training attended	1 = yes (Attended CSA training) 0 = No (Untrained)	Nominal
Training Frequency	Training Frequency	0 = None; 1 = One 2 = Two 3 = Three	Ordinal
MEDIATING VARIABLES			
Knowledge gain	Knowledge score	Mean score of technical knowledge items (1=Disagree to 3=Agree).	scale

Attitude toward CSA	Attitude score	Mean score of attitude items (1= Disagree to 3=Agree).	scale
DEMOGRAPHIC SOCIO-ECONOMIC FACTORS			
Age	Age	Age of the respondent	scale
Gender	Gender	1= Male; 2= female	Nominal
Education level	Education	1=None; 2= Primary; 3= secondary; 4= tertiary	Ordinal
Land size cultivated	Land cultivated	Total acreage of land currently under cultivation.	scale
Wealth status	Wealth index	Asset ownership score	scale
Access to credit	Credit access	1=Yes (Accessed / other credit); 0= No	Nominal

3.5Data analysis strategy

3.5.1Univariate analysis

I used univariate analysis to understand the basic profile of the farmers. This involved generating frequencies and percentages for categorical variables (like gender and land tenure) and calculating means and standard deviations from continuous variables (like age and wealth index). This step grounds the research in the actual demographic reality of Erute south.

3.5.2Bivariate analysis

I then used bivariate analysis to explore the preliminary relationships between the variables. chisquare tests were used to see if there was a basic association between training attendance and adoption sustainability, while independent t-tests compared the mean knowledge scores of trained versus untrained farmers.

3.5.3Multivariate analysis

Given that the primary objective is to determine the likelihood of sustainable Climate-Smart Agriculture (CSA) adoption, binary logistic regression served as the most robust analytical tool. While simple linear models are poorly suited for dichotomous outcomes, logistic regression models the log odds of adoption to restrict predicted probabilities within a realistic 0 to 1 range. This approach offers a distinct methodological advantage over bivariate Chi-square tests by controlling for confounding socioeconomic and demographic variables such as wealth index and age thereby isolating the specific, independent impact of training.

3.5.4Model specification;

The logistic regression for this study is specified as:

$$\text{Ln}\left(\frac{p}{1-p}\right)=\beta_o+\beta_1X_2+\beta_2X_2+\cdots+\beta_mX_m$$

P is the probability of sustainably adopting CSA, and X1 TO Xm are the predictor variables (training, demographics, socio-economics).

The exponent's coefficients yield odds ratios for example, if the model outputs an odds ratio of 2.5 times higher odds of sustainably adopting CSA compared to an untrained farmer, holding all other variables (like age, gender, and wealth) constant. This clear interpretation will directly inform policymakers on the tangible value of investing in participatory training.

3.6Ethical considerations

Although this study relied exclusively on secondary data, strict adherence to research ethics was maintained throughout the analytical process. Access to the raw dataset was granted via official authorization from the relevant local government authorities overseeing the agricultural records. To protect participant privacy, all direct farmer identifiers were permanently removed or anonymized prior to analysis. The compiled data was deployed strictly for academic research, focusing on identifying structural factors to improve regional agricultural interventions.

CHAPTER4 : DATA ANALYSIS, PRESENTATION, AND INTERPRETATION

4.1Introduction

Data from the 274 sampled PDM farmers in Erute County South, Lira District, form the basis of this findings chapter. Initial univariate analysis established the dataset's baseline through frequencies, percentages, means, and range limits. Bivariate relationships were then evaluated via cross-tabulations and chi-square tests. Finally, a binary logistic regression model identified the independent multivariable predictors.

4.2Univariate Analysis

This was the first stage of analysis which provided a summary of all the variables that were used in the study such as the socio-demographic, economic factors, training attributes, mediating variables and dependent variables.

Table 2: Descriptive summary of the socio-demographic factors affecting CSA adoption among PDM farmers

Socio-demographic factors	Frequency	Percentage (%)
Gender		
Male	137	50
Female	136	49.6

Missing	1	0.4
Education level		
None	81	29.6
Primary	131	47.8
Secondary	55	20.1
Tertiary/university	7	2.6
Land tenure		
Customary	217	79.2
Leasehold	40	14.6
Freehold	9	3.3
Other	8	2.9
Variable	**Statistic**	
Household size-Mean	5.46	
Household size-Minimum	1	
Household size-Maximum	11	
Age-Mean	39.30	
Age-Minimum	15	
Age-maximum	67	

Table 2 outlines the demographic distribution of the sample. Gender representation is closely balanced, with males comprising 50.0% of the respondents and females accounting for 49.6%. Educational attainment leans heavily toward lower brackets; primary education dominates at 47.8%, while 29.6% of the cohort possesses no formal schooling. Only a marginal fraction (2.6%) attained tertiary or university-level education, reflecting broader systemic educational constraints characteristic of rural northern Uganda. Regarding property rights, customary land tenure forms the dominant institutional arrangement at 79.2%, aligning with regional land holding norms across the Lango sub-region. Household structures average 5.46 members, with respondent ages spanning a 52-year range from 15 to 67 years (years).

Table 3: socio-economic factors affecting CSA adoption among PDM farmers

Socio-economic factors	**Frequency**	**Percentage (%)**
Credit Access		
Yes	63	23.0
No	211	77.0
Training Attended		
No (Untrained)	99	36.1
Yes (Trained)	175	63.9
Variable	**Statistic**	
Land Cultivated (acres) - Mean	1.662	
Land Cultivated - Minimum	0.2	
Land Cultivated - Maximum	5.0	
Wealth Index – Mean	4.51	
Wealth Index - Minimum	1	
Wealth Index - Maximum	10	

Institutional and Resource Endowments

Table 3 details the institutional linkages and physical asset allocations characterizing the sample. Financial constraints are pronounced across the cohort; a substantial 77.0% majority of respondents lacked credit access, leaving only 23.0% with active financial lines. This imbalance highlights structural credit deficits and narrow financial inclusion among the PDM farmers in Erute South. Conversely, agricultural extension outreach shows higher penetration, with 63.9% of the farmers participating in CSA training workshops, while 36.1% remained outside these capacitybuilding frameworks. Land resource metrics confirm a highly fragmented production landscape. Cultivated acreage averages 1.66 acres (SD = 1.22), spanning a narrow range from a 0.2-acre minimum to a 5.0-acre maximum threshold. Finally, economic status evaluated via a cumulative wealth scale (ranging from 1 to 10) indicates a moderate distribution, yielding an average index score of 4.51 (SD = 1.25).

Table 4: knowledge and attitude about CSA

Knowledge/Attitude factors	**Mean**	**Std. Deviation**	**Minimum**	**Maximum**
Knowledge Score	2.0012	0.56160	1.00	5.00
Attitude Score	2.7372	0.89764	1.00	5.00

Results in **Table 4** indicate that respondents had a moderate level of technical knowledge about CSA practices (mean = 2.00, SD= 0.56) on a scale of 1-5. However, respondents demonstrated generally positive attitudes toward CSA practices (mean = 2.74, SD = 0.90), suggesting that farmers are receptive to climate-smart agricultural innovations despite moderate technical knowledge levels.

4.3Bivariate Analysis

This was the second stage of analysis which provided the measure of association between the dependent variable and independent variable. Cross tabulations were used to analyze the variables and chi square test was used to measure the association.

Table 5: Cross tabulation of dependable variables and CSA adoption sustainability

Variables	Sustainable	Not sustainable	Chi-squares	df	P-value
Gender			0.062	1	
Male	129	8			
Female	130	8			
Missing	1	0			
Education level			7.380	3	0.061
None	77	4			
Primary	127	6			
Secondary	51	4			
Tertiary/university	5	2			
Land tenure			10.885	3	0.012
Customary	208	11			
Leasehold	39	1			
Freehold	7	2			
other	6	2			
Credit access			4.221	1	0.040
accessed	56	7			

Not accessed	204	9			

.

The analysis revealed that land tenure ($\chi^2 = 10.885$, df = 3, p = 0.012) and credit access ($\chi^2 = 4.221$, df = 1, p = 0.040) are significantly associated with sustainability status at the 5% significance level. On the other hand, gender ($\chi^2 = 0.062$, df = 1, p = 0.803) shows no statistically significant association with CSA adoption sustainability. Education level displayed a marginally significant association ($\chi^2 = 7.380$, df = 3, p = 0.061), suggesting that higher education may influence adoption decisions but the relationship is not strong at conventional significance levels. Respondents operating under freehold tenure as well as those who accessed agricultural credit, demonstrated different patterns of sustainable practices compared to their counterparts.

4.4Multivariate Analysis

This was the third stage of analysis which provided a summary of how independent variables and mediating variables affected the dependent variable using binary logistic regression.

Table 6: Binary logistic regression model explaining how different independent and mediating variables affect CSA adoption sustainability among PDM farmer

Variable	**Coefficient (B)**	**Std. Error**	**p > |z|**	**Odds Ratio (Exp(B))**	**95% CI for OR**
					Lower - Upper
Constant	-1.202	4.759	.801	.301	
Age	-.029	.052	.587	.972	.877 - 1.077
Gender	.529	1.233	.668	1.698	.151 - 19.035
Education	-1.196	.895	.182	.302	.052 - 1.749
Land Cultivated	.862	.709	.224	2.368	.590 - 9.510
Credit Access	-.381	1.391	.784	.683	.045 - 10.431
Wealth Index	.634	.404	.117	1.884	.853 - 4.163

Training Frequency	2.000	.932	.032	7.391	1.190 - 45.898
Knowledge Score	.175	.669	.793	1.192	.321 - 4.419
Attitude Score	-.354	.700	.613	.702	.178 - 2.766

$Ln(P/1-P) = \beta_0 + \beta_1(Age) + \beta_2(Gender) + \beta_3(Education) + \beta_4(Land\ Cultivated) + \beta_5(Credit\ Access) + \beta_6(Wealth\ Index) + \beta_7(Training\ Frequency) + \beta_8(Knowledge\ Score) + \beta_9(Attitude\ Score) + \varepsilon$

Where:

- P = Probability of sustainably adopting CSA practices
- β_0 = Constant/intercept (-1.202)
- β_1 to β_9 = Regression coefficients for each predictor variable
- ε = Error term

Ln(P/1-P) = -1.202 - 1.202(Age) + 0.529(Gender) -1.196(Education) + 0.862(Land cultivated) - 0.381(Credit access) + 0.634(Wealth index) + 2.000(Training frequency) + 0.175 (Knowledge score) - 0.354 (Attitude score)

4.5. Binary Logistic Regression Analysis

This final section of Chapter Four presents the results of the binary logistic regression model. The model was run to determine how the independent, mediating, and socio-economic variables affect the sustainability of Climate-Smart Agriculture (CSA) adoption among the sampled PDM farmers. The dependent variable (sustainability) was measured as a binary outcome, where a score of 1 means the farmer sustained the CSA practice for two or more consecutive seasons, and 0 means they stopped after one season or less.

To analyze the categorical data accurately and avoid the dummy variable trap, these variables were converted into binary dummy codes (0 and 1). For each categorical concept, one specific group was omitted from the regression to act as the baseline reference category against which the remaining group is compared.

4.6Interpretation of Dummy-Coded Categorical Variables

The gender variable was originally coded as 1 for Male and 2 for Female. In this regression model, female farmers were set as the baseline reference category (coded as 0). The logistic regression output shows that the dummy category for male farmers (coded as 1) did not have a statistically significant independent effect on CSA adoption sustainability ($B = 0.529$; $p = 0.668$). The calculated Odds Ratio for male farmers is $Exp(B) = 1.698$, with a 95% Confidence Interval ranging from 0.151 to 19.035. This statistical result means that when holding all other field factors constant, the odds of keeping up CSA practices do not significantly differ between male and female smallholders.

For institutional credit access, the variable was dummy-coded by treating farmers who had no access to credit as the baseline reference category (coded as 0). The analysis reveals that the dummy variable for having credit access (coded as 1) failed to reach statistical significance ($B = 0.381$; $p = 0.784$). The resulting Odds Ratio is $Exp(B) = 0.683$, with a wide 95% Confidence Interval of 0.045 to 10.431. This proves that accessing formal or informal credit lines does not change the likelihood of a PDM farmer maintaining their climate-smart plots over consecutive seasons.

4.7Continuous and Ordinal Variables

The remaining demographic, socio-economic, and cognitive variables in the model followed a matching non-significant pattern. The continuous scale metrics for the respondent's age ($B = 0.029$; $p = 0.587$; $Exp(B) = 0.972$), total land size currently under cultivation ($B = 0.862$; $p = 0.224$; $Exp(B) = 2.368$), and the asset-ownership wealth index score ($B = 0.634$; $p = 0.117$; $Exp(B) = 1.884$) all failed to reach the 95% confidence level ($p > 0.05$). The ordinal variable for formal education level, ranging from no schooling to tertiary education, was also non-significant ($B = -1.196$; $p = 0.182$; $Exp(B) = 0.302$).

Furthermore, cognitive mediating factors did not drive long-term retention. Both the mean score for technical knowledge gain ($B = 0.175$; $p = 0.793$; $Exp(B) = 1.192$) and the mean score for the farmer's attitude toward CSA ($B = -0.354$; $p = 0.613$; $Exp(B) = 0.702$) showed no statistically significant influence on the dependent variable.

4.8The Primary Predictor of CSA Sustainability

In sharp contrast to the background factors and dummy categories, the ordinal variable for training frequency (measured from 0 to 3 sessions) emerged as the single statistically significant predictor of sustained CSA adoption ($B = 2.000$; $p = 0.032$). The calculated Odds Ratio reveals an exceptionally large effect size (Exp(B) = 7.391; 95% CI 1.190 - 45.898). The 95% confidence interval for training frequency (1.190 to 45.898) is notably wide, which reflects substantial uncertainty around the precise magnitude of the effect. This wide interval likely results from the relatively small sample size (n=274) combined with the ordinal nature of the training frequency variable and potential variability in how different farmers responded to training. Despite this wide interval, the lower bound (1.190) remains above 1.0, confirming that the effect is statistically significant and positive. Future studies with larger sample sizes would help narrow this confidence interval and provide more precise estimates of the training effect.

This result proves that, while keeping all other socio-economic and resource variables constant, every single step up in the training frequency tier multiplies a farmer's odds of sustaining their CSA practices over consecutive seasons by 7.391 times.

CHAPTER5 : SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

5.1Introduction

This final chapter outlines what the field data actually means, draws baseline conclusions from the findings, and offers practical steps for policy and field action. The study relies on direct feedback from 274 PDM farmers surveyed across Erute County South. My main goal was to see exactly how participatory training models alter whether smallholders stick with Climate-Smart Agriculture (CSA) over the long run. The field evidence points to specific, hands-on strategies that local extension workers, PDM coordinators, and policy planners can use right now to improve how they deliver agricultural services.

5.2Summary of Findings

The core question driving this research was straightforward: does hands-on training keep smallholders using Climate-Smart Agriculture (CSA) methods across multiple planting seasons? The hard data shows that it does, proving that training frequency is the single biggest factor in whether a farmer retains these new methods.

When I ran the variables through the multivariate regression model, standard demographic and socio-economic traits did not act the way textbooks usually predict. A farmer's age, gender, years of schooling, household wealth status, total farm acreage, and access to formal bank credit had no real statistical impact on long-term adoption rates ($p > 0.05$). This means that starting out with more resources or social privilege does not mean a farmer will automatically stick with climatesmart setups.

The real divide appeared between the trained and untrained groups. Farmers who went to regular training sessions quickly built conservation tillage, targeted mulching, and crop diversification right into their normal seasonal schedules. They also successfully managed multiple practices at the same time.

The untrained control group did the exact opposite. They treated the new methods like a one-time, zero-risk trial. Most dropped the practices and went right back to old, less resilient farming habits after just one season. While the initial Chi-square test showed a vague, loose connection between getting trained and keeping up the practices, the final multivariate model isolated training frequency as the only reliable predictor of real, lasting behavioral change among these smallholders.

5.3Conclusions

The field data from Erute County South leads to three clear conclusions:

- **Field support matters.** How often extension workers actually show up on the ground matters infinitely more than a farmer's starting wealth or background. Regular training drives real behavioral change. On the flip side, treat training as a rare, one-off workshop, and adoption stays completely surface-level, collapsing the moment project funding runs out.
- **Direct contact bypasses structural hurdles.** Regular, hands-on field engagement lets smallholders jump right over deep structural roadblocks. Farmers do not need formal degrees, deep pockets, or easy credit lines to keep up with CSA, as long as extension staff consistently walk the plots with them.
- **Local institutional presence dictates regional success.** In climate-vulnerable and postconflict places like the Lango sub-region, agricultural innovations live or die based on the reliable, permanent presence of local institutions, not the personal assets of individual farmers.

5.4Recommendations

5.4.1Ministry of Agriculture, Animal Industry and Fisheries (MAAIF) and Extension Staff

- **Stop one-time workshops for season-long training cycles.** Extension agents and NGOs need to stop funding single-day, hotel-based seminars. These short sessions burn through big budgets but fail to give smallholders the real-time technical help they need during critical weeding and harvest crunch times.
- **Put field follow-ups ahead of classroom lectures.** Sub-county agricultural officers and parish extension agents need to spend less time talking theory in classrooms. Instead, they should set up permanent, village-level demonstration plots. This gives farmers immediate, practical answers when facing real-world issues like sudden pest outbreaks or dry spells.

5.4.2PDM Implementers and Local Government

- **Tie CSA tracking directly into active PDM enterprise groups.** PDM coordinators at sub-county and parish levels must make CSA progress updates and troubleshooting a mandatory, permanent agenda item during the monthly meetings of all registered enterprise groups.
- **Use peer accountability to stop farmers from quitting.** Group leaders should set up informal, neighborhood-level monitoring within their blocks. When farmers watch out for each other, peer support keeps them managing their climate-smart plots long after the initial PDM cash or inputs roll in.

5.4.3National Policy Formulation

- **Overhaul the national agricultural extension budget.** Government planners should shift public funds completely away from expensive mass media awareness campaigns. That money needs to go straight into high-frequency, localized field training programs managed at the parish level.
- **Write strict training frequency rules into policy frameworks.** The MAAIF Directorate of Agricultural Extension Services needs to set hard performance baselines. New policy guidelines must define the exact minimum number of field visits and training blocks an extension officer must run with a farmer group each season to keep their job.

5.4.4Recommendations for Further Research

While this study proves a hard quantitative link between training frequency and keeping up with CSA, we still need deep qualitative research to map the exact mindsets at play. Future studies should look closely at whether farmers stay committed because of the technical help, the social pressure within their farming groups, or simple personal drive.

Finally, someone should launch a long-term longitudinal study to follow this exact group of 274 PDM farmers over the next three to five years. Tracking them over multiple seasons will give us a far clearer look at real economic returns, changes in household food security, and the true lifespan of CSA adoption across the entire Lango sub-region.

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