Exploring How Regional Context Shapes Agroforestry Adoption among Smallholder Coffee Farmers in Uganda

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Abstract

Agroforestry is a promising sustainable solution that can help mitigate climate change impact for smallholder coffee farmers in Uganda. However, adoption remains limited. This study explores the interaction between regional context and factors influencing adoption. The data is comprised of 120 observations from farmers in three regions in Uganda: Easter Uganda, Central Uganda and West Nile. A negative binomial regression model was used to explore the relationship between the independent variable and their impact on adoption intensity, measured by the count of trees planted. Results show that for the variables: selling benefits and annual income, the strength of their impact was influenced by region. The results of this study suggest that regionally contextualized interventions can be more effective than generalized practices.

Contents

Introduction

Coffee farming represents a key industry in Uganda, accounting for over 15% of Uganda's annual export revenue and serving as the primary income source for many families and communities (Uganda Coffee Development Authority (UCDA), 2017). However, recent trends in soil usage and climate change put the industry's viability at risk. Temperature changes can affect coffee yields and even render farming areas unsuitable. Unreliable rainy seasons also affect the critical months for crop growth (Jassogne et al., 2013) .

One possible solution to this problem is agroforestry. The practice has the potential to partially mitigate climate change effects and improve the suitability of coffee farming in Uganda (Abigaba et al., 2024). However, barriers to adoption still exist, disproportionately affecting smallholder farmers, who often lack the capital needed to reinvest in their farms, resulting in slower adoption rates (Jassogne et al., 2013). Incentives such as carbon credits and training programs have been proposed as a solution to improve agroforestry adoption. The MISACI research project aims to explore the key elements influencing smallholder coffee farmers in Uganda to participate in agroforestry-based carbon farming initiatives. By analysing farmers' behavior and socio-economic circumstances, it explores the impact of gamified training on farmer engagement and the role of carbon payments on household income. (A. Sidi, personal communication, June 2025) The project is based in three regions in Uganda: Central Uganda, Eastern Uganda, and West Nile. Among the three regions, a difference in adoption intensity has been observed.

This raises the question: How do regional factors shape the adoption of agroforestry among smallholder coffee farmers in Uganda?

Identifying these interactions and their impact can provide additional insight and can help future programs contextualize regional differences, improving their effectiveness in promoting agroforestry adoption. The study objective is to explore these regional interactions and their impact on farmers' agroforestry adoption intensity. The research is guided by the following hypotheses:

- **1**: Regional context moderates the relationship between communication channels and agroforestry adoption intensity.
- **2**: Regional context moderates the relationship between innovation characteristics and agroforestry adoption intensity.
- **3**: Regional context moderates the relationship between adopters' characteristics and

agroforestry adoption intensity.

The study hypothesizes that relationships between factors and adoption intensity differ among regions, with the same factor but in a different regional context having significant, stronger, or weaker effects. The study will follow a rigorous structure, ensuring all relevant aspects of the topic are covered. Chapter 2, Literature Review, covers the theoretical background of this study and ensures the methods and approach are appropriate. Chapter 3, Methodology, explores the data, model selection, and the analysis. Chapter 4, Results, interprets the analysis output and its implications. Chapter 5, Discussion, identifies key limitations of the study and suggests possible topics for future research. The research concludes with chapter 5, Conclusions, which provides a short and compressed explanation of the entire study and the findings.

Literature Review

The literature review was conducted in a systematic manner, ensuring a comprehensive understanding of the topic, particularly the factors influencing agroforestry adoption in relation to smallholder farmers, with a focus on research conducted in Uganda. To ensure a robust approach, the review process follows the principles of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework (Page et al., 2021) , allowing for transparent search and selection procedures. Studies were selected following the eligibility criteria:

Topic relevance: the primary focus of the study had to be on the adoption, drivers, barriers or impact of agroforestry practices. Geographical relevance: studies had to be conducted in the Global South, with a strong preference for studies specifically located in Uganda. Language: only studies published in English were considered. Publication date: the search was limited to studies published between January 1, 2010, and May 1, 2025

Studies were excluded for the following criteria: Lacked clear methodological descriptions, preventing an assessment of their rigor and reliability. Their findings were inconclusive or lacked substantive relevance to the research objectives The search strategy was conducted on two academic databases: Google Scholar, utilized for its broad coverage of academic papers, and SpringerLink, selected for its strong collection of peer-reviewed journals.

The following combination of keywords was employed to search relevant studies: "Agroforestry adoption", "Smallholder farmers", "Coffee farmers", "Uganda", "Regional differences", "Contextual factors" , "Socio-economic factors" , "Demographic factors", "Agroforestry ", "innovation"

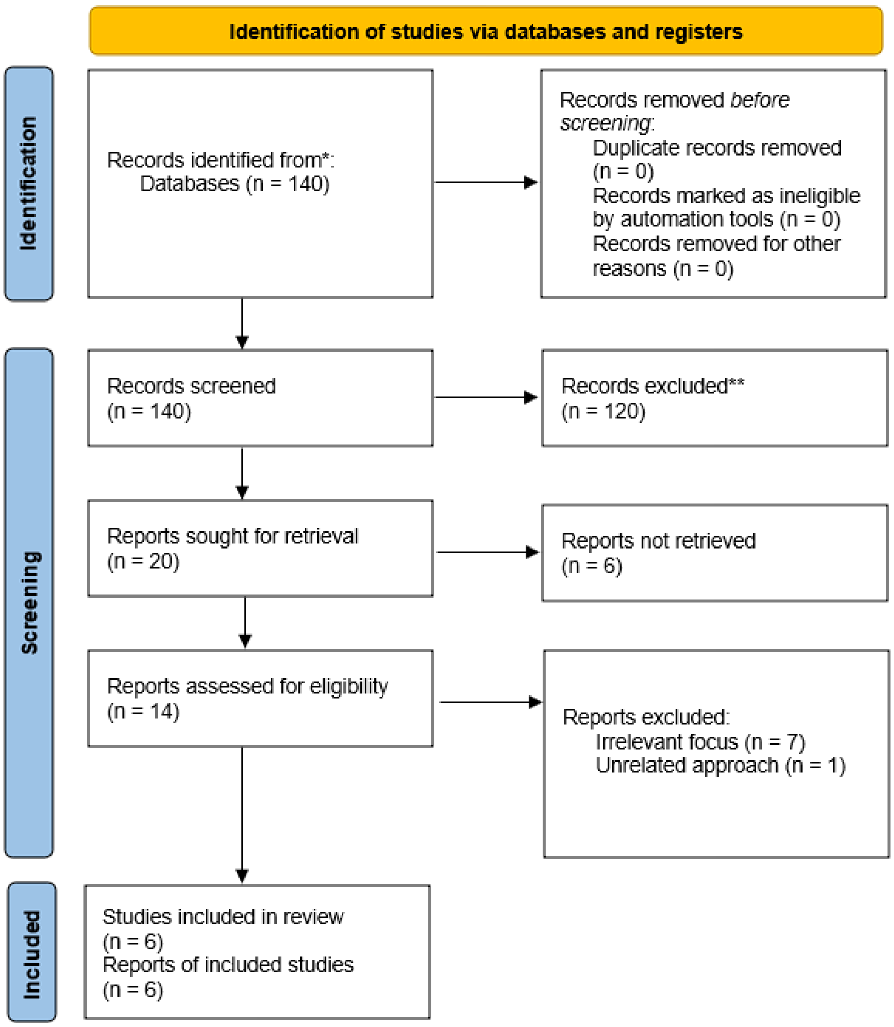

Figure 1

PRISMA flow diagram showing the literature screening process

In addition to the database search guided by PRISMA, additional relevant studies were identified through citation chaining, review of governmental reports, and inclusion of key papers used to support methodological explanations.

Review of relevant literature

Agroforestry adoption has been thoroughly researched in recent years. Wienhold and Goulao (2023) provide a contextualized review that explores the factors influencing adoption and resistance to coffee agroforestry systems. The review explores country-specific studies of coffee production and farmers in 15 countries, including Uganda. The review results conclude that agroforestry provides significant benefits for the farmers and the environment, having both a local and global impact. The agricultural benefits include increased yields and farm profitability, and for coffee farmers, a higher quality product. Late-stage agroforestry systems have also been linked to improved soil fertility, erosion control and timber production. However, the study also identifies insignificantly reduced coffee production as a potential outcome in some contexts. This finding is presented without further clarification on whether insignificantly refers to a lack of statistical significance or just the small size of the reduction. Socio-economic benefits are also highlighted, with farmers enjoying income diversification, food sovereignty, food security, and reduced production costs. The authors also explore farmers' challenges, such as labor shortages in coffee-growing regions, likely due to demographic shifts, and climate change. The study also explores the effects in Uganda, where the changes in temperature cause farmers severe difficulties in successfully growing coffee. However, economic limitations, such as tree planting and maintenance slow agroforestry adoption. Households in poverty are the least likely to adopt the practice, as they prioritise short-term benefits over long-term returns. Wienhold and Goulao (2023) also explore implementation programs and identifies a frequent source of friction in rural development initiatives stems from a misalignment of priorities and perception between program implementers and local farmers. The epistemological disconnect suggests that the success of agroforestry adoption initiatives is connected with the ability of programs to bridge these fundamental differences in understanding, valuing, and perceiving the innovation.

In Uganda specifically, Wienhold and Goulao (2023) mentions that farmers have a positive view of agroforestry however, the means are unclear. They argue that the explored literature review suggests that these diverse priorities, capabilities, and needs can be addressed using participatory program design and improved planning. This process can benefit from the findings of my research, as the explored regional differences can contribute to the program design and planning.

Kalanzi et al. (2021) Elaborates on the issue of agroforestry implementation and system selection. Collecting cross-sectional surveys from 277 farmers in the eastern highlands of Uganda the paper explores farmers characteristics using descriptive analysis and ensure the validity of the research through multiple test analysis such as Kaiser-Meyer-Olkin (KMO) Measure ($p > 0.5$), Bartlett's Test of Sphericity ($p \leq 0.05$) and a multi-collinearity check. The study employed an alternative-specific conditional logit model for its ability to factor in both the case-specific characteristics as well as the system-specific factors. In the context of my study, case-specific variables and influence are highly relevant. The study identifies specific systems factors, such as gender, training, land size, and peer influence play a role in the farmer's decision. Peer influence can be highly relevant, as the study highlights, using farmer interviews, the need for neighbourhood collaboration for agroforestry adoption. The paper also mentions several limitations, including the lack of climate and institutional variables, and the need for study replication in larger areas for generalization.

Research Gap

Explored literature explored numerous factors affecting the adoption process, including behavioral, economic, demographic, and geographical factors (Wienhold & Goulao, 2023). However, one particular aspect that has been underexplored is the cross-analysis of the regional variables. Explored literature focused on investigating the factors that influence agroforestry adoption, and provided limited insights regarding how these factors interact with regional context. Additionally, most studies collect data from single regions or large areas, limiting their insights about the regional context's impact on their study. Kalanzi et al. (2021) mentions in his study this limitation, mentioning that the study results should only be applied in similar regions, acknowledging the impact regional context can have on the explored factors. Larger studies such as the one conducted by Abigaba et al. (2024) often overlook local area insights, instead focusing on larger trends and patterns such as climate effects. This paper aims to address this gap by providing a comprehensive analysis that explores how regional context influences the factors' impact on agroforestry adoption intensity.

Theoretical Framework

Several theoretical frameworks have been used for studies exploring agroforestry adoption. One of the most recognizable of them is the Theory of Planned Behavior (Ajzen, 1991). Despite its frequency in reviewed papers, Kalanzi et al. (2021) opts for the Decomposed Theory of Planned Behavior (DTPB) (Taylor & Todd, 1995), which, he argues, addresses some of TPB's criticisms. DTPB integrates aspects from Innovation Diffusion Theory (DOI) (Rogers, 1983) into TPB, splitting attitude into three constructs, allowing for a better understanding of behavioral elements. DTPB and TPB are highly effective in exploring the individual processes impacting behavioral intentions and specific choices however, their focus remains on individual psychological factors. DOI is comprised of 5 elements: Innovation, Communication Channels, Adopters, Time, and Social System, and focuses more on the exploration of innovation diffusion. The framework focus is more relevant for my topic compared to TPB or DTPB who primarily focus on individual psychological drivers. DOI will be further contextualized to align with my research goal.

Conceptual framework

The contextual framework for this research adapts the elements explored by DOI, adjusting factors and interactions to the objectives and questions proposed. This study will focus on four key elements of DOI: the innovation, communication channels, adopters, and the social system. While time is a fundamental element for a comprehensive understanding of diffusion, its impact in this cross-regional study is not a primary focus, however, the effects of time are reflected in the adoption despite them not being empirically explored in this research. The other elements are contextualized. Innovation characteristics considers the perceived benefits, such as environmental benefits, and challenges of implementation, such as seedling limitations. This aligns with the characteristics of relative advantage and complexity. Communication channels represent the methods farmers are being informed about the practice or method. In our project, this is done through training offered by the program and the use of gamification as a channel of communication. Adopters characteristics are focused on economic and demographic factors such as age, income, and household size. Social systems are a combination of external influences and internal influences. This is encapsulated by the regional aspect of the research. The interaction between elements is also adjusted according to the diagram 2. The following relationships are considered. Innovation, communication channels, and adapters all have a direct impact on adoption intensity. The social system moderates the impact of these elements. Using this framework, we can understand what factors impact adoption and explore how social systems influence them.

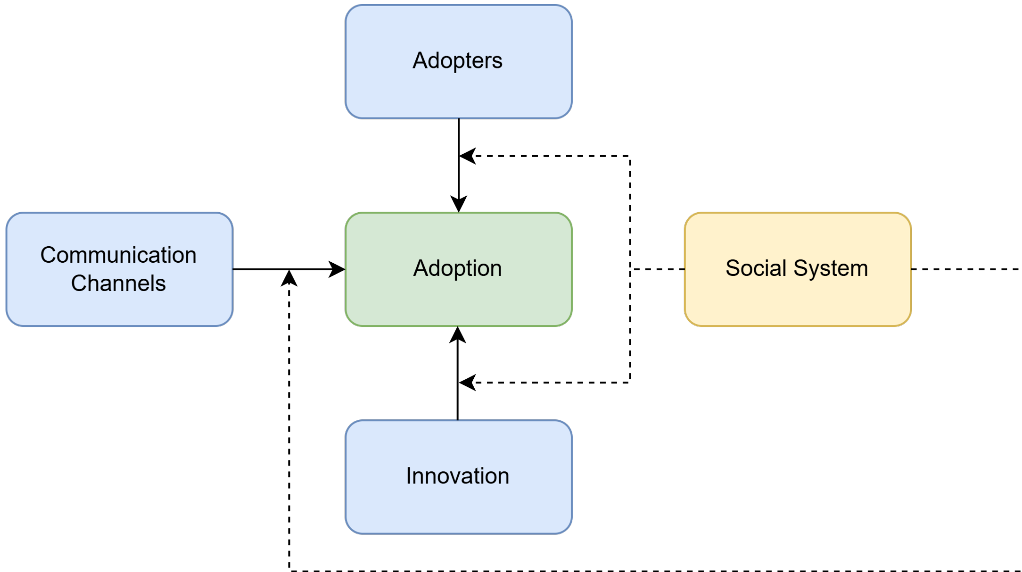

Figure 2

Conceptual framework, adapted from Rogers (1983)

Methodology

The study analyzes the data collected during the MISACI research project. The study analysis was performed using RStudio, implementing libraries such as MASS and emmeans for statistical analyses and regression modeling.

Study design

This study conducts a quantitative analysis using a cross-sectional design. The research is designed to compare regional factors across the three explored regions, Eastern Uganda, West Nile, and Central Uganda, aiming to identify the effect regional context has on relationships directly influencing agroforestry adoption intensity. The dependent variable is represented by the count of trees planted, which is used in this study as a representation of adoption intensity. The independent variables are represented by key characteristics of the framework elements. The study will perform negative binomial regressions that explore the moderating effect of regional context. The relationships are separated into 3 models, each model exploring one element of the framework. All the variables will be included in each model as control variables to ensure the results are interpretable. Statistical tests are performed to ensure the model's robustness. Two of the models failed the goodness of fit test, indicating possible model misfit. To address this, a sensitivity analysis was implemented by removing statistical outliers. Both models are kept for transparency, and their results are compared and interpreted. The negative binomial regressions compare the effects to the reference point, Central Uganda, and the interaction findings can only be interpreted in relation to the other regions. To examine the interaction between the 2 non-reference regions, a post hoc analysis was implemented. The results will be critically examined, and any significant moderating effect will be discussed. The significant interactions between region and variables specific to each element will be used to test the 3 hypotheses of the study.

Data

This study utilizes secondary data from the MISACI project, and while complete documentation of the original sampling methodology is unavailable, the dataset's structure and composition are well-defined.

The dataset consists of 120 farmers equally divided across the three regions. The farmers are categorized into groups based on the training and support they obtained during the project. The first group consists of 75 farmers who received gamified training during the initiative. The second group, which consists of 10 farmers from each region, participates in the agroforestry project without receiving the gamified training. The third group did not receive any training and consists of 5 farmers from each region.

The data is formatted as semi-structured survey answers from the farmers. The questions were formatted as categorical questions, numerical input questions, and open questions, designed to capture the farmers' opinions and insights. Economic and demographic variables such as age, income, household size, gender, land tenure, and education were collected. The data also contains survey answers from farmers that represent their motivation, challenges, and prior interaction with support programs.

For this study, answers were codified into codified binary dummies, with challenges being categorized into: Irrigation-related challenges, Seedling-related challenges, and Pesticide-related challenges. Motivation for their participation was also categorized into: Knowledge-inspired motivation, environmental-inspired motivation, and economic-inspired motivation.

The data is collected in the same time frame, and the regions are located in the same country, limiting the impact of larger patterns, such as climate change.

Variable Selection

Zabala et al. (2025) explores in his research the methods and variables used in agroforestry adoption analysis. His study provides a comprehensive list of variables used. The paper identifies 96 variables used in models across multiple papers examined (n=79). The list provides a strong theoretical foundation for variable selection in this study. The following variables, which are present in the list and the MISACI dataset, are identified as relevant for this study: Environmental, Training, Age, Household size, Annual Income and Cultivated Land. Additional variables have been introduced due to their alignment with this study's research aim: Seedlings, Pesticides, Selling, Gamification

Considering the research conceptual framework, the variables were categorized accordingly: adopter characteristics, communication channels, and innovation characteristics 1. Provided the limited number of observations (n=120), the variable count was limited to (n=10). The model design only uses key elements that capture the theoretical objective of this study. This approach reduces the risk of overfitting and improves the model's robustness.

Table 1

Categorization of Variables by Conceptual Framework

Category	Subcategory	Variables
Innovation	**Challenges**	Seedlings, Pesticides
	Benefits	Selling, Environmental
Communication Channels		Gamification, Training
Adopters	**Demographic**	Age, Household size
	Economic	Annual income, Cultivated land

Additional data exploration was performed on the selected variables 2. The descriptive statistics reveal a significant difference between the third quartile and maximum values. A box plot visualisation was performed to investigate the outliers A1. The box plot identifies a limited number of extreme outliers on the upper end. The data in real-world applications is prone to higher outliers, and removing them could artificially improve the model while not fully capturing the true interactions. A more appropriate solution is the implementation of a sensitivity analysis. This ensures the results are robust by comparing the output of both models and identifying significant differences.

Table 2

Descriptive Statistics for Study Variables

Variable	Min	1st Quartile	Median	Mean	3rd Quartile	Max
Dependent Variable						
trees planted	0.00	20.00	30.00	37.50	40.00	400.00
Independent Variables						
Categorical Variables						
Seedlings	0.00	0.00	0.00	0.39	1.00	1.00
Pesticides	0.00	0.00	0.00	0.34	1.00	1.00
Irrigation	0.00	0.00	0.00	0.15	0.00	1.00
trading	0.00	0.00	0.00	0.28	1.00	1.00
selling	0.00	1.00	1.00	0.76	1.00	1.00
Economic	0.00	0.00	0.00	0.45	1.00	1.00
Enviormental	0.00	0.00	0.00	0.29	1.00	1.00
Training	0.00	0.00	0.00	0.44	1.00	1.00
Gamification	0.00	0.00	1.00	0.63	1.00	1.00
A.3 Gender	0.00	0.00	1.00	0.66	1.00	1.00
literacy level	0.00	1.00	2.00	1.77	3.00	3.00
Continuous Variables						
A.2 Age	24.00	40.00	51.00	50.67	61.50	82.00
household size	2.00	5.00	6.00	6.86	8.00	24.00
annual income (millions)	0.35	2.00	3.00	6.45	5.00	80.00
cultivated land	1.00	2.00	2.00	3.49	3.00	35.00

Ethical Consideration

All the survey respondents expressed their consent to conduct the interview. The study analysis is only performed on the farmers who have agreed to the interview being conducted. This ensures that the data was collected transparently and ethically.

Data analysis

Zabala et al. (2025) provides a broad, systematic, and in-depth overview of models used in this field. He explores 27 papers that conduct a quantitative regression model analysis and categorizes them based on the model. The recurring models are Logit 13, Probit 5, Multinomial probit 2, and Ordered probit 2. Logit models and Probit models are mostly used for binary variables and, therefore, are not suitable for my research. Kule et al. (2025) research is more aligned with my objectives and provides a more suitable research method. In his study, he employs a Poisson regression model (PRM), a generalized linear model used for count data analysis. According to Liu (2008), the formula can be expressed as:

$$f(Y_i \mid \mathbf{X}_i) = \frac{\exp(-u_i) u_i^{Y_i}}{Y_i!},$$

where

$$u_i = \exp(\mathbf{X}_i \beta),$$

with Y_i representing the count outcome variable for observation i, u_i the expected count conditional on predictors, $\mathbf{X}_i$ a dimensional vector consisting of n independent variables, and β a vector of regression coefficients.

The author also mentions that one of the key assumptions of PRM is that it follows a Poisson distribution. To ensure the suitability of the model, the assumption of equidispersion is tested.

$$E(Y_i) = \mathrm{Var}(Y_i) = \lambda_i$$

where Y_i represents the count response variable for observation i, and λ_i is the expected count (mean) conditional on predictor variables. The results confirm that the observed variance is greater than the mean, resulting in overdispersion.

$$\mathrm{Var}(Y_i) > E(Y_i)$$

Therefore, PRM is not a suitable solution for our study.

Table 3

Dispersion Test Results

Region	**Dispersion**	**p-value**
Eastern Uganda	1.93	.034
Central Uganda	5.13	< .001
West Nile (Nebbi)	10.51	< .001
All Regions	6.33	< .001

Liu (2008) notes that equi-dispersion is rarely true in a real-world application, and he provides an alternative. Negative binomial regression (NBR) is highlighted for its ability to deal with count data with over-dispersion. In the paper, he expressed the formula as:

$$u_i = \exp(\mathbf{X}_i\beta + e_i) = \exp(\mathbf{X}_i\beta)\exp(e_i), \text{ where } \exp(e_i) \sim \text{Gamma}(\alpha^{-1}, \alpha^{-1})$$

where u_i is the expected count for observation i, $\mathbf{X}_i$ is a vector of predictor variables, and β is a vector of regression coefficients. Additionally, to ensure the model's accuracy, a VIF test is performed on all models. The VIF is automatically transformed by the car: package in R studio into GVIF to account for the interaction factors. The model performs a moderation analysis, which consists of a new interaction predictor x_1x_2 being calculated.

$$Y = b_0 + b_1x_1 + b_2x_2 + b_3(x_1 \times x_2) + \varepsilon \tag{1}$$

This new predictor is prone to multicollinearity issues do to the correlation between the main factors and the interaction factors. To address this, mean-centering is applied as a possible solution for reducing multicollinearity (Iacobucci et al., 2016; Gujarati & Porter, 2009) . The effects of centering were significant, and the Gvif values are within reasonable values (A1), ensuring the model is robust.

First we consider the dispersion parameter θ, which is indicative of overdispersion in all the models, reinforcing negative binomial regression selection as the preferred model. Kule et al. (2025) performs the following methods: pseudo R-squared, Log-Likelihood, and Pearson Chi-square to check the model fit of its Poisson regression model.

These same tests were performed on the Negative Binomial regression models in the current study. These metrics provide crucial insights into how well our model aligns with the observed data.

Table 4

Model Fit Statistics for the Three Negative Binomial Regression Models

Fit Statistic	Innovation Model	Communication Model	Adaptors Model
Pseudo R^2	0.086	0.079	0.081
Log-Likelihood	-500.32	-503.90	-502.98
GOF Pearson chi	125.14 (p = .03)	131.30 (p = .03)	115.11 (p = .11)
Dispersion (Theta)	3.564 (SE = 0.422)	3.725 (SE = 0.469)	3.287 (SE = 0.396)

The pseudo R^2 indicates the models explains 7.9 percent to 8.6 percent of the variation. The goodness-of-fit Pearson chi-square test, however, indicates that the model is not a good fit for the data for the Innovation model and the Communication model. This lack of fit can be caused by outliers significantly disturbing the model fit. Considering that significant extreme outliers were identified in the dataset, additional regression models excluding these outliers will be estimated. A sensitivity analysis will then be conducted to assess the robustness of the results by evaluating how the outliers impact the relationship between variables and adoption intensity.

The Interquartile Range (IQR) method was applied to address outliers in this study. This technique offers a consistent and statistically robust approach, enabling all three models to be estimated using the same set of observations

Table 5

Model Fit Statistics for Negative Binomial Regression Models (Outliers Removed)

Fit Statistic	Innovation Model	Communication Model	Adaptor Model
Pseudo R^2	0.056	0.049	0.062
Log-Likelihood	-335.44	-337.71	-333.22
GOF Pearson chi	79.27 (p = .095)	75.06 (p = .260)	69.63 (p = .294)
Dispersion (Theta)	5.06	4.69	5.54

The new models dispersion parameter θ, confirms the negative binomial model fit, and the pearson chi-square test is non-significant for all three models. This indicates that the models are a good fit for the data. However the elimination of the outliers can change the effects and interaction of variables by removing real observations. As such, a sensitivity analysis is performed that compares the results and identifies effects that align across both iterations of the model.

A post hoc analysis was also conducted to estimate the slopes of the interaction effects and main effects of the predictors in the two non-reference regions.

Results

The full model output interpretation is limited in its initial form A2 A3. Hilbe (2011) argues that estimates for count models such as negative binomial regression should be expressed in incident risk or risk ratio. Therefore, any significant results will be converted into the incident rate ratio (IRR) for a more comprehensive interpretation of the results. The models interpretation will be organized in categories based on the relationship they explore.The results will then be interpreted for the 2 models types: one performed using the full dataset and one performed with a cleaned dataset that removes outliers. The significant outputs will be presented side by side, and a sensitivity analysis will be performed to compare the findings. The interpretation is performed assuming all other things stay equal other than the increase in the selected variable.

Adopters Characteristics

The sensitivity analysis identified two independent variables that are significant in both models. Training showed a positive effect, with a 43 percent increase in the full model (IRR = 1.43, $p = .009$) and a 32 percent increase in the cleaned model (IRR = 1.32, $p = .038$). The annual income effect shows a 4 percent increase per million UGX above mean in the full model (IRR = 1.04, $p = .001$), and a 15 percent increase in the second model (IRR = 1.15, $p = .013$). The direction of both variables remains the same across both models, suggesting a robust finding. Several variables, including selling, environmental benefits, and West Nile region, become significant in the no outlier model, while remaining insignificant in the first model. This suggests a possible effect however, the lack of significance in the full model mean we cannot confidently conclude the effects.

Interaction terms explore the difference between regions and test the hypothesis of the paper by investigating the moderating effect of region on the relationship between adopter characteristics and adoption intensity.

Both models identify the interaction between Central Uganda and West Nile annual income as significant. The annual income increase has a weaker impact in West Nile compared to Central Uganda, the first model estimates the annual income impact is 14 percent weaker (IRR = 0.86, $p = .018$), while the second model estimates a 29 percent weaker impact (IRR = 0.71, $p < .001$). To calculate the impact Annual income has in West Nile we can multiply the interaction with the main effect in Central Uganda to determine to effect. In the first model $1.15 \times 0.71 = 0.82$ (IRR), or an 11 percent decrease in adoption intensity. According to the second model, $1.15 \times 0.71 = 0.82$ (IRR), or an 18 percent decrease in adoption intensity. This means that not only does the region impact the strength but also the direction of the variable effect. A similar effect was identified between Central Uganda and Eastern Uganda, with income in Eastern Uganda having a 14 percent weaker impact according to the first model (IRR = 0.86, $p = .263$) and a 29 percent weaker impact according to the second model (IRR = 0.71, $p = .009$). However, these results are only significant in the second model. Additionally, the first model identifies the household size interaction between West Nile and Central Uganda as a significantly stronger effect (IRR = 1.13, p =

.021) however, this result differ compared to the second model, where the interaction is not significant (IRR = 0.91, p = .302) and its coefficient suggests a weaker effect. Therefore, this interaction is considered unreliable.

The findings clearly show that the region has a moderating effect on adopter characteristics, influencing the strength and direction of the variables. As indicated by the interacting terms, certain characteristics, such as annual income, can have a stronger or weaker impact on adoption intensity depending on the region. Therefore, the first hypothesis: regional context moderates the relationship between adopters' characteristics and agroforestry adoption intensity, is accepted.

Table 6

Significant incidence rate ratios (IRRs) for adopter models

Predictor	Full data model	No outliers model
Intercept	13.36 (p < .001***)	17.89 (p < .001***)
Selling	1.14 (p = .392)	1.40 (p = .038*)
Environmental	1.16 (p = .329)	1.52 (p = .008**)
Training	1.43 (p = .009**)	1.32 (p = .038*)
Annual income (million, centered)	1.04 (p = .001 **)	1.15 (p = .013*)
Region: West Nile	0.87 (p = .928)	0.25 (p = .011*)
Interaction terms		
Household size × Region: West Nile	1.13 (p = .021*)	0.91 (p = .302)
Annual income × Region: West Nile	0.86 (p = .018*)	0.71 (p = .0003***)
Annual income × Region: Eastern Uganda	0.86 (p = .263)	0.71 (p = .009**)

Note. IRRs are exponentiated coefficients rounded to two decimals. Only predictors with p < .05 in either model are shown. Reference region is Central Uganda. *p < .05. **p < .01. ***p < .001.

Innovation characteristics

The innovation models maintain the structure and variables used, however, interactions are performed on innovation characteristics. The sensitivity analysis identifies two independent variables that have an effect on adoption intensity in the reference region. Annual income is significant in the full dataset model and indicates a 4 percent increase for each million UGX above the mean income (IRR = 1.04, p < .001). The no outlier model indicates a nonsignificant 2 percent decrease (IRR = 0.98, p = .634), suggesting that the findings are not aligned and are not reliable. The direction of Region West Nile is aligned in both models; however, the coefficients differ, with the second model indicating a 65 percent decrease (IRR = 0.35, p = .028), while the first model indicates a nonsignificant 46 percent decrease (IRR = 0.54, p = .139). These findings suggest the impact is there, however, the lack of statistical significance in the full model means we do not have sufficient evidence to confidently conclude the effect.

The results identify two interactions that are present and significant in both models. Selling has a 275 percent stronger impact in West Nile than in Central Uganda, according to the first model (IRR = 3.75, p = .002) and a 497 percent stronger impact according to the second model (IRR = 5.97, p < .001). Selling also has a 253 percent stronger impact in Eastern Uganda, according to the first model (IRR = 3.53, p = .010) and a 292 percent stronger impact according to the second model (IRR = 3.92, p = .002). The results are significant and aligned for both interactions across both models, indicating robust findings. To identify the actual effect selling has in West Nile, we multiply the main effect in Central Uganda with the interaction term $0.98 \times 3.75 = 3.68$ (IRR), or a 268 percent increase in adoption intensity in West Nile in the first model and $0.672 \times 5.972 = 4.01$ (IRR) or a 301 percent increase in adoption intensity according to the second model.

The model results confirm the hypothesis: regional context moderates the relationship between innovation characteristics and agroforestry adoption intensity. This statement is supported by the effect of selling being significantly stronger in West Nile than in the reference region and Eastern Uganda in both models.

Table 7

Significant incidence rate ratios (IRRs) for innovation models

Predictor	Innovation	Innovation (No outliers)
Intercept	19.51 (p < .001***)	18.13 (p < .001***)
Annual income (million, centered)	1.04 (p < .001***)	0.98 (p = .634)
Region: West Nile	0.54 (p = .139)	0.35 (p = .028*)
Interaction terms		
Selling × Region: West Nile	3.75 (p = .002**)	5.97 (p < .001***)
Post hoc: Selling × (Eastern – West)	3.53 (p = .010**)	3.92 (p = .002**)

Note. Only predictors with p < .05 in either model are shown. IRRs are incidence rate ratios, rounded to two decimals. The reference region is Central Uganda. *p < .05. **p < .01. ***p < .001.

Communication channels

The communication model retains the structure of previous models, with the interaction performed on the communication channels. The sensitivity analysis identifies Economic, Training, and Annual income as significant variables. Among them, only the Eastern region is significant in both models. The first model identifies a 124 percent increase (IRR = 2.24, p = .002) in adoption for farmers residing in eastern Uganda, while the second model identifies a 128 percent increase (IRR = 2.28, p = .002). The results align and are robust. The effects of the variables Economic, Training, and Annual income are not significant in both models, and, as such, we cannot confidently conclude their effect.

The analysis identifies a single interaction that is only significant in the first model. The gamification effect is 139 percent stronger in West Nile compared to Eastern Uganda, according to the first model (IRR = 2.39, p = .007) and 83 percent stronger according to the second model (IRR = 1.83, p = .071). The results align, however, the non-significance of the interaction in the second model means we cannot confidently conclude its effect.

Therefore, the hypothesis: regional context moderates the relationship between communication channels and agroforestry adoption intensity cannot be confidently confirmed since the results are not significant in both models.

Table 8

Significant Incidence Rate Ratios (IRRs) for Communication Models

Predictor	**Communication**	**Communication (No outliers)**
Intercept	13.29 ($< .001^{***}$)	8.66 ($< .001^{***}$)
Economic	1.23 ($p = .160$)	1.49 ($p = .017^{*}$)
Training	1.38 ($p = .226$)	2.07 ($p = .025^{*}$)
Region: Eastern Uganda	2.24 ($p = .002^{**}$)	2.28 ($p = .002^{**}$)
Annual income (million, centered)	1.03 ($p = .001^{**}$)	0.98 ($p = .668$)
Interaction terms		
Gamification West Nile × Eastern	2.39 ($p = .007^{**}$)	1.83 ($p = .071$)

Note. Only predictors with p < .05 in either model are shown. IRRs are incidence rate ratios, rounded to two decimals. The reference region is Central Uganda. *p < .05. **p < .01. ***p < .001.

Discussion

This study examined the interaction between regional context and adoption intensity. The study identifies that adopter characteristics and innovation characteristics are influenced by region. The reason behind this is not explored however cultural or systemic differences could have a significant impact. This suggests that agroforestry implementation should be contextualized by region. This is in line with Abigaba et al. (2024) findings, who also identifies the need to consider regional differences in agroforestry adoption.

The implication of this study suggests that adjustments can be made to improve the adoption intensity. For example, in West Nile, the impact of selling is stronger than in Central Uganda, while income has a weaker impact. Providing farmers in West Nile with tools and support that allow for the selling of agroforestry byproducts will be more effective than in Central Uganda. Similarly, providing financial incentives will be more effective in Central Uganda.

Limitation

Several limitations are worth noting. The study does not consider the time element, as the data is collected in a single time period. The analysis also ignores several key elements that impact adoption intensity, such as: climate in the region, local policy, and soil data. While some of the impact might be mitigated by the relatively proximity of the regions, the effects of this cannot be estimated. The limited data size (n=120) for this study constrained the number of variables that could be modeled in the regression, limiting the explanatory power of the model and missing possible insights. Additionally, the study doesn't provide an explanation for why the moderating effect happens. This limits the ability to generalize and implement the findings. Finally the study doesn't account for the coffee plant used by farmers. Abigaba et al. (2024) incorporates coffee types in the study and determines that temperature-related variables have a stronger impact on arabica coffee, while precipitation-related variables have a stronger impact on robusta coffee. Therefore, it is possible that coffee type can shape the interaction with adoption intensity.

Future research

Future research can focus on addressing some of the limitations. Additional data can be collected to improve the model and the estimates. Longitudinal studies could also identify patterns and relationships that haven't been explored yet. Possible future topics include: Longitudinal exploration of regional context. By examining the change in interactions over a longer period of time, we can determine if the moderating effects are caused by short-term circumstances or longer, systematic factors.

Explaining the moderating effect of regional context. By investigating the cause of this interaction, more generalized results can be discovered. For example, if the selling strength in West Nile is the result of access to a fruit market, the moderating effect could be applied to all regions that fit the criteria.

Exploring the coffee type influence on adoption intensity. This would address the limitation of coffee generalization by modeling and identifying the relation between adoption intensity and the specific coffee types.

Adapting programs to regional context. This study can provide a practical implementation of the research findings. It can explore methods to adapt future programs to fit the region. For example, programs might want to focus more on financial incentives in regions where annual income has a stronger relative impact.

Conclusion

Agriculture represents a key industry in Uganda. Despite its importance, climate change puts the sustainable farm area at risk, affecting smallholder farmers' livelihoods in the process. Promoting sustainable farming innovation can mitigate this risk however, adoption faces many barriers. Contextualizing the regional factor and exploring its effect on the relationship between key factors and adoption intensity is therefore essential for effective adoption. The purpose of this research was to explore this interaction among Central Uganda, Eastern Uganda and West Nile. The study used a negative binomial regression to analyse the interactions, significance, and impact. The results identify significant differences in the strength relative to other regions for Innovation characteristics and Adopters characteristics. These findings suggest that adjustments to support programs can be made based on regional context to improve their effectiveness

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Appendix

Table A1

Generalized Variance Inflation Factors (GVIF$^{1/(2Df)}$) for the Three Negative Binomial Models

Variable	Innovation Model	Communication Model	Adaptors Model
trading	3.79	1.31	1.36
selling	2.06	1.17	1.21
Economic	2.08	1.37	1.33
Enviormental	1.87	1.32	1.35
region	3.13	1.94	3.45
Training	1.44	2.46	1.29
Gamification	1.18	2.10	1.22
A.2_Age_c	1.15	1.12	2.25
household_size_c	1.17	1.12	2.87
annual_income_c_million	2.17	2.18	2.63
cultivated_land_c	1.97	1.98	2.71
trading:region	2.39	–	–
selling:region	2.93	–	–
Economic:region	1.95	–	–
Enviormental:region	1.34	–	–
Training:region	–	2.15	–
Gamification:region	–	2.09	–
A.2_Age_c:region	–	–	1.56
household_size_c:region	–	–	1.83
annual_income_c_million:region	–	–	3.31
cultivated_land_c:region	–	–	1.43

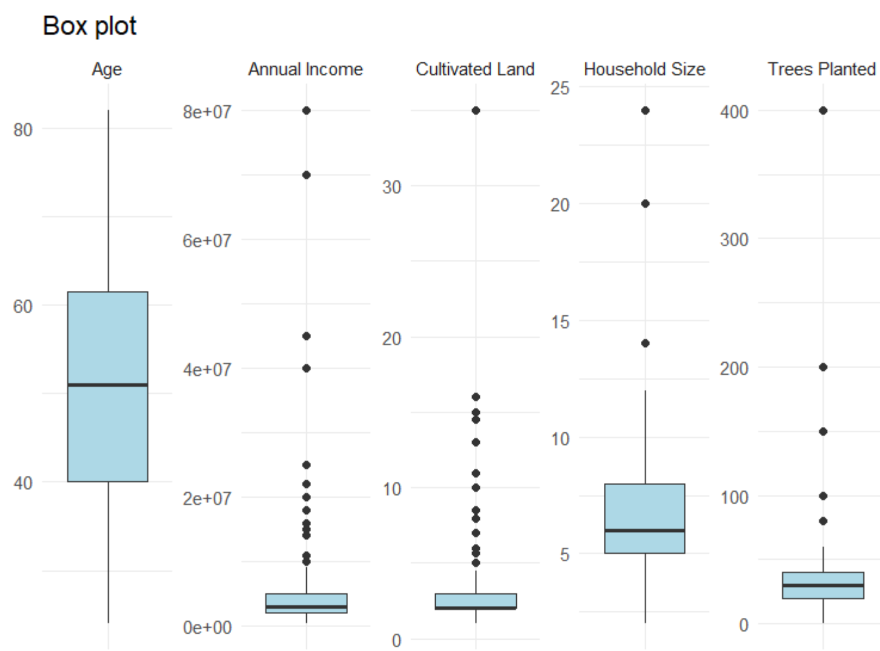

Figure A1

Box plot

Table A2

Summary of Negative Binomial Models

Variable / Statistic	Innovation Model	Communication Model	Adaptors Model
(Intercept)	2.971***	2.587***	2.592***
trading	-0.367	-0.105	-0.131
selling	-0.019	0.180	0.130
Economic	-0.201	0.205	0.034
Enviormental	0.046	0.222	0.151
regionEastern Uganda	0.295	0.804**	0.009
regionWest Nile	-0.611	0.296	-0.031
Training	0.242	0.319	0.356**
Gamification	0.154	0.213	0.204
A.2_Age_c	-0.0003	0.004	0.009
household_size_c	-0.005	0.009	-0.070
annual_income_c_million	0.044***	0.033**	0.038**
cultivated_land_c	-0.010	0.009	0.001
trading:regionEastern Uganda	0.274	—	—
trading:regionWest Nile	0.577	—	—
selling:regionEastern Uganda	-0.044	—	—
selling:regionWest Nile	1.322**	—	—
Economic:regionEastern Uganda	0.366	—	—
Economic:regionWest Nile	0.628$^{\cdot}$	—	—
Enviormental:regionEastern	0.445	—	—
Enviormental:regionWest Nile	-0.201	—	—
Training:regionEastern Uganda	—	-0.186	—
Training:regionWest Nile	—	0.183	—
Gamification:regionEastern	—	-0.509$^{\cdot}$	—
Gamification:regionWest Nile	—	0.364	—
A.2_Age_c:regionEastern	—	—	-0.019$^{\cdot}$
A.2_Age_c:regionWest Nile	—	—	-0.002
household_size_c:regionEastern	—	—	0.113
household_size_c:regionWest Nile	—	—	0.128*
annual_income_c_million:regionEastern	—	—	-0.151
annual_income_c_million:regionWest	—	—	-0.154*
cultivated_land_c:regionEastern	—	—	-0.073
cultivated_land_c:regionWest	—	—	0.010
Pseudo R-squared (McFadden's)	0.086	0.079	0.081
Log-Likelihood	-500.32	-503.90	-502.98
GOF (Pearson Chi-square, p)	125.14, (0.03)	131.30, (0.03)	115.11, (0.11)
Degrees of Freedom (df)	98	102	98
Theta (Dispersion)	3.564 (0.422)	3.725 (0.469)	3.287 (0.396)

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A3

Summary of Negative Binomial Models excl outliers

Variable / Statistic	Innovation Model	Communication Model	Adopters Model
Intercept	2.897***	2.159***	2.884***
trading	-0.555	-0.144	-0.269$^{\cdot}$
selling	-0.398	0.275$^{\cdot}$	0.338*
Economic	0.304	0.399*	0.089
Environmental	-0.037	0.284$^{\cdot}$	0.420**
Training	0.152	0.726*	0.279*
Gamification	0.104	0.293	0.131
regionEastern Uganda	0.088	0.822**	-0.537
regionWest Nile	-1.040*	0.250	-1.391*
A.2_Age_c	-0.002	0.002	0.001
household_size_c	-0.002	0.037	0.115
annual_income_c_million	-0.022	-0.019	0.139*
cultivated_land_c	0.012	-0.025	0.188
Selected Interaction Terms			
trading:regionEastern Uganda	0.406	—	—
trading:regionWest Nile	0.635	—	—
selling:regionEastern Uganda	0.526	—	—
selling:regionWest Nile	1.787***	—	—
Economic:regionEastern Uganda	-0.094	—	—
Economic:regionWest Nile	-0.113	—	—
Enviormental:regionEastern	0.480	—	—
Enviormental:regionWest Nile	0.139	—	—
Training:regionEastern	—	-0.738	—
Training:regionWest	—	-0.220	—
Gamification:regionEastern	—	-0.502	—
Gamification:regionWest	—	0.101	—
A.2_Age_c:regionEastern	—	—	-0.009
A.2_Age_c:regionWest	—	—	0.011
household_size_c:regionEastern	—	—	-0.032
household_size_c:regionWest	—	—	-0.094
annual_income_c_million:regionEastern	—	—	-0.335**
annual_income_c_million:regionWest	—	—	-0.338***
cultivated_land_c:regionEastern	—	—	-0.113
cultivated_land_c:regionWest	—	—	-0.329
Model Fit Statistics			
Pseudo R-squared (McFadden's)	0.0555	0.0491	0.0617
Log-Likelihood	-335.435	-337.709	-333.219
GOF Pearson Chi-square (p-value)	79.27 (0.0946)	75.06 (0.2604)	69.63 (0.2937)
Degrees of Freedom (df)	64	68	64
Theta (Dispersion)	5.06	4.690	5.54

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Official Statement of Original Thesis

By signing this statement, I hereby acknowledge the submitted thesis (hereafter mentioned as "product"), titled: Exploring How Regional Context Shapes Agroforestry Adoption among Smallholder Coffee Farmers in Uganda to be produced independently by me, without external help.

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