CZECH UNIVERSITY OF LIFE SCIENCES PRAGUE

Study Programme: M.Sc. Tropical Forestry and Agroforestry

Faculty of Tropical AgriSciences

Adoption Drivers of Carbon Farming and Sustainable Practices among Small Farmers in Western Kenya

MASTER'S THESIS

Prague 2025

Author: Mohan Krishna Chowdry Avilineni

Supervisor: prof. Ing. Bohdan Lojka, Ph.D.

Co-supervisor: Adeeth Cariappa Ajjikuttira Girish, Ph.D.

Declaration

I hereby declare that I have independently completed this thesis entitled "Adoption Drivers of Carbon Farming and Sustainable Practices among Small Farmers in Western Kenya." All text within this thesis is original, and all sources have been properly cited and acknowledged in accordance with the citation guidelines of the FTA. Furthermore, I confirm that I have utilized AI tools in compliance with the internal regulations of the Czech University of Life Sciences and the principles of academic integrity and ethics.

In Prague 31.08.2025

....

Mohan Krishna Chowdry Avilineni

Acknowledgements

I extend my heartfelt gratitude to the Erasmus Mundus Joint Master in Global Forestry (GLOFOR) committee for their generous funding to pursue two years of education and chase my dreams in Europe, which I once only imagined.

I would like to thank my supervisor, prof. Bohdan Lojka (CZU Prague), for being a supportive guide and an affable mentor. Every meeting with you instilled optimism, helping me face challenges with confidence. I'm equally grateful to Dr. Adeeth Cariappa (Associate Scientist, CIMMYT India) for his steady support and sharp insights, which helped me navigate the toughest parts of this work. Special thanks to Marianne Zandersen (Professor, Aarhus University, Denmark) for helping me access a critical data analysis software, and to Keerthana Sri (University of Göttingen, Germany) and Michelle Kanini Ndambuki (Project Officer, ADSE NGO, Kenya) for their valuable insights, which brought this thesis to life and improved the quality.

I'm incredibly indebted to prof. Jayasankar Subramanian (University of Guelph, Canada) and his network for their support since my undergraduate days. Your generosity made me realize how kindness can change one's life. Thanks to Timm Tennigkeit, Till Pistorius and Christoper Williams (unique land use GmbH, Freiburg, Germany) for igniting my passion for carbon farming through an internship opportunity, which made me dive into this research with determination.

Finally, I appreciate my own resilience and determination throughout the journey. I would not be the person I am today without the collective support of my parents, teachers, seniors, friends and many other generous people who offered mentorship, shared meals, provided financial support, or offered a kind word. This thesis belongs to every person who stood by me, and I will forever cherish their kindness.

Abstract

Climate change has adverse effects on agriculture and the livelihoods of over 80% of Kenya's population, necessitating an urgent shift towards climate-smart systems such as carbon farming. Carbon farming mitigates climate change through soil carbon sequestration, improved soil fertility and yields, and increased resilience. This study examines gender-differentiated motivations, barriers, adoption patterns and determinants of carbon farming among smallholders in Western Kenya.

Quantitative survey data were collected from 859 households (427 male-headed and 432 female-headed) across four counties and carbon projects and analyzed using Stata 18. Farmers were primarily motivated by ecological benefits rather than carbon payments. Extension agents and NGOs were key information channels, while a lack of awareness and weak outreach limited participation. Among 23 carbon farming practices, organic fertilizer use, agroforestry, and intercropping were the most widely adopted, with no significant gender differences. Logistic regressions showed that ethnicity and project affiliation negatively influenced agroforestry adoption for female-headed households, while organizational membership increased adoption likelihood among male-headed households. Carbon payments were highly project-dependent and shaped by ethnicity and organizational membership. Age, secondary education and organizational membership significantly influenced the carbon farming participation, while household and land size exerted positive marginal effects for both genders.

The findings highlight the need for gender-sensitive and site-specific program design. Strengthening extension services, improving land access and supporting social networks, particularly for women, are critical for scaling adoption. Hybrid payments that combine the provision of inputs with financial incentives could reduce upfront costs. This study has a few limitations, and future research should explore unexplained barriers, the role of education levels, land tenure and ethnic dynamics across genders to ensure equitable and effective carbon farming programs.

Keywords: Agroforestry, carbon payments, climate-smart agriculture, gender dynamics, participation drivers

Contents

List of tables

List of figures

List of the abbreviations used in the thesis

AF	Agroforestry
AFOLU	Agriculture, Forestry and Other Land Use
CAPI	Computer-Assisted Personal Interviewing
CC	Carbon Credits
CF	Carbon Farming
CFP	Carbon Farming Practice
CSA	Climate-Smart Agriculture
ENB	Emiti Nibwo Bulora
FHH	Female-headed Household
FLLoCA	Financing Locally-led Climate Action
FTMA	Farm to Market Alliance
GHG	Greenhouse Gases
GIZ	Deutsche Gesellschaft für Internationale Zusammenarbeit
HH	Household
HHH	Household Head
KACP	Kenya Agricultural Carbon Project
KOAN	Kenyan Organic Agriculture Network
MHH	Male-headed Household
MRV	Measuring, Reporting and Verification
PES	Payment for Ecosystem Services
RA	Regenerative Agriculture
SALM	Sustainable Agricultural Land Management
SCCS	Soil-Carbon Certification Services
SCEP	Soil Carbon Enhancing Practices
SOC	Soil Organic Carbon
TGB	Trees for Global Benefits
TIST	International Small Group & Tree Planting Program
WKCP	Western Kenya Soil Carbon Project
WKSCAP	Western Kenya Smallholder Agricultural Carbon Project

1. Introduction

1.1 Climate Change and its Impact on Kenyan Agriculture

Earth's climate has undergone rapid changes due to the human-induced greenhouse gas (GHG) emissions of carbon dioxide (CO_2), nitrous oxide (N_2O), and methane (CH_4), which cause negative impacts on the ecosystem and livelihoods, particularly those dependent on agriculture (Mogaka et al. 2021; Kioko et al. 2024; Singh et al. 2024). Among the GHGs, CO_2 is a major contributor to climate change, with atmospheric concentrations rising from approximately 280 ppm before 1850 to 417 ppm in 2023 (Richardson et al. 2023; Singh et al. 2024). This represents an average annual increase of 0.88 ppm or roughly 3.4 gigatons of carbon per year (Pachauri et al. 2014; Singh et al. 2024).

Although climate change is a global phenomenon, developing countries of Sub-Saharan Africa (SSA), including Kenya, are particularly vulnerable due to high dependence on rainfed agriculture and low adaptive capacity (Mogaka et al. 2021; Steenkamp & Thebuho 2022; Njue et al. 2023; Kioko et al. 2024; John et al. 2025; Mnukwa et al. 2025). The agriculture, forestry, and land-use (AFOLU) sector contributes approximately 25% of global GHG emissions (Singh et al. 2024). Particularly, agricultural land expansion releases about 110 billion tons of carbon from surface soils, which is equivalent to the United States' emissions over 80 years (Sanderman et al. 2017; EIA 2020).

The agricultural sector in Kenya ranges from nomadic pastoralism in arid regions to intensive export farming in high-rainfall areas. It contributes 24% of the national GDP, 65% of foreign exchange, and provides support to approximately 80% of the population (Mutimba et al. 2010; Ellis et al. 2013; John et al. 2025). However, climate change effects, such as rising temperatures, erratic rainfall, prolonged droughts, and heatwaves, are adversely affecting soil and water resources, disrupting agricultural systems, and causing significant losses in crop and livestock production (Wekesa et al. 2018; Mogaka et al. 2021; Adhikari & Timsina 2022; Ogisi & Begho 2023; Kioko et al. 2024).

The large extent of Kenya falls under Arid and Semi-Arid Lands (ASALs), which have low agricultural potential and are highly vulnerable to rising temperatures, dry spells and erratic rainfall (Shahzad et al. 2021; Kioko et al. 2024). With the global population projected to reach 9 billion by 2050 and exceed 10 billion by 2100, agricultural production must increase substantially (Wekesa et al. 2018; Kioko et al. 2024; Srinivasan & Yadav 2024). Without effective adaptation measures, crop productivity in SSA could decline by up to 30% by 2050, and net farm revenues could fall by 90% by 2100 (Mnukwa et al. 2025). This highlights the urgent need for sustainable and resilient farming practices.

1.2 Carbon Farming as a Natural Climate Solution

To address these challenges, farmers must transform their conventional agricultural systems into a more climate-resilient system. One way of doing so is by adopting climate-smart agricultural (CSA) practices that aim to increase agricultural productivity and income while reducing GHG emissions and building adaptive capacity by sequestering carbon in the soil (Ngigi & Muange 2022; Ogisi & Begho 2023). This fundamental shift is imperative to meet the Paris Agreement's 1.5°C target, with global net-zero CO_2 emissions projected by the early 2050s and interim reductions of 43% by 2030 and 60% by 2035 (Umweltbundesamt 2025).

Agricultural lands typically have low soil organic carbon (SOC) relative to natural landscapes, making them significant sources of emissions if mismanaged (FAO 2021; Barbato & Strong 2023). Therefore, natural climate solutions (NCS) such as reforestation, sustainable forest management, urban greening, wetland restoration, and carbon farming, which aim to increase carbon storage or avoid emissions, contributing to global net-zero efforts, are increasingly gaining attention (Griscom et al. 2017; Seddon et al. 2020, 2021; Denny et al. 2023; Kiran et al. 2023; Schilling et al. 2023; Singh et al. 2024). Further, it is projected that the adoption of enhanced agricultural methods could sequester approximately 20 pentagrams of carbon (Pg C) over 25 years, amounting to more than 10% of the global anthropogenic emissions (Hayduk et al. 2015; Singh et al. 2024). In effect, agriculture must shift from being a carbon source to a vital carbon sink.

Looking at soil as a potential sink and reservoir of carbon, carbon farming (CF) offers a scalable, cost-effective and efficient approach to achieve negative emissions, while promoting co-benefits such as soil and water conservation, reduced economic risks through input saving and increased resilience to extreme temperatures (Wollenberg et al. 2021; Singh et al. 2024). As a form of CSA and a type of payment for ecosystem services (PES), carbon farming incentivizes farmers to adopt soil carbon-enhancing practices

(SCEPs) that mitigate climate change (Schilling et al. 2023; Figueredo 2024; Singh et al. 2024). Agricultural carbon markets act as a market mechanism to incentivize carbon offsets by generating revenue for each ton of CO_2 sequestered through sustainable agricultural land management (SALM) practices (Lee 2017; Öborn et al. 2017; Raina et al. 2024; Awazi et al. 2025).

1.3 Motivations and Barriers for Carbon Farming

Participation in carbon farming programs and the adoption of associated practices are motivated by economic, ecological, and socio-cultural factors (Lee 2017; Antwi-Agyei et al. 2021; Schilling et al. 2023; Figueredo 2024; Pudasaini et al. 2024). Economic incentives, including payments for carbon sequestration, cost-sharing schemes, and reduced income risk, serve to enhance financial security and encourage engagement (Tamba et al. 2021; Schilling et al. 2023; Tennigkeit et al. 2023; Figueredo 2024; Raina et al. 2024). Ecological benefits, such as improved soil health, increased biodiversity, and enhanced resilience to climate variability, provide co-benefits to farmers and support long-term productivity (Lee 2017; Buck & Palumbo-Compton 2022; Barbato & Strong 2023; Schilling et al. 2023; Figueredo 2024; Pudasaini et al. 2024). Socio-cultural factors, including environmental stewardship, adherence to traditions, peer influence, and non-monetary community benefits, further drive adoption(Saha et al. 2011; Lee 2017; Rois-Díaz et al. 2018; Schilling et al. 2023; Beacham et al. 2023; Carmichael et al. 2023).

Despite these benefits, smallholder farmers are often reluctant and face barriers such as diverse program conditions, limited land, inadequate financial resources, poor market access, insufficient government support, and low awareness or skepticism about carbon farming practices (Streck 2012; Ellis et al. 2013; Lee 2017; Ngigi & Muange 2022; Schilling et al. 2023; Tennigkeit et al. 2023; Raina et al. 2024). Some perceive that replacing conventional methods with sustainable alternatives may reduce short-term yields (Ellis et al. 2013; Schilling et al. 2023; Figueredo 2024). At the market level, concerns over non-permanence, leakage, non-additionality, and the lack of robust monitoring, reporting, and verification (MRV) standards can weaken incentive structures, compromise market integrity, and limit climate change mitigation outcomes (Jackson Hammond et al. 2021; Schilling et al. 2023; Figueredo 2024; Raina et al. 2024).

1.4 Gendered Dynamics and Study Rationale

Beyond structural and market constraints, gender inequalities in agriculture further shape the adoption of carbon farming practices, interacting with socio-demographic, socio-economic, and institutional factors. Access to resources, decision-making power, and preferences often differ between male- and female-headed households (Bernier et al. 2015; Mungai et al. 2017; Ngigi & Muange 2022; Li et al. 2023; Ogisi & Begho 2023; Hailemariam et al. 2024). Cultural norms may restrict women's participation in certain practices, such as agroforestry, though addressing these barriers has been shown to enhance women's engagement in CSA (Wekesah et al. 2019; Ogisi & Begho 2023).

Despite the prevalence of carbon farming programs in Western Kenya, research on the motivations and barriers shaping smallholder farmers' participation, and the adoption of carbon farming practices through a gendered lens, remains limited (Bernier et al. 2015; Hailemariam et al. 2024; Awoke et al. 2025). Though this study may not fully bridge the research gap, it underscores subtle gendered dynamics in shaping smallholder participation in carbon farming programs in Western Kenya, by examining motivations and barriers, assessing the adoption of CF practices like agroforestry and carbon payment receipt, and identifying socio-demographic and institutional factors, particularly gender differences. By investigating how male and female-headed households engage with carbon farming initiatives, the research seeks to provide evidence-based insights to inform the design of equitable and effective programs that promote sustainable agriculture, climate resilience, and improved livelihoods in Western Kenya.

To provide a coherent narrative of the research process and findings, this thesis is organized as follows: Chapter 1 introduces the study, outlining the background, context, and rationale. Chapter 2 reviews relevant literature on carbon farming, highlighting key motivations, barriers, and gendered dynamics. Chapter 3 presents the aims of the thesis, including the objectives, research questions, and hypotheses. Chapter 4 details the methodology, describing the study area, data collection procedures, and analytical approaches. Chapter 5 reports the results of the study, and Chapter 6 discusses the findings, draws conclusions, and provides recommendations for policy and practice.

2. Literature Review

2.1 Carbon Farming: Definitions, Principles and Significance

2.1.1 Definitions

Carbon farming (CF) lacks a unified definition (Schilling et al. 2023), and the term often overlaps with regenerative agriculture (RA) principles and practices (Marks 2020). Petropoulos et al. (2025) and McDonald et al. (2021) assert that CF practices adoption varies across regions, and so there cannot be a one-size-fits-all solution; however, it should be tailored to local conditions.

Petropoulos et al. (2025) delineated carbon farming focus areas into three main actions: (a) carbon sequestration, (b) emission avoidance, and (c) emission reduction on farms. According to Schilling et al. (2023), there are two groups of carbon farming definitions based on the differences and similarities across all definitions: 1. Focus on the ecosystem services provision, i.e., carbon sequestration in vegetation and soils, and 2. Emphasize the business model of receiving economic benefits for carbon sequestration.

Reflecting the first category, carbon farming is a sustainable agricultural land management (SALM) practice that uses regenerative agricultural practices to sequester carbon in natural sinks, such as biomass (Paul et al. 2023; Figueredo 2024; Kashyap et al. 2024) and soil (Barbato & Strong 2023; Kashyap et al. 2024; Singh et al. 2024) in the form of soil organic carbon (SOC), and to abate greenhouse gas emissions from agricultural production (Paul et al. 2023; Figueredo 2024; Kashyap et al. 2024). The second definition of carbon farming is often used to refer to a new business model that incentivizes farmers to adopt climate-friendly farm management practices that upscale climate mitigation and deliver climate benefits at the farm level (McDonald et al. 2021; Kashyap et al. 2024).

The EU defines carbon farming as a "green business model" encouraging landowners and managers to improve land management practices, leading to increased carbon sequestration in living biomass and soil (Tang et al. 2019; Vistarte et al. 2024).

2.1.2 Principles

The carbon cycle in agriculture is a complex process involving the absorption of carbon dioxide from the atmosphere by plants during photosynthesis, the transfer of carbon to the soil through plant roots and plant residues, and the release of carbon back to the atmosphere through soil respiration (Matis & Saatkamp 2023). Carbon farming utilizes photosynthesis as a mechanism to store carbon, such that the carbon leaving a given ecosystem is lower than the carbon entering, achieving a carbon-negative state (Marks 2020; Kashyap et al. 2024).

Farmers practicing carbon farming rely upon five key RA techniques: (1) minimizing soil disturbance (e.g., reducing tillage), (2) promoting crop diversity, (3) maintaining soil cover to enhance carbon sequestration, (4) retaining plant roots or using longer-rooted crops and incorporating organic matter into soil, and (5) integrating livestock (e.g., goats, cattle, buffalo, sheep) during dormant periods (Marks 2020). These align with the five soil health principles outlined by North Dakota regenerative farmer Gabe Brown in his book "Dirt to Soil" (Brown 2018; Sands et al. 2023).

Schreefel et al. (2020) through a qualitative analysis of 28 studies, proposed a provisional RA definition as "an approach to farming that uses soil conservation as the entry equine to regenerate and contribute to multiple provisioning, regulating, and supporting services, with the objective that this will enhance not only the environmental, but also the social and economic dimensions of sustainable food production" (Khangura et al. 2023). The core philosophy of regenerative agriculture is to restore soil through building biological systems (cover crops, crop rotation, composting, manure, inoculation, and other microbial activities) and improving resource use efficiency without relying on mineral fertilizers or external inputs (Amede et al. 2023). In the CF context, RA should be defined not only by practices such as no-till farming or cover cropping, but also by measurable outcomes, particularly the amount of carbon sequestered in the soil or vegetation. This is critical, as funders (e.g., donors, investors, taxpayers) often require verifiable evidence of carbon sequestration rather than assumptions about the practice's efficacy (Newton et al. 2020).

2.1.3 Significance

The importance of soil carbon storage has gained global attention through various international initiatives, with carbon farming increasingly recognized as a key strategy for climate change mitigation and soil health improvement (Barbato & Strong 2023; Günther et al. 2024). The Paris Agreement's "4 per 1000" initiative, emerging from the Lima-Paris Plan of Action, emphasizes the role of soil organic carbon (SOC) sequestration in agriculture, inspiring national-level projects that aim to enhance soil health and strengthen food security (Tennigkeit et al. 2023; Phelan et al. 2024). In the European Union, policies and programs such as the EU Soil Initiative (2021), revisions to the Common Agricultural Policy (CAP), "LIFE Carbon Farming" (2021), "INTERREG Carbon Farming" (2018), and the "Farm to Fork Strategy" (2020) actively promote carbon farming to reduce greenhouse gas (GHG) emissions and support biodiversity conservation (BirdLife Europe & EEB 2022; ENRD 2022). Globally, initiatives such as the Special Initiative for the Transformation of Agricultural and Food Systems have also emphasized the adoption of sustainable agricultural land management (SALM) practices (Tennigkeit et al. 2023).

In Kenya, the government, World Bank, and other public and private actors advocate for sustainable land-use practices to achieve triple benefits: enhanced climate mitigation through soil carbon sequestration, improved soil fertility leading to higher agricultural yields, and increased resilience to climate change (Shames et al. 2012; Ellis et al. 2013; Lee et al. 2016; Kanyenji et al. 2022; Tennigkeit et al. 2023; Boomitra Inc 2025; Pennynar 2025). Given limited public funding, initiatives such as the CompensACTION approach and voluntary carbon markets provide mechanisms to leverage both public and private capital. These platforms enable trading of GHG reductions, emission avoidance, or carbon sequestration in the form of carbon credits, thereby offering financial incentives for sustainable agricultural practices (Lal et al. 2018; Jackson Hammond et al. 2021; Schilling et al. 2023; Von Braun et al. 2023; Tennigkeit et al. 2023). Private and non-governmental offset programs, including the American Carbon Registry (ACR), Climate Action Reserve (CAR), Verra, Gold Standard, Plan Vivo, Label Bas Carbone, Pure Sky Registry, and Regen Network, facilitate carbon offset certification and trading through established soil carbon methodologies. Their operations are increasingly driven by sustainability goals, regulatory requirements, and opportunities for additional revenue streams (Figueredo 2024; QCI 2024; Cariappa & Krishna 2025).

Kenya's carbon market has experienced exponential growth in recent years, with the number of registered projects increasing from just eight in 2012 to over 80 in 2023, according to the United Nations Framework Convention on Climate Change (UNFCCC) registry. Among these, afforestation, reforestation, and revegetation (ARR) projects constitute the majority (68%), followed by renewable energy initiatives (22%), with SALM activities representing the remaining 10% (Owuor Odhiambo 2025). Recent data indicate that agricultural carbon credits account for only 1.5% of AFOLU projects, compared with 37.4% for forestry and other land-use credits (Haya et al. 2025). However, this represents a steady increase from less than 1% reported in 2021 (Tennigkeit et al. 2023).

2.2 Carbon Farming: Practices and Benefits

2.2.1 Practices

Carbon farming encompasses a wide range of agronomic practices, land use changes and technological solutions (McDonald et al. 2021) aimed at regenerating soil health by increasing carbon sequestration, decreasing carbon losses and promoting the accumulation of additional organic biomass (Barbato & Strong 2023; Figueredo 2024). Such practices employed will not only sequester carbon and reduce emissions but also derive numerous co-benefits such as improving soil quality, increasing biodiversity, reducing soil erosion, and enhancing agricultural productivity (McDonald et al. 2021; Figueredo 2024).

Practices such as cover cropping, crop rotation and diversification, crop residue retention, minimum/no tillage, mulching and using hedges, reducing the use of synthetic fertilizers, composting and applying biochar as soil amendment, agroforestry, perennial cropping systems, fertilizer timing and irrigation optimization, rotational grazing and use of animal manures are the most common strategies promoted by carbon farming initiatives to increase SOC stocks and abate greenhouse gas emissions from agricultural production (Marks 2020; Almaraz et al. 2021; Matis & Saatkamp 2023; Sands et al. 2023; Khangura et al. 2023; Figueredo 2024; Singh et al. 2024; Vistarte et al. 2024). Most of these interventions, either alone or as a combination, are adopted as climate-smart agriculture or conservation agriculture practices by farmers in Africa and Kenya, including Western Kenya (Sommer et al. 2018; Wekesa et al. 2018; Kalungu & Leal Filho 2018; Musafiri et al. 2022; Akanmu et al. 2023; Kioko et al. 2024).

According to McDonald et al. (2021), the carbon farming practices can be classified into five main sub-categories in the EU context: 1) Managing peatlands, 2) Agroforestry, 3) Maintaining and enhancing SOC on mineral soils, 4) Livestock and manure management and 5) Nutrient management on croplands and grasslands. These sub-categories vary in their potential to increase carbon removals or reduce GHG emissions and pose different opportunities and challenges in terms of co-benefits, risks, costs, and incentives as described in Table 1.

In contrast to McDonald et al. (2021), Schilling et al. (2023) classified the group of CF practices into five categories, such as 1) agroforestry, 2) crop and soil management, 3) livestock management, 4) nutrient management, and 5) management of peatlands, in the context of Africa (Figure 1).

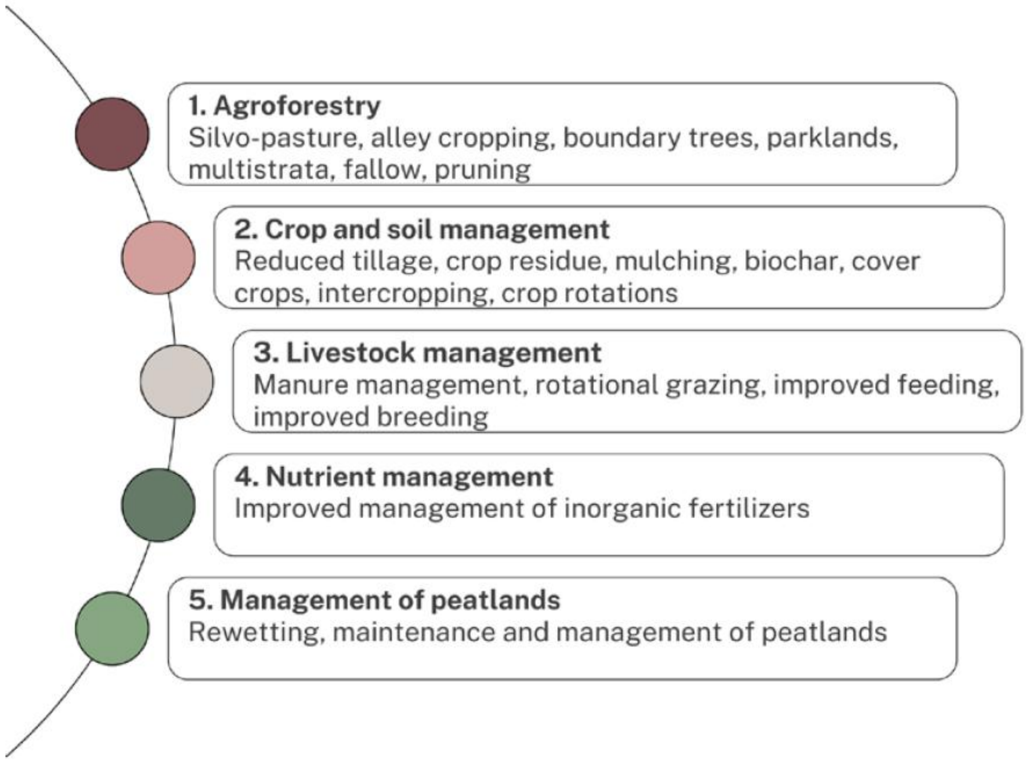

Figure 1. Carbon farming practices (Source: Schilling et al. 2023)

Table 1. Overview of carbon farming options (Source: McDonald et al. 2021)

Assessment Criterion	Managing Peatlands	Agroforestry	Maintain/ Enhance SOC on Mineral Soils	Livestock and Manure Management	Nutrient Management on Croplands/ Grasslands
Carbon farming actions	Rewetting, maintaining, and managing peatlands	Creating, restoring, and managing woody landscape features	Managing cropland and grassland	Technologies to reduce enteric methane, manage manure, and improve herd/feed efficiency	Improved nutrient planning, timing, and fertiliser application; reduced fertilizer use
Total EU mitigation potential (Mt CO_2e/yr)	51 - 54	8 - 235	9 - 70	14 - 66	19
Per hectare mitigation potential (t CO_2e/ha/yr)	3.5 - 29	0.03 – 27	0.5 - 7	Not available	Not available
Mitigation mechanism	Avoided emissions	Removal	Removal and avoided emissions	Reduced emissions	Reduced emissions
Type of change	Land use	Management	Management and land use	Management	Management
Co-benefits for farmers	Potential for paludiculture (productive use of wet peatlands)	Diversified outputs reduce crop failure risk	Better soil water retention, workability, and productivity	Lower feed, fertiliser, and energy costs; improved soil health and productivity	Lower input costs
Societal Co-benefits	Enhanced biodiversity, flood regulation, and water quality	Improved water retention, microclimate, soil health, and biodiversity	Better water retention, soil health, and biodiversity	Reduced nutrient runoff and ammonia emissions	Reduced nutrient runoff and ammonia emissions
Risks	CH_4 emissions (net GHG benefit); reduced production	Non-native species impacting biodiversity	Biochar/off-farm compost affecting soil health/biodiversity	Animal welfare; water quality impacts of feed additive	Nitrification inhibitor water quality impacts

Firstly, agroforestry systems integrate woody vegetation, such as trees or shrubs, with crops or livestock, employing techniques such as silvopasture, alley cropping, and boundary planting. These systems contribute significantly to biodiversity conservation, soil health improvement, and carbon sequestration (Lamanna et al. 2020; McDonald et al. 2021; Schilling et al. 2023), both in woody biomass and soil.

Secondly, crop and soil management practices, including cover cropping, intercropping, improved crop rotations, and the adoption of enhanced crop varieties, are complemented by soil-focused techniques such as reduced tillage, crop residue retention, mulching, and biochar application. Together, these approaches enhance agricultural productivity, system resilience, and long-term soil fertility (Lamanna et al. 2020; Schilling et al. 2023).

Thirdly, livestock and manure management strategies aim to reduce enteric methane emissions while improving herd productivity and feed efficiency. This is achieved through improved feeding regimes, selective breeding, rotational/holistic grazing, and comprehensive manure management, which encompasses the entire manure lifecycle, from collection and storage to treatment and application. These strategies are intricately linked with sustainable grassland management practices (Lamanna et al. 2020; McDonald et al. 2021; Schilling et al. 2023).

Fourthly, nutrient management prioritises the efficient use of inorganic fertilizers through improved planning, timing, and application methods, thereby minimizing environmental impacts such as nutrient leaching and greenhouse gas emissions. Organic fertilizers are addressed within the broader domains of crop, soil, and livestock management to avoid thematic redundancy (McDonald et al. 2021; Schilling et al. 2023).

Finally, peatland management, involving rewetting, ongoing maintenance, and sustainable use, plays a critical role in conserving carbon-rich ecosystems and mitigating greenhouse gas emissions by preventing peat degradation (McDonald et al. 2021; Schilling et al. 2023).

2.2.2 Benefits

Carbon farming drives a shift in agricultural practices towards a model that not only focuses on food and fibre production but also on enhancing carbon sequestration and other ecosystem services. The ultimate objective of carbon farming is to increase soil carbon through the implementation of carbon farming practices. This increase in soil carbon and/or the transition from conventional practices may subsequently lead to potential benefits, such as the enhancement of other ecosystem services such as food, fibre, and water; regulating services such as regulation of floods, drought, land degradation, and disease; supporting services such as soil formation and nutrient cycling; and cultural services such as recreational, spiritual, religious and other non-material benefits (Vidaller & Dutoit 2022; Matis & Saatkamp 2023), as conceptualized in Figure 2.

The agronomic practices having carbon sequestration and GHG emissions reduction potential are sectioned into crops and animals, depending on the nature of the practice (Kashyap et al. 2024) (Table 2). Such practices are crucial to carbon farming programs, not only for regulating the climate but also for supporting farmers in uplifting their socio-economic status and transferring indigenous technical knowledge (ITK). The various provisioning, regulating, supporting and cultural services of CF practices are illustrated in Figure 3 (Baumber et al. 2019).

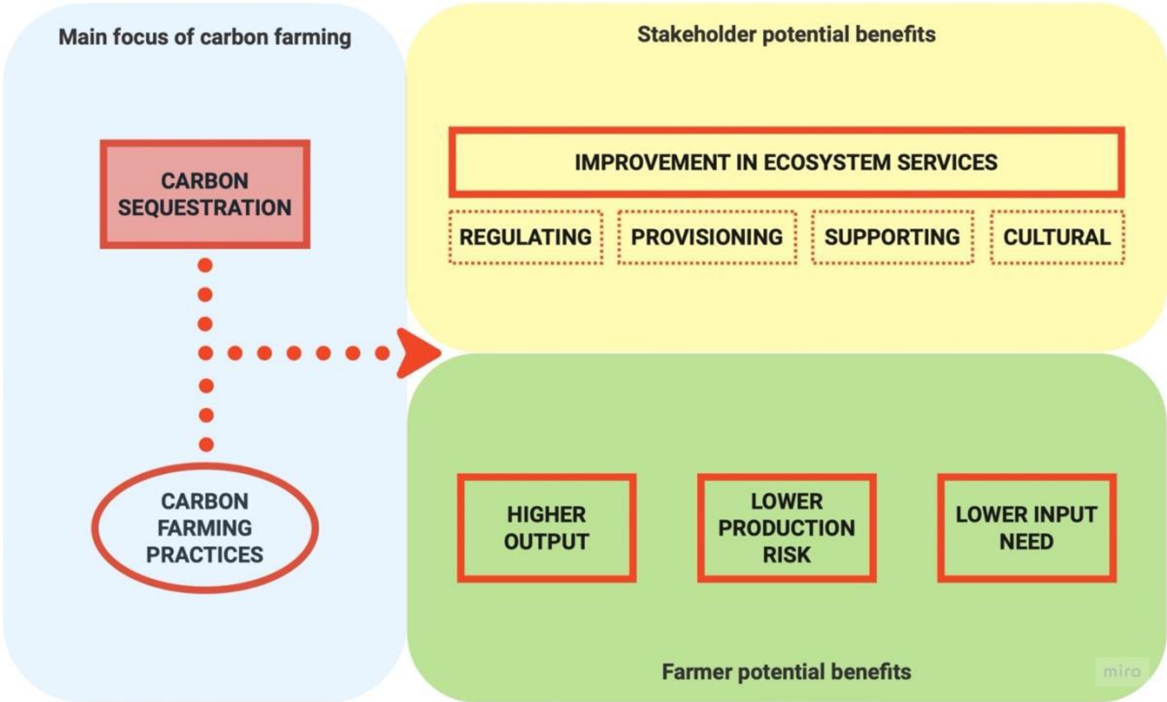

Figure 2. Conceptualization of the potential benefits of carbon farming (Source: Matis & Saatkamp 2023)

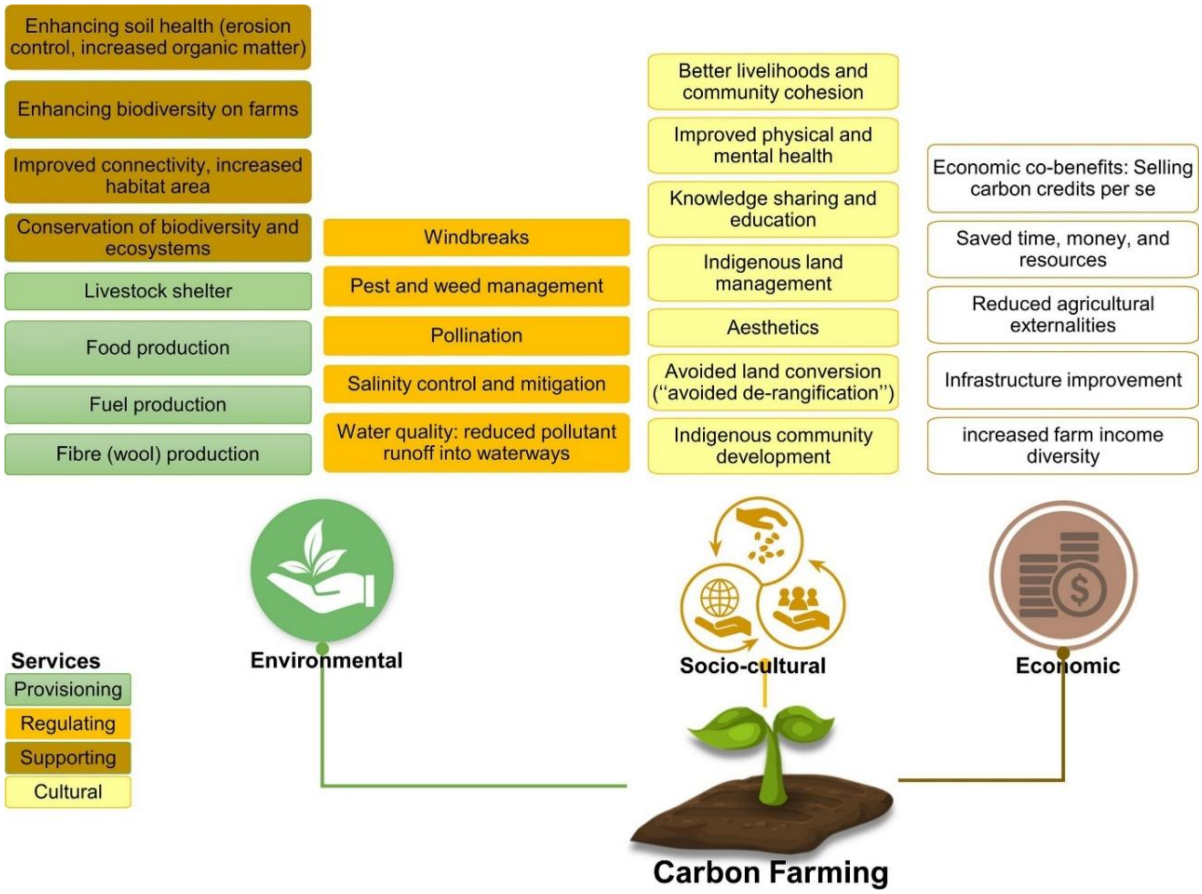

Figure 3. Potential environmental and socio-economic co-benefits of carbon farming in addition to climate regulation (Source: Baumber et al. 2019)

Table 2. List of carbon farming agronomic practices, their GHG objectives and benefits (Source: Kashyap et al. 2024)

Agronomic Practices	GHG Objectives	Additional Benefits
Crops		
Conservation tillage and reduced field passes	Sequestration, emission reduction	Enhances soil, water, and air quality
Efficient nutrient management	Sequestration, emission reduction	Improves water quality, saves nutrients
Crop diversity via rotations and cover crops	Sequestration	Reduces erosion and water needs
Animals		
Manure management	Emission reduction	Provides biogas fuel, electricity for large operations, and crop nutrients
Rotational grazing and improved forage	Sequestration, emission reduction	Lowers water requirements
Feed management	Emission reduction	Reduces nutrient use, improves water quality, and enhances feed efficiency

2.3 Motivations and Barriers of Carbon Farming

2.3.1 Motivations

As global efforts intensify to address climate change, carbon farming has gained traction as a strategy that not only supports environmental sustainability but also offers tangible benefits to farmers. The motivations for adopting carbon farming practices are multifaceted, encompassing economic incentives, ecological co-benefits, and socio-cultural factors (Table 3).

Table 3. Motivations for the adoption of carbon farming

Motivations	Description	Reference
Economic		
Financial incentives	Payments for carbon sequestration, cost-sharing, tax credits, and insurance discounts	Nandakishor et al. 2022; Jassim et al. 2022; Schilling et al. 2023; Figueredo 2024
Reduced income risk	Steady carbon payments provide financial security	Schilling et al. 2023
Ecological		
Improved soil health	Enhanced soil quality and reduced erosion through carbon sequestration practices	Buck & Palumbo-Compton 2022; Barbato & Strong 2023; Figueredo 2024
Enhanced biodiversity	Increased ecosystem diversity through practices like agroforestry	Barbato & Strong 2023; Figueredo 2024
Climate change resilience	Water conservation, temperature regulation, and crop diversification	Schilling et al. 2023
Co-benefits beyond carbon	Improved pest control, reduced input costs and higher yields due to improved soil health and fertility	Antwi-Agyei et al. 2021; Buck & Palumbo-Compton 2022; Ogisi & Begho 2023; Schilling et al. 2023; Figueredo 2024
Socio-cultural		
Environmental stewardship	Responsibility to care for the land for future generations	Beacham et al. 2023; Carmichael et al. 2023; Figueredo 2024
Cultural traditions and peer influence	Preservation of traditional practices and learning from peers	Saha et al. 2011; Rois-Díaz et al. 2018; Figueredo 2024
Non-income benefits	Building social and human capital through community engagement and training	Schilling et al. 2023

2.3.1.1 Economic Motivations

Economic incentives primarily drive farmers to adopt carbon farming practices, while financial mechanisms, such as payments for carbon sequestration, cost-sharing programs, tax credits, and crop insurance discounts, provide direct economic benefits (Nandakishor et al. 2022; Jassim et al. 2022; Figueredo 2024). These incentives are particularly compelling in regions where agricultural enterprises face economic challenges, such as Kenya and India and carbon farming schemes are seen to diversify income and provide financial security in such regions where agricultural incomes are often unpredictable (Nandakishor et al. 2022; Schilling et al. 2023).

For smallholder farmers in Africa, carbon payments serve as a critical income source, helping to offset high initial costs and limited access to credit (Schilling et al. 2023). Farmers receive monetary compensation through structured carbon payment mechanisms, often facilitated by project developers who provide inputs such as advisory services, training, and input materials (e.g., seedlings or tools), thereby reducing or eliminating the need for upfront farmer investment or credit (Lee 2017; Nyberg et al. 2020; Boomitra Inc 2025). These mechanisms typically fall into three categories: result-based payments (rewarding verified carbon sequestration outcomes), action-based payments (rewarding adoption of specific practices), and hybrid approaches combining both (Raina et al. 2024).

Result-based payments, for instance, are common in projects like the Kenya Agricultural Carbon Project (KACP), where smallholder farmers in Western Kenya implement Sustainable Agricultural Land Management (SALM) practices such as agroforestry, composting, and terracing to sequester carbon in soil and biomass (Öborn et al., 2018; Nyberg et al., 2020). Here, carbon sequestration is measured and monitored using the Verified Carbon Standard (VCS) methodology, which accounts for carbon pools (aboveground biomass, belowground biomass, and soil organic carbon) and emission sources (e.g., fertilizer use) through annual farm-level surveys, activity-based models (e.g., Roth-C model), and periodic third-party validation/verification (Lee 2017; Öborn et al. 2017). Farmers receive payments post-verification, with the World Bank BioCarbon Fund acting as the buyer under an Emission Reduction Purchase Agreement. In the KACP, payments averaged 3.29 USD per hectare per year (based on an estimated 1.37 tons of CO_2-equivalent sequestered per hectare annually at 4 USD per ton), with farmers retaining 60% of the revenue (approximately 1.97 USD per hectare) and 40% allocated to project administration and advisory services (Lee 2017; Öborn et al. 2017). The first payment in 2013 covered sequestration from 2010–2011, but actual farmer receipts were low due to deductions (e.g., only 90% of sequestered carbon was paid out to account for uncertainties), emphasizing co-benefits like increased maize yields (30–50% higher) over direct payments (Öborn et al. 2017). Other than carbon payments and advisory services, the project did not provide any free tools, seedlings, or credit (Lee 2017). Similarly, in the Western Kenya Carbon Project (WKCP), developed by Soil-Carbon Certification Services (SCCS), farmers do not receive direct carbon revenue payments but are instead supported through agricultural advisory services and the provision of selected inputs for a period of up to 30 years (Tennigkeit et al. 2023).

Action-based payment schemes provide upfront or instalment-based incentives for the adoption of specified practices, with monitoring prioritizing implementation over measured outcomes (Raina et al. 2024). In Uganda, the Trees for Global Benefits Program (TGB) disburses payments to farmers over 10 years according to tree numbers, species composition, and milestone achievements, allocating 55% of revenue to growers and distributing the remainder among other stakeholders (Öborn et al. 2017). Monitoring, reporting, and verification (MRV) employ the Plan Vivo standard, estimating carbon sequestration via tree-growth measurements and allometric equations. Payments, averaging USD 2-5 per tCO_2e, vary by system type and growth rate, supporting long-term livelihood investments and generating co-benefits including timber, fruit, fodder, and value-chain development. As project proponent, ECOTRUST aggregates carbon credits from farmer groups and brokers sales in the voluntary carbon market, thereby enabling smallholder access to otherwise inaccessible markets (Öborn et al. 2017).

Hybrid payment mechanisms resemble result-based payments but reward farmers for both actions and outcomes, drawing funds from sellers and donors, as well as from participation in carbon markets through the sale of carbon credits (Raina et al., 2024). By combining action- and results-based elements, they provide guaranteed payments for specified practices alongside performance-based bonuses, thereby reducing farmer risk while promoting measurable environmental outcomes (Raina et al., 2024). For example, the International Small Group & Tree Planting Program (TIST) program in Kenya provides farmers with upfront payments of USD 0.018 per tree to offset planting costs during the contract period and further pays them carbon credits generated per household according to the sequestration measured at the end of the contract period (Lee et al. 2016; Tamba et al. 2021; Raina et al. 2024). In Boomitra's carbon farming project in Kenya, the farmers receive payments that support them to initiate the project activities (e.g., land preparation), followed by carbon payments based on MRV outcomes (Boomitra Inc 2025).

2.3.1.2 Ecological Motivations

Farmers are also motivated by the ecological co-benefits of carbon farming. Practices that increase soil organic carbon, such as cover cropping, no-tillage, and crop rotation, contribute to improved soil quality, reduced erosion, and enhanced biodiversity (Barbato & Strong 2023; Figueredo 2024). These benefits align with broader sustainability goals and support long-term agricultural productivity, making them attractive to farmers in regions like the US and Europe (Buck & Palumbo-Compton 2022; Barbato & Strong 2023).

Carbon farming also enhances resilience to climate change. Techniques such as water and soil conservation mitigate the impacts of water shortages, while agroforestry provides shelter from extreme temperatures and diversifies crop production, reducing vulnerability to climate variability (Schilling et al. 2023). In Africa, where climate change poses significant threats to agriculture, these resilience benefits are particularly critical for smallholder farmers (Schilling et al. 2023). Additionally, co-benefits beyond carbon sequestration, such as improved pest control through practices like push-pull farming, biodiversity conservation, higher crop yields and reduced input costs by improving soil health and fertility, further incentivize adoption, especially when carbon payments are low (Antwi-Agyei et al. 2021; Buck & Palumbo-Compton 2022; Ogisi & Begho 2023; Schilling et al. 2023; Figueredo 2024). These co-benefits are significant motivators for farmers to join in carbon farming projects (Pudasaini et al. 2024). For instance, increased yields have motivated smallholder farmers to participate in the Kenya Agricultural Carbon Project (KACP), as their livelihoods depend heavily on consistent agricultural output (Nyberg et al. 2020).

2.3.1.3 Socio-Cultural Motivations

Socio-cultural factors play a significant role in motivating farmers to adopt carbon farming. Many farmers are driven by environmental values and a sense of stewardship, feeling a responsibility to preserve the land for future generations (Beacham et al. 2023; Carmichael et al. 2023; Figueredo 2024). This intrinsic motivation is particularly evident in regions like Canada and the UK, where farmers view themselves as caretakers of the land, prioritizing ecological benefits over purely financial gains (Beacham et al. 2023; Carmichael et al. 2023).

Cultural traditions and peer influence also contribute to the adoption of carbon farming practices (Lee 2017). In regions like Europe and India, practices such as agroforestry are valued for preserving traditional agricultural methods and community knowledge (Saha et al. 2011; Rois-Díaz et al. 2018). Furthermore, non-income benefits, such as building social capital and increasing human capital through training and community organisation, provide additional incentives, particularly for smallholder farmers in Africa (Schilling et al. 2023). These socio-cultural motivations highlight the importance of community and shared values in driving agricultural change.

2.3.2 Barriers

The adoption of carbon farming by farmers is constrained by multiple barriers, which can be grouped into six categories: economic, technical and practical, knowledge and information, market-related, uncertainty and risk, and social and behavioural, modified from categories proposed by Pudasaini et al. (2024) (Table 4).

2.3.2.1 Economic Barriers

Financial constraints are a significant impediment to carbon farming projects in two ways: 1) cost for project establishment, and 2) cost for the implementation of new management practices (Pudasaini et al. 2024). From the project establishment side, upfront investments for baseline assessment, soil sampling and analysis, development of monitoring systems and capacity building incur huge costs, especially when working with a larger area consisting of many smallholders, as in the case of Kenya (Tennigkeit et al. 2023; Pudasaini et al. 2024). For instance, the cost of baseline sampling varied between USD 30 and 100/ha, depending on the region and sampling strategy in Australia (Pudasaini et al. 2024). In WKCP, the costs for agricultural extension service were a major share (76%), varying from USD 10 to 50/ha/year, followed by fixed project management costs (15%) and monitoring and carbon transaction costs (9%) (Tennigkeit et al. 2023). In addition, there will be huge transaction costs for the project that include registration, auditing and verification by carbon registries and third-party and costs of finding a marketplace (Pudasaini et al. 2024). As carbon projects tend to operate on shorter time frames with limited public funding, the project developers are more concerned about efficiency over equity objectives of reaching poor farmers and including them in the decision-making process (Lee 2017).

On the other hand, high initial costs for implementing practices such as conservation tillage, cover cropping, or biochar application, along with ongoing expenses for maintenance and monitoring, pose substantial challenges, for farmers to join carbon farming (Lee 2017; McDonald et al. 2021; Sharma et al. 2021; Figueredo 2024; Pudasaini et al. 2024). For instance, monitoring, reporting, and verification (MRV) costs, such as consultant visits or certification processes, can be prohibitively expensive, with examples like EUR 2000 per farm every five years (McDonald et al. 2021). Additionally, inadequate financial compensation and low carbon prices in voluntary markets fail to offset these costs, reducing economic viability (Schilling et al. 2023; Figueredo 2024; Pudasaini et al. 2024). Limited access to credit, high transaction costs, and the need for specialized equipment further exacerbate financial barriers, especially for resource-constrained farmers in developing regions (Schilling et al. 2023; Kashyap et al. 2024).

2.3.2.2 Technical and Practical Barriers

The technical complexity of carbon farming practices presents significant challenges. Measuring and monitoring soil carbon levels is labour-intensive and costly, complicated by issues such as soil depth sampling and density changes, which can lead to inaccurate carbon stock estimates (Matis & Saatkamp 2023). Additionally, the suitability of carbon farming practices varies depending on farm-specific factors, such as soil type, climate, and existing land use, making universal application difficult (Sharma et al. 2021; Figueredo 2024). Inadequate training and skills further limit farmers' ability to adopt and manage these practices effectively (Sharma et al. 2021; Figueredo 2024).

Complex scheme designs and bureaucratic hurdles, such as extensive paperwork and compliance requirements, create administrative burdens that discourage participation (Sharma et al. 2021; Figueredo 2024; Pudasaini et al. 2024). Further, rules requiring additionality, where carbon sequestration must be additional to existing practices, can exclude farmers already implementing sustainable methods, discouraging participation (McDonald et al. 2021; Figueredo 2024). Moreover, potential negative externalities, such as increased nitrous oxide (N_2O) emissions from certain practices (e.g., alternate wetting and drying) and difficulty in the quantification of co-benefits, can undermine the environmental benefits of carbon farming, deterring adoption (Matis & Saatkamp 2023; Pudasaini et al. 2024).

2.3.2.3 Knowledge and Information Barriers

Landholder participation in carbon farming projects depends on understanding the extent of benefits attainable through practice changes relative to existing management systems (Pudasaini et al. 2024). A lack of awareness and understanding about carbon farming practices significantly hinders the adoption of these practices. Many farmers are unfamiliar with the benefits, processes, or requirements of carbon farming schemes, which limit their willingness to participate (Sharma et al. 2021; Figueredo 2024). Insufficient access to targeted information, coupled with a lack of education and technical assistance, creates knowledge gaps that deter farmers from adopting new practices (Schilling et al. 2023; Kashyap et al. 2024). For example, farmers may not know how to navigate carbon markets or implement specific techniques like soil carbon sequestration, underscoring the need for robust extension services and capacity-building programs (Schilling et al. 2023).

2.3.2.4 Market Barriers

The underdeveloped state of carbon markets poses significant barriers to adoption. Farmers often express concerns about the fairness and transparency of market-based mechanisms, fearing that large-scale agriculture benefits disproportionately (Figueredo 2024). Volatility in carbon credit prices and uncertainty about selling practices in carbon markets create financial risks, reducing the attractiveness of carbon farming (McDonald et al. 2021; Sharma et al. 2021). Furthermore, limited market development and recognition for carbon farming products, such as carbon credits or certified sustainable crops, restrict economic incentives (Schilling et al. 2023; Kashyap et al. 2024). Economic incentives favouring monocropping over diversified or sustainable practices also discourage farmers from transitioning (Kashyap et al. 2024).

2.3.2.5 Uncertainty and Risk Barriers

Uncertainties surrounding the environmental and economic outcomes of carbon farming significantly impede adoption. Carbon farming often requires long-term commitments, such as multi-year contracts or permanence clauses, which limit farmers' flexibility in land management decisions (Sharma et al. 2021; Figueredo 2024; Pudasaini et al. 2024). This is particularly challenging for farmers with short-term land rental contracts or those who value adaptability in their operations (Kashyap et al. 2024). Scientific uncertainties, such as the variable potential for soil carbon sequestration or the risk of carbon loss (i.e., non-permanence) due to climate change and reversal of practice change, create doubts about the efficacy of these practices (Matis & Saatkamp 2023; Schilling et al. 2023).

Farmers also face uncertainty about the financial benefits, exacerbated by volatile carbon markets and result-based payment mechanisms (McDonald et al. 2021; Schilling et al. 2023; Tennigkeit et al. 2023). Uncertainty about future governance and regulations, coupled with a lack of political support, further complicates adoption, as farmers fear policy instability (Matis & Saatkamp 2023; Tennigkeit et al. 2023; Figueredo 2024; Pudasaini et al. 2024). For smallholder farmers, participation rules that favour large-scale operations or require secure land tenancy can be exclusionary (Schilling et al. 2023; Kashyap et al. 2024). These uncertainties, combined with perceived risks of transitioning, such as potential yield losses or increased labour demands, make farmers hesitant to adopt carbon farming (Sharma et al. 2021; Figueredo 2024).

2.3.2.6 Social and Behavioural Barriers

Social and behavioural factors play a critical role in shaping farmers' decisions (Lee 2017; Ogisi & Begho 2023). Risk aversion and apprehensions about potential yield reductions or economic losses during the transition to carbon farming deter many farmers (Schilling et al. 2023; Figueredo 2024). Resistance within farming communities, driven by a preference for familiar practices or concerns about complexity, further slows adoption (Kashyap et al. 2024). For instance, the adoption of carbon farming practices is likely to increase if peer networks recommend the practice and social networking with existing carbon farmers (Pudasaini et al. 2024).

Vulnerable farmers, characterized by low social status, limited land access and education, low use of advisory services and low level of awareness about climate risks, may not be confident enough to accept the change and often require targeted support to engage in carbon farming (Lee 2017; Mills et al. 2020; Kashyap et al. 2024; Pudasaini et al. 2024). Additionally, farmers' personal interests and "path dependency" shaped by existing government policies favouring conventional agriculture can hinder the shift to sustainable practices (Kashyap et al. 2024).

Table 4. Barriers to the adoption of carbon farming

Category	Specific Barriers	References
Economic	High initial and ongoing costs (e.g., baseline assessments, soil sampling, conservation tillage, cover cropping, biochar), substantial monitoring, reporting, and verification (MRV) costs (e.g., EUR 2000/farm/5 years), transaction costs (e.g., registration, auditing, marketplace access), inadequate financial compensation, low and volatile carbon prices, challenges selling carbon credits or tree plantation products, limited access to credit, insufficient investment in equipment, infrastructure, and expertise, high extension service costs (e.g., USD 10-50/ha/year in WKCP), financial risks from long-term commitments.	Lee 2017; McDonald et al. 2021; Sharma et al. 2021; Schilling et al. 2023; Tennigkeit et al. 2023; Figueredo 2024; Kashyap et al. 2024; Pudasaini et al. 2024
Technical and Practical	Inadequate farmer training and skills, challenges in measuring and monitoring soil carbon (e.g., soil depth, density issues), lack of standardized methods and certification processes, incompatibility with existing farm practices due to soil type, climate, or land use, soil carbon saturation, permanence issues, negative externalities (e.g., increased N_2O emissions), difficulty quantifying co-benefits, exclusion due to additionality requirements.	McDonald et al. 2021; Sharma et al. 2021; Matis & Saatkamp 2023; Schilling et al. 2023; Figueredo 2024; Pudasaini et al. 2024
Knowledge and Information	Limited awareness of carbon farming benefits and processes, insufficient access to targeted information and technical assistance, knowledge gaps in carbon market navigation and practice implementation, lack of experience, inadequate extension services and capacity-building programs.	Sharma et al. 2021; Schilling et al. 2023; Figueredo 2024; Kashyap et al. 2024; Pudasaini et al. 2024
Market-related	Concerns over fairness and transparency in carbon markets, volatile carbon credit prices, uncertainty in selling practices, limited market development for carbon credits and sustainable crops, scarcity of markets for diverse products, and economic incentives favouring monocropping.	McDonald et al. 2021; Sharma et al. 2021; Schilling et al. 2023; Tennigkeit et al. 2023; Figueredo 2024; Kashyap et al. 2024; Pudasaini et al. 2024
Uncertainty and Risk	Risks of transitioning (e.g., yield losses, increased labour), uncertain environmental outcomes (e.g., variable carbon sequestration, carbon loss risks), financial uncertainties from volatile markets and result-based payments, scientific uncertainties in mitigation potential and measurement, regulatory and governance instability, bureaucratic hurdles (e.g., complex compliance), discriminatory participation rules favouring large-scale systems, insecure land tenure, short-term land contracts, lack of decision-making flexibility, concerns over permanence and additionality.	McDonald et al. 2021; Sharma et al. 2021; Matis & Saatkamp 2023; Schilling et al. 2023; Tennigkeit et al. 2023; Figueredo 2024; Kashyap et al. 2024; Pudasaini et al. 2024
Social and Behavioural	Risk aversion and fear of yield or economic losses, resistance to complex or unfamiliar practices, community resistance due to economic concerns, vulnerability of farmers (e.g., low social status, limited land access, low education), lack of peer network support, and path dependency from policies favouring conventional agriculture.	Lee 2017; Mills et al. 2020; Schilling et al. 2023; Figueredo 2024; Kashyap et al. 2024; Pudasaini et al. 2024

2.4 Adoption of Carbon Farming Practices

2.4.1 Adoption Patterns

Carbon farming practices (CFPs) represent a critical pathway for addressing the multifaceted challenges confronting agricultural systems in many rural parts of Sub-Saharan Africa (SSA), including climate change, erratic rainfall patterns, and persistent low agricultural productivity (Sithole & Olorunfemi 2024). Adoption patterns of CFPs, however, remain highly heterogeneous across the region. Farmers' preferences are typically shaped by perceived gains in crop productivity, soil fertility, and resilience to crop failure (Ogisi & Begho 2023). Empirical evidence suggests higher adoption rates in East Africa relative to West Africa (García de Jalón et al. 2018; Ngigi & Muange 2022; Musafiri et al. 2022; Andati et al. 2022), with Kenya providing a particularly relevant case: although uptake of individual climate-smart agriculture (CSA) technologies remains uneven, over 80% of smallholders report adopting at least one such practice (Ngigi & Muange 2022; Musafiri et al. 2022; Andati et al. 2022).

Adoption patterns are not gender neutral, and studies indicate that women disproportionately adopt crop-related CFPs, while men are more likely to implement livestock-based interventions and agroforestry systems (Nchanji et al. 2022; Ogisi & Begho 2023; Santhyami et al. 2023). These differences are not merely preference-driven but stem from entrenched gendered inequalities in access to land, labour, capital, and decision-making power, thereby shaping both the scale and nature of CFP adoption (Bernier et al. 2015; Lee 2017; Mungai et al. 2017; Ngigi & Muange 2022; Ogisi & Begho 2023; Hailemariam et al. 2024).

Western Kenya presents a compelling case for the study of CFP adoption, characterized by a high population density that exerts considerable pressure on available arable land. This demographic reality, coupled with historical agricultural practices, has led to significant challenges, notably widespread soil fertility degradation, resulting in agricultural yields falling considerably below their potential (Karanja & Jalango 2019). The prevailing conditions in the region underscore an urgent need for the effective uptake of CFPs. Such adoption is vital not only for rejuvenating degraded agricultural land but also for directly contributing to improved household income and enhancing food security for the local population (Nyuma et al. 2025).

Empirical evidence from Vihiga and Kakamega counties illustrates both widespread engagement and localized variations in adoption. A 2019 study, utilizing 2018 survey data from 334 households in Vihiga and Kakamega counties, Western Kenya, documents high adoption rates of soil carbon-enhancing practices (Karanja & Jalango 2019). Intercropping was prevalent, with 76.16% of Kakamega and 74.69% of Vihiga farmers employing it to optimize resource use and enhance food security on smallholder farms (Karanja & Jalango 2019; Buleti et al. 2023). Terracing, vital for soil conservation, was more prevalent in Vihiga (78.4%) than in Kakamega (61.05%), due to Vihiga's hilly topography and heightened erosion risks. Agroforestry is practiced by 72.67% of Kakamega and 62.35% of Vihiga farmers, reflecting significant integration of trees into agricultural systems. However, a recent study by Nyuma et al. (2025) indicates that agroforestry adoption specifically for soil fertility management and crop yield enhancement remains low, as farmers often prioritize trees for shade, fodder, or fuelwood rather than nutrient cycling due to limited knowledge of management techniques (e.g., pruning for green manure), time lags in benefits, or competing priorities.

Qualitative studies in Kisumu, Vihiga, and Siaya counties further indicate widespread adoption of crop-livestock farming, crop rotation, intercropping, manure and inorganic fertiliser application, and improved maize varieties (Buleti et al. 2023). Integrated Soil Fertility Management (ISFM) practices, including legume-maize rotation and maize-legume intercropping, are adopted by almost all farmers of Western Kenya, highlighting the efficacy of targeted ISFM programs in promoting integrated, sustainable farming systems (Karanja & Jalango 2019).

In Kenya, practices such as Integrated Pest Management (IPM), water harvesting, and resistant crop varieties are increasingly adopted, though with regional variations (Assèdé et al. 2025). Post-2018 literature lacks specific IPM adoption rates for Western Kenya, but a study in Embu County (Eastern Kenya) reports a 56.7% adoption rate for advanced pest management and 59% for mango fruit fly IPM, with 17% disadoption, indicating variable uptake and persistence across contexts (Otieno et al. 2025). Conservation tillage, a recognized CFP for improving yields and soil health, has been adopted by only 14% of farmers in a sample of 300 households in Embu County (Jena 2022). Water harvesting is widely practiced, with a Murang'a County (Central Kenya) study showing high adoption of simpler techniques like rooftop rainwater harvesting (67.71%), mulching (67.45%), and terraces (67.45%) but lower uptake for complex practices like retention ditches (22.92%), water pans (17.45%), and negarim microcatchments (11.20%), suggesting barriers to capital-intensive methods (Irungu et al. 2024). Regionally, a systematic review indicates a 56.7% adoption rate for Climate-Smart Agriculture (CSA) practices across Eastern Africa, including Kenya, reflecting significant engagement by smallholder farmers with sustainable approaches (Mnukwa et al. 2025).

Taken together, these findings highlight three critical dynamics: (1) adoption of CFPs is high but uneven, with farmers favouring practices that deliver short-term and visible benefits; (2) adoption is shaped by biophysical conditions, regional contexts, and policy interventions; and (3) gendered inequalities significantly condition adoption patterns, influencing not only which practices are chosen but also how benefits are distributed within households and communities.

2.4.2 Agroforestry in Kenya

Agroforestry can be defined as an ecologically based land-use system that integrates trees with crops and/or livestock. It not only enhances agricultural productivity and biodiversity but also mitigates climate change, while promising ecological and socio-economic benefits for both present and future generations (Leakey 2017; Wanjira & Muriuki 2020). Therefore, AF aligns well with the Paris Agreement and national initiatives of Kenya, like Vision 2030 of Kenya (Wanjira & Muriuki 2020; Mayr et al. 2025).

The climate variability and declining soil fertility in Western Kenya are constantly diminishing the agricultural potential. Therefore, promoting agroforestry in the region is critical for the reclamation of land, mitigating climate change and diversifying livelihood opportunities with a wider scope for carbon market integration (De Giusti et al. 2019; Reppin et al. 2020). In the Nyando basin, encompassing Kisumu and parts of Kakamega, agroforestry enhances soil fertility and resilience to erratic rainfall, supporting food security (De Giusti et al. 2019). Local benefits include increased crop yields, diversified income from fruits, timber, and fodder, and reduced pressure on natural forests in densely populated areas (Wanjira & Muriuki 2020). Although livelihood priorities such as fuelwood and fodder self-sufficiency often take precedence over mitigation objectives, the greater tree density in Kakamega and Bungoma is associated with a carbon stock of 4.07 ± 0.68 Mg C ha^{-1} (Reppin et al. 2020). From a study by Montagnini & Nair (2004), it is understood that the average carbon storage by agroforestry practices varies across climatic regions. For instance, the average carbon stock ranged from 9 Mg C ha^{-1} in semi-arid to 63 Mg C ha^{-1} in temperate regions, considering only the tree component based on growth rate and wood production. The carbon stock is dynamic, and so it will be different in tropical regions even with similar agroforestry systems. This is mainly because of the diversity of practices and climate variability (Nair & Nair 2014; Reppin et al. 2020; Awazi et al. 2025). The rate of C sequestration ranged between 1.5 to 3.5 Mg C ha^{-1} $year^{-1}$ in the smallholder AF systems of the tropics (Montagnini & Nair 2004).

The agroforestry systems practiced in Trans Nzoia, Kakamega, Kisumu, and Bungoma counties of Western Kenya vary based on the agroecological zones and resource availability. Few agroforestry systems in practice include intercropping, boundary planting, woodlots, and homegardens (Reppin et al. 2020; Wanjira & Muriuki 2020). In the highlands of Trans Nzoia and Bungoma, nitrogen-fixing trees like *Calliandra calothyrsus* and *Leucaena leucocephala* are intercropped with maize, beans, fodder crops, avocado and mango for diversified production (Wanjira & Muriuki 2020). Larger farms in Trans Nzoia's North Rift Valley cultivate timber-based systems with *Eucalyptus spp.*, while smaller holdings in Southern Bungoma prefer mixed crop-tree systems to address soil degradation (Wanjira & Muriuki 2020). In lowland Kisumu and Kakamega, silvopastoral systems are prevalent with *Grevillea robusta*. This supports both livestock grazing and crop production while providing shade, fodder, and timber (De Giusti et al. 2019).

However, adoption rates were driven by agroecological and socio-economic factors, and implementation rates differed between the counties. The factors such as farm size, gender, tree density, and access to extension services favoured the likelihood of agroforestry in Western Kenya (Reppin et al. 2020). Kakamega and Bungoma reported up to 70% adoption due to favourable rainfall and soil conditions. Between 60-65% was reported in Trans Nzoia, reflecting commercial timber interests. The proportion of Kisumu was less than other counties (50%) due to land constraints (Reppin et al. 2020; Wanjira & Muriuki 2020).

Gender dynamics significantly influence agroforestry adoption and benefits. Male-headed households exhibit higher adoption rates than female-headed households due to greater access to resources, extension services, and decision-making power over land (De Giusti et al. 2019; Karanja & Jalango 2019; Waaswa et al. 2022; Ogisi & Begho 2023; Ngaiwi et al. 2023). Women of SSA are often restricted from adopting agroforestry, as it is portrayed as a culturally inappropriate action (Ogisi & Begho 2023). These disparities highlight the need for gender-targeted interventions to ensure equitable adoption and benefit-sharing.

2.4.3 Agroforestry Carbon Market

Carbon markets, including voluntary carbon markets (VCMs), incentivize agroforestry adoption by monetizing sequestration efforts (Wanjira & Muriuki 2020). Initiatives like the ACORN Platform and Payments for Ecosystem Services (PES) schemes have piloted carbon credit programs in the region, offering financial rewards (e.g., USD 40-80 per hectare annually at carbon prices of USD 20 per ton for practices like timber production, which provide high mitigation benefits through long-term carbon storage (Santhyami et al. 2023; Awazi et al. 2025; Mayr et al. 2025). Recent projects underscore this growth; for instance, the Western Kenya Soil Carbon Project focuses on soil sequestration alongside agroforestry to boost food security and generate credits, while the Kenya Agricultural Carbon Project (KACP) by Vi Agroforestry empowers 30,000 smallholders with sustainable practices, including agroforestry, to access VCMs (Lee 2017; Öborn et al. 2017; Nyberg et al. 2020; Tennigkeit et al. 2023; Verra 2025). High-profile deals, such as Microsoft's 2024 purchase of 350,000 tonnes of carbon removal credits from Kenyan agroforestry projects, underscore the region's growing role in VCMs, with Kenya's carbon market projected to grow from USD 629.8 million in 2025 to USD 4,491.8 million by 2032 at a 32.4% CAGR (Velev 2024; Coherent MI 2025).

Kenya's policy framework supports agroforestry through the National Agroforestry Strategy (2021–2030), Forest Conservation and Management Act (2016), and Climate Change Act (2016), which promote tree integration and carbon trading to meet Sustainable Development Goals (SDGs) 13 (climate action) and 15 (life on land) (Wanjira & Muriuki 2020). The Climate Change (Carbon Markets) Regulations, 2024, establish a national carbon registry and equitable benefit-sharing mechanisms, enhancing VCM participation (Awazi et al. 2025). Programs like the Plantation Establishment and Livelihood Improvement Scheme (PELIS) encourage on-farm tree planting in Bungoma and Trans Nzoia (Wanjira & Muriuki 2020). However, challenges persist, including small farm sizes (<1 ha), high transaction costs for payment for ecosystem services (PES), and gender norms limiting women's access to tree benefits (De Giusti et al. 2019; Mayr et al. 2025). Biophysical constraints, such as soil erosion and low rainfall in Bungoma's semi-arid areas, and socio-economic barriers, including limited technical knowledge and insecure land tenure, hinder scaling (Reppin et al. 2020; Awazi et al. 2025). Carbon market challenges, such as verification issues and inequitable benefit-sharing, further complicate adoption, necessitating simplified certification processes and capacity-building to enhance smallholder inclusion (Mayr et al. 2025).

This review underscores agroforestry's potential in Western Kenya to address climate and livelihood challenges, supported by robust policies and growing carbon market opportunities. However, overcoming adoption barriers requires targeted interventions to align practices with both environmental and socio-economic goals, providing a foundation for further research into optimizing agroforestry systems and their integration into carbon markets.

2.5 Socio-Demographic Determinants of Carbon Farming

Socio-demographic factors are the "resource" that farmers innately possess, and they back up farmers' decision-making and practice adoption. The identified factors include age, gender, education, farming experience, household size, land size, income, land tenure security, membership in social groups, access to extension services, access to information channels, access to credit and risk perception. Understanding the key factors influencing the adoption of CSA or CFPs is crucial to increasing their adoption (Bernier et al. 2015; Mungai et al. 2017; Ngigi & Muange 2022; Li et al. 2023; Ogisi & Begho 2023; Hailemariam et al. 2024). The main factors relevant to this thesis are reviewed below (Table 5).

Age

In a systematic review of 190 studies, Li et al. (2023) indicates that age can act as both a barrier and a facilitator, influencing farmers' participation in the adoption of carbon farming practices through its effects on physical capacity, experience, and risk aversion. Older farmers may be less likely to adopt labour-intensive practices, such as crop diversification or mulching, due to declining physical function and increased risk sensitivity, as observed in studies from Vietnam and Nigeria (Tran et al. 2020; Mailumo et al. 2021). Similarly, in Western Kenya, old farmers practice agroforestry, cover crops, zero tillage and animal manure application, whereas young farmers use more of intercropping, crop rotation, and mulching (Mogaka et al. 2021; Musafiri et al. 2022; Ngaiwi et al. 2023). Further, older farmers of Western Kenya demonstrated a lower likelihood of utilizing inorganic fertilizer, a trend potentially attributable to perceived energy loss for labour-intensive applications, increased risk aversion towards new inputs, or a focus on shorter-term planning horizons that may not align with the long-term benefits of certain investments (Karanja & Jalango 2019). These findings suggest that older and conservative small-scale farmers prefer to stick to the already known practices rather than try out new exploits due to their long-standing, local attitudes, values and beliefs (Negera et al. 2022; Jassim et al. 2022; Pudasaini et al. 2024).

Gender

The prevailing gender differences in resource access, social capital, and decision-making roles significantly influence the adoption of CFPs (Bernier et al. 2015; Mungai et al. 2017; Ngigi & Muange 2022; Li et al. 2023; Ogisi & Begho 2023; Hailemariam et al. 2024). The studies from Vietnam and Zimbabwe showed that female households are less likely to adopt CFPs due to less social capital and limited channels to access practices (Tran et al. 2020; Mutombo &

Musarandega 2023). However, increasing women's empowerment accelerated female farmers to adopt CFPs, showing heterogeneity in their preferences (Musafiri et al. 2022; Li et al. 2023). Female farmers prefer to adopt animal manure application, whereas male farmers favour crop diversification and agroforestry (Karanja & Jalango 2019; Waaswa et al. 2022; Musafiri et al. 2022; Ngaiwi et al. 2023). Musafiri et al. (2022) highlighted that female-headed households in Western Kenya are more likely to adopt agroforestry practices involving crops of little commercial value (e.g., sorghum). This might be possibly due to cultural perceptions that millets are poor people's food and women-targeted agricultural empowerment programs. In addition, women prioritize household food security reflecting the higher rates of intercropping in female-headed plots, mainly due to its immediate production benefits and income generation (Karanja & Jalango 2019).

Education

Education influences the adoption of carbon farming by enhancing farmers' knowledge of climate change and the benefits of CFPs (Li et al. 2023). Evidence from Indonesia, Turkey, and Nigeria showed that the willingness of farmers to adopt climate-smart practices increased with higher education levels, as they can better access and apply information from diverse sources such as extension services and the Internet (Saptutyningsih et al. 2020; Everest 2021; Mashi et al. 2022). In Western Kenya, animal manure application, organic fertilizer use, liming and terracing are positively associated with formal education, as literate farmers are in a better position to apply correct methods and understand the soil and crop management benefits than illiterate ones (Karanja & Jalango 2019; Mogaka et al. 2021; Musafiri et al. 2022). Furthermore, the productivity of drought-tolerant pulses was significantly increased with an average of 11 years of schooling in Makueni County, highlighting effective CSA adoption (Kioko et al. 2024).

Farming Experience

Farming experience, often linked to age, has mixed effects on CSA adoption. In Makueni County, farmers with an average of 17 years of experience are better equipped to implement CSA practices, as evidenced by increased pigeon pea productivity (Kioko et al., 2024). However, in Kisii County, farming experience negatively correlates with CSA adoption, possibly due to resistance to new practices among experienced farmers (Nyang'au et al. 2021). Li et al. (2023) suggest that experienced farmers may be more knowledgeable but also more risk-averse. For instance, when agricultural production risk is perceived, risk-averse farmers may be more likely to adopt improved practices to mitigate it, and vice versa (Li et al. 2024).

Household Size

Household size influences CSA adoption by affecting labour availability for carbon farming practices. In Western Kenya, household size is part of the socio-demographic profile and may support labour-intensive practices like soil conservation, mixed cropping, and application of manure (Nyang'au et al. 2021). The larger household size positively influenced the adoption of intercropping, implying that a greater number of household members provides the necessary labour for the practice. Conversely, a higher dependency ratio within a household can reduce the likelihood of intercropping adoption due to limited available labour (Karanja & Jalango 2019). Musafiri et al. (2022) argued that large families were less likely to adopt agroforestry because smaller families often compensate for their limited labour by hiring workers, which helps them implement agricultural innovations.

Land Size

Land size influences the farmer's decision to adopt CSA practices and their adoption intensity (Li et al. 2023). Larger arable land size positively influenced the adoption of practices like silvopastoral agroforestry (crop-livestock integration) in Western Kenya (Musafiri et al. 2022) and cover cropping in Cameroon (Ngaiwi et al. 2023). Larger farm sizes (average 2 ha) supported more extensive CSA adoption and improved green gram and cowpea productivity in Makueni County (Kioko et al. 2024). Similarly, farmers with a larger plot size chose intercropping compared to farmers with a smaller plot size (Mogaka et al. 2021).

Organizational Membership

Membership in farmer organizations or groups significantly enhances CSA adoption by facilitating knowledge sharing and collective action, thereby increasing bargaining ability, access to input and output markets and risk resilience (Ma et al. 2018; Li et al. 2023; Zhou et al. 2024). Haldar & Damodaran (2022) and Zhou et al. (2024) highlight that participation in agricultural organizations or cooperatives significantly promotes the adoption of organic and CSA practices among farmers in India and China, respectively. In Makueni County of Kenya, 54.6% of farmers in groups showed improved green gram productivity, likely due to access to information and resources (Kioko et al. 2024). Farmer groups act as an easy platform for farmer training by extension officers, thus playing a critical role in promoting carbon farming through enhanced access to knowledge and support (Kioko et al. 2024).

Access to Extension Services and Training

Extension services are a critical source of knowledge and skills for implementing improved agricultural practices, especially in developing countries with an underdeveloped agricultural market (Li et al. 2023). The CSA practice adoption can be promoted through extension services in three ways: 1) enrich farmers' knowledge of climate change and CSA practices by transmitting information, 2) organize field guidance and training to farmers, and 3) provide supplementary inputs such as farm machinery to adopt CSA practices more conveniently (Musafiri et al. 2022; Li et al. 2023; Mutombo & Musarandega 2023; Kioko et al. 2024). For example, the contact with extension agents in Cameroon had a significant influence on cover crop uptake, whereas mulching had an insignificant effect (Ngaiwi et al. 2023). In Western Kenya, Musafiri et al. (2022) found that contact with extension agents positively influenced the adoption of soil water conservation and crop diversification, while animal manure application had a negative effect. Also, the extension services had a negative and significant impact on terracing adoption, questioning the competence of the agents (Karanja & Jalango 2019). On the contrary, the FYM application was more likely to be adopted by farmers receiving extension services in Ethiopia (Diro et al. 2022). From this, it is evident that the promotion of CSA practices through extension services varies across countries and regions (Autio et al. 2021; Li et al. 2023).

Access to Information Channels

Lack of access to information channels through which smallholders learn about CFPs is a significant barrier to participation in CF programs and to scaling up climate-smart practices (Djido et al. 2021; Autio et al. 2021; Ngigi & Muange 2022). The main information channels include extension agents, NGOs, private companies, research institutions, farmer organizations and mass communication channels such as television, radio, internet (Ngigi et al. 2017; Ngigi & Muange 2022; Ogisi & Begho 2023). A study by Al-Amin et al. (2019) revealed that the preferences for information channels are household gender specific and differ between male and female-headed households. In Kenya, men reported extension officers, print media, television, and local leaders as preferred information channels, while women rely on radio and social groups (Ngigi et al. 2017; Ngigi & Muange 2022; Ogisi & Begho 2023).

Table 5. Influence of socio-demographic factors on carbon farming practices adoption in Western Kenya and other regions

Factor	Practices	Region	Effect (+/-)	References
Age	Crop diversification, mulching	Vietnam, Nigeria	- (older)	Tran et al. 2020; Mailumo et al. 2021
	Agroforestry, cover crops, zero tillage, animal manure application	Western Kenya	+ (older)	Mogaka et al. 2021; Musafiri et al. 2022; Ngaiwi et al. 2023
	Intercropping, crop rotation, and mulching	Western Kenya	+ (younger)	Mogaka et al. 2021; Musafiri et al. 2022; Ngaiwi et al. 2023
	Inorganic fertilizer	Western Kenya	- (older)	Karanja & Jalango 2019
Gender	General CSA practices, crop diversification, mulching	Vietnam, Zimbabwe	- (female)	Tran et al. 2020; Mutombo & Musarandega 202
	Animal manure	Western Kenya	+ (female)	Musafiri et al. 2022
	Crop diversification	Western Kenya	+ (male)	Musafiri et al. 2022
	Agroforestry	Western Kenya	+ (male)	Karanja & Jalango 2019; Waaswa et al. 2022; Ngaiwi et al. 2023
	Agroforestry with low commercial value crop	Western Kenya	+ (female)	Musafiri et al. 2022
	Intercropping	Western Kenya	+ (female)	Karanja & Jalango 2019
Education	General CSA practices	Indonesia, Turkey, Nigeria	+	Saptutyningsih et al. 2020; Everest 2021; Mashi et al. 2022
	Animal manure, organic fertiliser, liming, and terracing	Western Kenya	+	Karanja & Jalango 2019; Mogaka et al. 2021; Musafiri et al. 2022
	Benches, crop diversification, soil conservation practices, minimum tillage and irrigation (Green gram and cowpea productivity)	Eastern Kenya	+	Kioko et al. 2024
Household Size	Soil conservation, mixed cropping, and manure application	Western Kenya	+	Nyang'au et al. 2021
	Intercropping	Western Kenya	+/-	Karanja & Jalango 2019
	Agroforestry	Western Kenya	-	Musafiri et al. 2022

Farming Experience	Benches, crop diversification, soil conservation practices, minimum tillage and irrigation (Green gram and cowpea productivity)	Eastern Kenya	+	Kioko et al. 2024
	CSA practices	Western Kenya	-	Nyang'au et al. 2021
Land Size	Silvopastoral agroforestry	Western Kenya	+	Musafiri et al. 2022
	Cover cropping	Cameroon	+	Ngaiwi et al. 2023
	Benches, crop diversification, soil conservation practices, minimum tillage and irrigation (Green gram and cowpea productivity)	Eastern Kenya	+	Kioko et al. 2024
	Intercropping	Western Kenya	+	Mogaka et al. 2021
Organizational Membership	Organic and CSA practices	India, China	+	Haldar & Damodaran 2022; Zhou et al. 2024
	Benches, crop diversification, soil conservation practices, minimum tillage and irrigation (Green gram productivity)	Eastern Kenya	+	Kioko et al. 2024
Access to Extension Services	Cover cropping	Cameroon	+	Ngaiwi et al. 2023
	Soil water conservation, crop diversification	Western Kenya	+	Musafiri et al. 2022
	Mulching	Cameroon	+/-	Ngaiwi et al. 2023
	Animal manure application	Western Kenya	-	Musafiri et al. 2022
	Terracing	Western Kenya	-	Karanja & Jalango 2019
	Farmyard manure (FYM) application	Ethiopia	+	Diro et al. 2022
Access to Information Channels	Extension officers, print media, television, and local leaders	Kenya	+ (male)	Ngigi et al. 2017; Ngigi & Muange 2022; Ogisi & Begho 2023
	Radio and social groups	Kenya	+ (female)	Ngigi et al. 2017; Ngigi & Muange 2022; Ogisi & Begho 2023

3. Aims of the Thesis

The general objective of the thesis is to examine the motivations and barriers influencing farmers' participation in carbon farming programs, and to identify socio-demographic and institutional factors determining the adoption of carbon farming practices in Western Kenya, using a gender lens.

The specific objectives of the thesis were:

1. To examine the motivations and barriers behind farmers' participation in carbon farming programs.
2. To assess the adoption patterns of carbon farming practices among farmers enrolled in carbon farming programs and to analyze the socio-demographic and institutional factors influencing agroforestry adoption and carbon payment receipt.

3. To identify socio-demographic factors influencing farmers' participation in carbon farming programs.

Based on these objectives, the following research questions and hypotheses were formulated:

RQ1: What are the key motivations and barriers influencing farmers' decisions to participate in or refrain from carbon farming programs?

H1: Farmers are highly motivated by carbon revenues to participate in carbon farming programs, while a lack of awareness is a major barrier limiting participation.

RQ2: What are the gender differences in the adoption of specific carbon farming practices, and what factors influence agroforestry adoption and carbon payment receipt?

H2: Adoption patterns of carbon farming practices are not gender neutral, and factors such as age, education, land size, project affiliation and organizational membership significantly influence agroforestry adoption and carbon farming payment receipt.

RQ3: Which socio-demographic factors are significantly associated with farmers' participation in carbon farming programs?

H3: Farmers with greater age, higher education, more land, larger family and membership in organizations are more likely to participate in carbon farming programs.

4. Methodology

4.1 Study Area

The study was conducted in four counties of Western Kenya, viz., Trans Nzoia, Bungoma, Kakamega, and Kisumu counties, between December 2024 and January 2025 (Figure 4). These counties vary in size (2,495-3,051 km²), elevation (1,144-4,321 m), temperature (10-33 °C), and annual rainfall (1,000-2,214 mm). A detailed list of study locations, including counties, sub-counties, wards and villages, is provided in Appendix 2.

Most of the population in the region is highly dependent on agricultural income and can be characterized as small landholders. The diverse agroecological zones, increasing climate risks, and the historical presence of voluntary carbon projects provide a suitable environment for examining the adoption drivers of carbon farming.

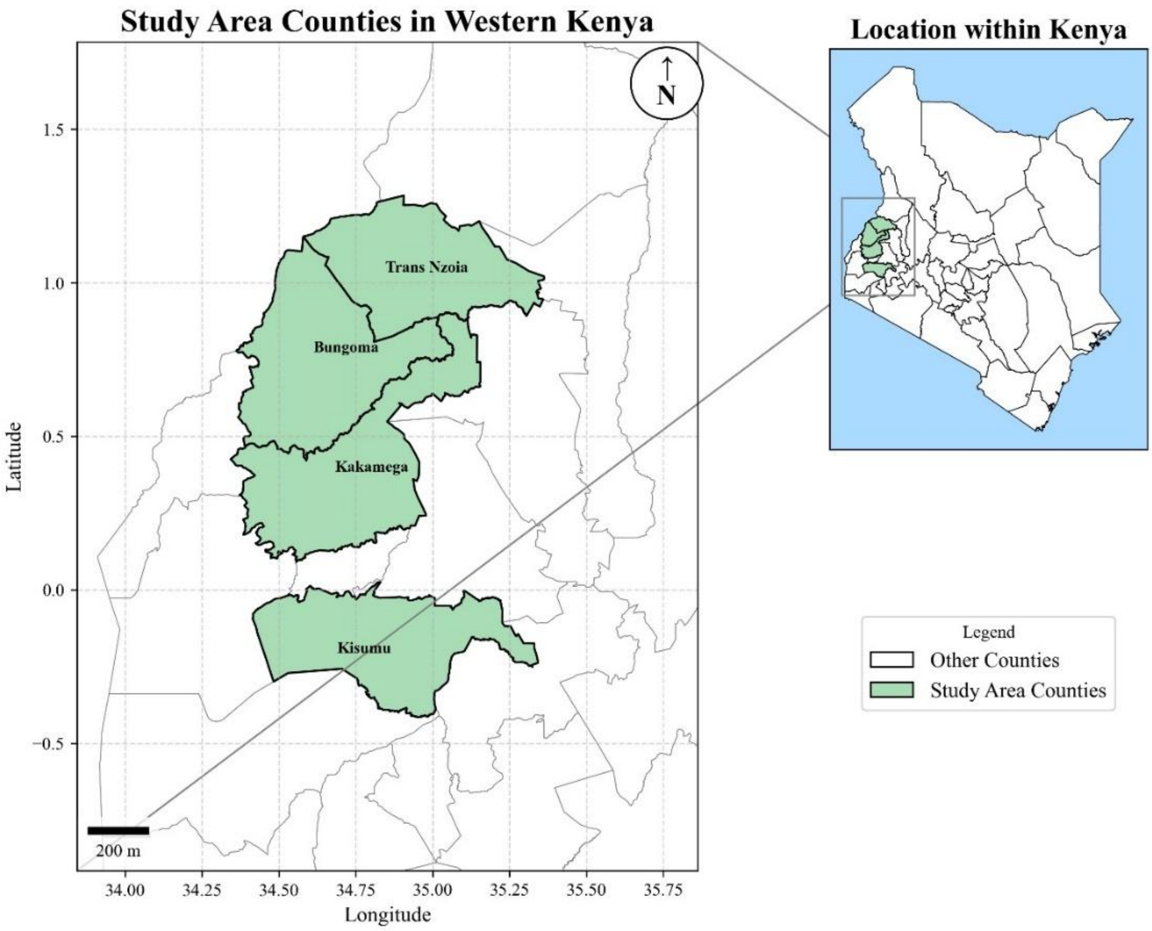

Figure 4. Map of the study area

4.1.1 Physiographic Features

Trans Nzoia and Bungoma counties are in Kenya’s North Rift, each possessing distinct natural features. Trans Nzoia is defined by Cherang’any Hills and Mt. Elgon, with fertile volcanic soils (red and brown clays, black cotton soils) and rivers like Sabwani, Rongai, and Nzoia that support agriculture (County Government of Trans Nzoia 2023). In contrast, Bungoma is characterized by Mt. Elgon as a vital water tower, Chetambe and Sang’alo hills, and rivers including Nzoia and Kuywa. Nabuyole and Teremi waterfalls are one of the notable features of Bungoma (County Government of Bungoma 2023). Kakamega is home to Kenya’s only tropical rainforest, the Kakamega Forest, and is traversed by Nzoia, Yala, and Lusumu rivers (County Government of Kakamega 2023a, 2023b). The significant area of Kisumu is covered by water as it is situated along Lake Victoria and encompasses Nyando and Sondu-Miriu rivers, the Kano Plains, and the Nyabondo Plateau (County Government of Kisumu 2023a, 2023b).

In terms of climate, all four counties experience tropical conditions with a bimodal rainfall pattern, featuring long rains (March-May) and short rains (October-December, or August-October in Bungoma) (Table 6). In Trans Nzoia, the western areas receive high rainfall, while Bungoma experiences less precipitation in its eastern regions (Tongaren and Webuye) and cooler temperatures near Mt. Elgon (County Government of Bungoma 2023; County Government of Trans Nzoia 2023). Kakamega’s humid climate supports a rainforest ecosystem and its rich biodiversity, whereas Kisumu occasionally experiences heavier rainfall (County Government of Kakamega 2023a; County Government of Kisumu 2023a).

Table 6. Physiographic features of the study area

County	Area (km²)	Elevation Range (m)	Temperature Range (°C)	Annual Rainfall (mm)
Trans Nzoia	2,495	1,660-4,299	11-29	1,000-1,700
Kakamega	3,051	1,240-2,000	18-29	1,280-2,214
Bungoma	3,024	1,200-4,321	10-25	1,000-1,800
Kisumu	2,653	1,144-1,525	23-33	1,200-1,500

4.1.2 Socio-Economic and Demographic Profile

As of 2019, the four counties collectively hosted approximately 5.7 million youth population, predominantly from rural areas (Table 7). High poverty, exacerbated by inadequate housing, nutrition, and infrastructure, high dependency ratios and ethnic diversity, drives community-based agricultural practices (County Government of Bungoma 2023; County Government of Kakamega 2023a, 2023b; County Government of Kisumu 2023a; County Government of Trans Nzoia 2023). Trans Nzoia significantly features Kalenjin and Luhya populations, with balanced gender ratios (County Government of Trans Nzoia 2023). Bungoma is dominated by Bukusu, Sabaot, and Iteso communities, with a slightly higher female population (County Government of Bungoma 2023). Kakamega has varying population densities across its sub-counties, with predominant presence of Luhya, including Bukusu, Maragoli, Isukha, and Idakho (County Government of Kakamega 2023a). Kisumu is primarily characterized by the Luo population, while Kisii and Luhya are minorities (County Government of Kisumu 2023a).

Table 7. Demographic and socio-economic features of the study area

County	Population (2019)	Density (persons/km²)	Dependency Ratio (%)	Poverty Rate (%)	Ethnic Groups
Trans Nzoia	990,341	490	67	34.1	Luhya, Kalenjin
Bungoma	1,670,570	552	-	35.7	Bukusu, Sabaot, Iteso
Kakamega	1,867,579	264-1,296	88	35.8	Luhya (Bukusu, Maragoli, Isukha, Idakho)
Kisumu	1,155,574	Varies (highest in Kisumu town)	-	40.0	Luo, Kisii, Luhya

4.1.3 Cropping Systems and Practices

Agriculture is a major contributor to the household income of Trans Nzoia (70%) and Kisumu (50%) (MoALF 2018a; MoALFC 2021a) and the gross county product of Bungoma (44.2%) and Kakamega (52.2%) (County Government of Bungoma 2023; County Government of Kakamega 2023a). The farmers in the region are smallholders with average farm sizes ranging between half and one hectare (County Government of

Bungoma 2023; County Government of Kakamega 2023a; County Government of Trans Nzoia 2023). Trans Nzoia produces about 500,000 MT of maize annually, along with beans, wheat, barley, finger millet, sorghum, sweet potatoes, bananas, tomatoes, coffee, sugarcane, tea, and livestock (dairy/beef cattle, poultry, goats). Recognizing its contribution to agricultural production, Trans Nzoia is fondly known as Kenya's "breadbasket." The crop and livestock production vary based on the agroecological zones within the county. For instance, sheep and dairy farming are prevalent in the upper highland, whereas maize and horticulture production in the upper midland (MoALFC 2021a; County Government of Trans Nzoia 2023). Further, the adoption of early-maturing varieties (e.g., HARAKA, Sungura and 5 series), agroforestry, conservation agriculture, and drought-tolerant fodder (e.g., *Brachiaria* grass) is persisting with the support of extension services (MoALFC 2021a). In Bungoma, crop cultivation of maize, beans, finger millet, sweet potatoes, bananas, Irish potatoes, vegetables, sugarcane, cotton, palm oil, coffee, sunflowers, tobacco, and livestock-based (cattle, sheep, goats, poultry) activities are in practice (MoALFC 2021b; County Government of Bungoma 2023). Kakamega cultivates maize, sugarcane, tea, beans, cassava, finger millet, sorghum, local vegetables (Amaranthus, African nightshade, spider plant, cowpeas, jute mallow), with significant livestock (145.8 million liters milk, 93.2 million eggs) and aquaculture (700,000 kg fish, mainly Nile Tilapia, Catfish) (MoALF 2018b; County Government of Kakamega 2023a). Kisumu focuses on rice (Kore Scheme), maize, sorghum, beans, sugarcane, cotton, and livestock (grade cattle, poultry, dairy goats), with aquaculture contributing to the maximum output (MoALF 2018a; County Government of Kisumu 2023b).

4.1.4 Climate Risks

Climate change significantly impacts agricultural productivity and livelihoods in all counties, where farmers are highly reliant on rainfed agriculture. In Trans Nzoia, unpredictable growing seasons (reducing growing periods by 20-70 days), moisture stress, excessive rainfall and inadequate infrastructure disrupted the cropping calendar, reducing yields, degrading land productivity and threatening food security (MoALFC 2021a). Decreased agricultural output, increased pest and disease incidence, and post-harvest losses are severe climate change issues in Bungoma, contributing to food insecurity and poverty (MoALFC 2021b). Kakamega County has experienced a temperature surge, from a 0.4°C increase in the first season to 0.3°C in the second, between 1981 to 2005, leading to more heat stress days. Also, increased precipitation rate of 15% in the first season and 30% in the second from 1981 to 2015, caused flood risks in the Nzoia River Basin. Further, landslides triggered by intense rainfall, soil erosion, deforestation, and hillside farming reduced yields and increased pest and disease prevalence (MoALF 2018b). Similarly, the negative effects of climate change and human-induced activities exacerbate food security and poverty in Kisumu (MoALF 2018a).

4.1.5 Carbon Farming Programs

Various carbon farming projects have been implemented in different parts of Western Kenya due to the region's bimodal rainfall, high smallholder farmer density, and history of initiatives like the Kenya Agricultural Carbon Project (KACP). Notably, KACP, started as Africa's first SALM project in 2009 in Bungoma, Kisumu and Siama counties of Western Kenya, has empowered around 30,000 smallholder farmers through no till, mulching, cover cropping, composting, terracing, water harvesting, reduced residue burning and agroforestry activities, spanning an area of 45,000 ha (Lee 2017; Öborn et al. 2017; Nyberg et al. 2020). Other initiatives include the Western Kenya Soil Carbon Project (WKCP), Boomitra's East Africa Carbon Farming Project, Financing Locally-Led Climate Action (FLLoCA) with SALM components, and the Western Kenya Smallholder Agricultural Carbon Project (WKSACP), collectively covering around 80,000-100,000 ha and supporting 50,000-80,000 farmers (Shames et al. 2012; Tennigkeit et al. 2023; Boomitra Inc 2025; Pennynar 2025).

As of today, three SALM carbon projects have been registered in Kenya, three others have requested registration (pending review), two are under development (pre-validation), and two are under validation in the Verra registry, attracting climate investments from global investors (Verra 2025).

4.2 Data Collection

4.2.1 Survey Design and Implementation

This study uses the secondary data collected by trained enumerators using the computer-assisted personal interviewing (CAPI) method (Cariappa & Krishna 2025). The collected data is a part of the Sustainable Agrifood System (SAS) research program, led by the International Maize and Wheat Improvement Centre (CIMMYT), Hyderabad, India.

The quantitative data has been collected by trained enumerators through face-to-face interviews. The CAPI-based questionnaire was pre-programmed to ensure consistency, data validation, and real-time quality checks during fieldwork. The survey covers a range of topics, including household socio-demographic characteristics, motivations and barriers to carbon farming participation, adoption of sustainable agricultural practices, institutional support, payment mechanisms, and carbon credit ownership details.

The following main questions were asked of the households, with the full questionnaire provided in Appendix 1: 1) Are you practicing carbon farming (Yes/No)? 2) If yes, how did you learn about carbon farming? 3) If no, why are the reasons for not participating? 4) What motivated you to get involved in carbon farming? 5) What new sustainable agriculture practices have you started because of the carbon credit program? 6) Have you received any training to practice carbon farming (Yes/No)? 7) What forms of support does the company offer? 8) Have you received any payment so far (Yes/No)? 9) If yes, how often do you get paid? 10) Do you own carbon credits (Yes/No)?

4.2.2 Sampling Strategy and Target Population

The survey targeted a total of 859 households (HHs) across four counties and their respective projects. The sample was stratified based on the gender of household head (HHH) (427 male-headed and 432 female-headed households) and carbon farming adoption (439 carbon farmers and 420 non-carbon farmers) to ensure balanced representation and comparability between groups. Respondents were household heads or, where appropriate, members most knowledgeable about farming, with an age range of 18 to 80 years. On average, a household comprised 6 members and cultivated a mean land size of 0.6 hectares, with agriculture being the main income source. Nearly half of the respondents had at least a primary education and represented diverse ethnic groups, including Luhya, Luo, Kalenjin, Kamba, Kikuyu and Kisii.

Table 8. Main characteristics of the respondents and descriptive statistics of variables included in the logistic regression analysis

Continuous Variables			
Variable	**Description**	**Mean**	**Range**
Age of HHH	Age of the household head in years	48.5	18-80
Household size	Number of members in the household	5.6	1-15
Household income earners	Number of income earners in the household	1.5	1-9
Land size	Total cultivated land in hectares in the last 12 months	0.6	0.03-4.9
Categorical Variables			
Variable	**Description**	**N**	**%**
Carbon farming participation (1=Yes)	Whether the household is engaged in carbon farming	439	51.1
Carbon farming payment (1=Yes)	Whether the farmer received any carbon farming payment	124	28.3
Agroforestry adoption (1=Yes)	Whether the farmer adopted an agroforestry practice	182	41.5
County of HHH	**County of the household head**		
Kakamega	HHH belongs to Kakamega	208	24.2
Kisumu	HHH belongs to Kisumu	272	31.7
Bungoma	HHH belongs to Bungoma	212	24.7
Trans Nzoia	HHH belongs to Trans Nzoia	167	19.4
Project affiliation			
Project 1	Households affiliated with Project 1	150	34.2
Project 2	Households affiliated with Project 2	91	20.7
Project 3	Households affiliated with Project 3	104	23.7
Project 4	Households affiliated with Project 4	94	21.4
Gender of HHH	Gender of the household head		
Male HH	0 = Male household head	427	49.7
Female HH	1 = Female household head	432	50.3
Education level of HHH	**Educational qualification of the household head**		
No formal education	HH with no formal education	44	5.1
Primary education	HH with some primary and completed primary education	389	45.3
Secondary education	HH with some lower secondary, completed lower secondary, high school and completed high school education	337	39.2

Vocational training/Diploma education	HH with vocational/technical education, college/diploma completed, and college/diploma dropout	70	8.2
University education	HH with university graduate, university dropout, postgraduate and above qualifications	19	2.2
Main income from agriculture (1 = Yes)	Main income from farming-related activities	777	90.5
Ethnicity of HHH	**Ethnic group of the household head**		
Kalenjin	HHH belongs to the Kalenjin ethnic group	106	12.3
Luhya	HHH belongs to the Luhya ethnic group	441	51.3
Luo	HHH belongs to the Luo ethnic group	278	32.4
Others	HHH belongs to other ethnic groups such as Kamba, Kikuyu and Kisii	34	4.0
Organizational membership (1 = Yes)	Household members having membership in the registered farmers'/social organization	500	58.2

4.2.3 Informed Consent and Ethical Protocol

Respondents were given prior information that the study was being conducted by CIMMYT, a non-profit international research organization, to understand farmer participation in carbon farming, sustainability practices, and their socio-economic and environmental outcomes. They were assured that taking part in the study was voluntary and they could skip the question or exit from the interview at any time without any consequences. No personal details were collected, and all data will remain anonymous and used strictly for academic and policy research purposes.

Participants were also made aware that their input would help improve agricultural policy and sustainable farming programs. For any questions or concerns, the enumerators provided contact information of the lead economist at CIMMYT-India (Dr. Adeeth Cariappa), ensuring transparency and accountability in line with established research ethics.

4.3 Data Analysis

4.3.1 Data Preparation and Analytical Framework

This section outlines the step-by-step analytical procedure undertaken to ensure the quality and rigour of the data used in this study. Following the completion of data collection through the CAPI method, the raw survey data were exported to Microsoft Excel for initial review and data preparation.

The data preparation process was carried out to attain analytical consistency, accuracy, and reproducibility. Preliminary data processing included the validation of logical consistency, correction of outliers, and recoding of open-text responses into standardized categories (Shan & Gubin 2019). Particular attention was given to harmonizing synonymous responses and ensuring lexical consistency across variables. The missing values were assessed in the dataset and handled through listwise deletion for outcome variables and appropriate classification for non-responses where necessary. All modifications were documented in a structured cleaning log to ensure transparency and reproducibility.

Once cleaned, the dataset was imported into Stata version 18 for statistical analysis. The software was selected for its capabilities in managing survey data and for its advanced tools for advanced programming, publication-quality graphics and easy reproducibility (StataCorp 2025). Data visualization was carried out using both Stata and Microsoft Excel. While Stata was used for regression analysis and predictive visualizations such as margins plots and ROC curves, Excel was employed to generate descriptive charts, including pie charts and grouped bar graphs.

The analytical framework was structured around three integrated components:

1) Descriptive statistics: To summarize key continuous and categorical variables.
2) Inferential statistics: To examine the associations and relationships between outcomes and predictors.
3) Exploratory data analysis (EDA): To visualize associations, detect anomalies, and assess potential interaction effects

The selection of statistical methods was based on the nature of the variables and the research questions, thereby ensuring methodological coherence and empirical robustness (Table 9).

Table 9. Research objectives and questions, with corresponding analytical methods

Research Objective/Question	Analytical Methods
Motivations and barriers to farmers' participation in carbon farming	Descriptive statistics Chi-square test
Adoption rate of sustainable agricultural practices among carbon farmers and socio-demographic factors influencing the likelihood of agroforestry and carbon payment receipt	Descriptive statistics Independent t-test Logistic regression Average marginal effects
Socio-demographic factors influencing farmers' participation in carbon farming	Descriptive statistics Logistic regression Average marginal effects

4.3.2 Statistical Analysis

This section details the statistical models and analytical strategies applied to each research question. All analyses were conducted using Stata 18, with a consistent application of robust standard errors to address potential heteroskedasticity (White 1980; Kaewkungwal 2025). Categorical variables, including ethnicity, county, education level, and project type, were modelled using Stata's factor variable notation (e.g., i.variable), which treats them as fixed effects and controls for unobserved heterogeneity across categories.

4.3.2.1 Motivations and Barriers Influencing Carbon Farming Participation

To address Research Question 1, descriptive statistics were employed to summarize the motivations, barriers, and enabling factors that influence farmers' decisions regarding participation in carbon farming initiatives. A chi-squared test was carried out to examine significant associations between gender categories. These included motivations such as environmental stewardship or financial incentives, information access channels, support mechanisms provided by carbon project actors, training attendance, and awareness of carbon credit ownership. Frequencies and proportions were calculated for both binary and categorical variables and visualized using grouped bar charts and pie charts. All variables were stratified by the gender of the household head to capture potential differences in access and engagement, thereby aligning the analysis with the study's gender-sensitive approach.

4.3.2.2 Adoption of Carbon Farming Practices

For Research Question 2, which focused on the adoption of agroforestry, the analysis began by calculating the adoption rates for a total of 23 carbon farming practices. Adoption data were summarized as percentages and disaggregated by gender to provide an overview of uptake patterns and visualized using pie-charts. The independent t-test is used to compare the mean land sizes of carbon and non-carbon farmers in both genders, and the results are visualized with a cumulative distribution function (CDF) plot. Subsequently, a binary logistic regression model was estimated to explore the socio-demographic determinants of agroforestry adoption. The model specification follows established formulas in recent literature (Syano et al. 2022; Ali et al. 2024).

$$\mathbf{logit(P_i^{(a)}) = ln(P_i^{(a)}/(1-P_i^{(a)})) = \beta_0^{(a)} + \Sigma^k_{j=1}\, \beta_j^{(a)}\, X_{ji} + \varepsilon_i^{(a)}} \text{ .... (Equation 1)}$$

where,

- $P_i^{(a)}$ is the probability of agroforestry adoption by household i,
- X_{ji} are explanatory covariates such as age, education, household size, land size, ethnicity, organizational membership and project,
- $\beta_j^{(a)}$ are estimated coefficients of the respective covariates, and
- $\varepsilon_i^{(a)}$ is the random error term.

To explore differences by gender, three logistic models were estimated: 1) a pooled model excluding gender and separate models for 2) male-headed (MHH) and 3) female-headed households (FHH). This strategy enhances inference by revealing within-group dynamics and avoiding biases from aggregated estimation (Khalikova et al. 2021). Several diagnostic procedures were tested to specify the robustness of the model (Appendix 5).

Multicollinearity among predictors was assessed using variance inflation factors (VIFs), all of which were below the accepted threshold of 10. Model calibration was assessed using the Hosmer–Lemeshow goodness-of-fit test, while model discrimination was evaluated using receiver operating characteristic (ROC) curves and the area under the curve (AUC) statistic (Das 2019; Tec 2025).

Classification performance was assessed at two decision thresholds. First, predictions were classified using the conventional cutpoint of 0.5. Second, an empirical cutpoint was estimated using the Liu method, which maximizes classification accuracy by balancing sensitivity and specificity. At both thresholds, classification metrics, including sensitivity, specificity, positive predictive value (PPV), and overall accuracy, were reported to assess the practical performance of the model (Liu 2012).

To enhance interpretability, average marginal effects (AMEs) were calculated using the post-estimation *"margins"* command in Stata. The marginal effect for a continuous predictor X_j in a logistic regression model is computed as:

$\partial \mathbf{P_i} / \partial \mathbf{X_j} = \boldsymbol{\beta_j} \cdot \mathbf{P_i} \, (\mathbf{1} - \mathbf{P_i})$ ……………… (Equation 2)

where,

- P_i is the predicted probability of adoption for observation i,
- β_j is the estimated coefficient for predictor X_j, and
- P_i $(1-P_i)$ represents the slope of the logistic cumulative distribution function (i.e., the derivative of the logistic function at point i).

These marginal effects vary across observations, since P_i depends on individual characteristics. Therefore, average marginal effects (AMEs) were computed by averaging these individual-level effects across all observations in the sample. This was done using Stata's *margins* command, which provides marginal effects at the means (MEMs), at representative values (MERs), or averaged over the sample (AMEs). The AMEs offer an intuitive measure of effect size: they indicate, on average, how a one-unit increase in a covariate (e.g., landholding size or education level) changes the probability (not the odds) of adopting agroforestry (Jann 2013; Dow et al. 2019; Wooldridge 2020; Rios-Avila 2021; Shaw 2022). In addition to agroforestry, a separate logistic regression model was estimated to assess the socio-demographic factors associated with receiving carbon farming payments. The binary outcome was defined as whether a household reported receiving any carbon-related payments. The model was specified as follows:

$\mathbf{logit(P_i^{(b)}) = ln(P_i^{(b)}/(1-P_i^{(b)})) = \boldsymbol{\beta}_0^{(b)} + \Sigma^k_{j=1} \boldsymbol{\beta}_j^{(b)} X_{ji} + \boldsymbol{\varepsilon}_i^{(b)}}$ ………….. (Equation 3)

where,

- $P_i^{(b)}$ is the probability of carbon payment receipt for household i,
- X_{ji} are explanatory covariates such as age, land size, gender, education, ethnicity, agroforestry adoption, project affiliation, and organizational membership,
- $\beta_j^{(b)}$ are estimated coefficients associated with the respective covariates, and
- $\varepsilon_i^{(b)}$ is the random error term.

AMEs and interaction effects were also examined in the same way as described for the agroforestry adoption model. Refer to Appendix 6 for model diagnostic tests and supplementary results.

4.3.2.3 Determinants of Carbon Farming Participation

Research Question 3 was addressed using a similar logistic regression framework, with the dependent variable defined as binary participation in a carbon farming program. The binary dependent variable was coded as 1 if the household was participating in a carbon farming program and 0 otherwise. The logistic regression model was specified as:

$$\mathbf{logit}(P_i^{(c)}) = \ln(P_i^{(c)}/(1-P_i^{(c)})) = \beta_0^{(c)} + \Sigma^{k}_{j=1}\, \beta_j^{(c)}\, X_{ji} + \delta^{(c)} + \varepsilon_i^{(c)} \text{ .... (Equation 4)}$$

where,

- $P_i^{(c)}$ is the predicted probability of participation for household I,
- $\beta_0^{(c)}$ is the model intercept,
- X_{ji} represents the value of predictor j for household i,
- $\beta_j^{(c)}$ is the estimated coefficient for each predictor,
- $\delta_c^{(c)}$ represents county-level fixed effects capturing unobserved heterogeneity across counties, and
- $\varepsilon_i^{(c)}$ is the random error term.

Explanatory variables such as age, education, household size, land size, ethnicity, main income from agriculture, organizational membership and county are included as predictors in the model. The same model diagnostics and estimation techniques applied to Research Question 2 were also used here, including AMEs and interaction effects (Appendix 7).

To facilitate interpretation and cross-model comparisons, regression results were visualized using forest plots that depicted odds ratios and AMEs across all three model specifications (Dow et al. 2019; Rios-Avila 2021; Shaw 2022; Ghajarzadeh 2025). Interaction effects were illustrated through marginal plots (Jann 2013). These visual strategies align with recommended practices for presenting regression results in policy-relevant agricultural and gender-focused research.

5. Results

5.1 Motivations and Barriers Influencing Carbon Farming Participation

The key motivations and barriers influencing farmers' decisions to participate in or refrain from carbon farming programs are examined by gender of household head and organized into three dimensions: motivations (with information channels and training providers), enabling conditions (company support, engagement, and carbon credit ownership) and barriers.

5.1.1 Motivations

Motivations for participating in carbon farming programs were largely shaped by production and environmental concerns (Figure 5a, Table 3.1a). From a production standpoint, poor soil health (35-37%) and declining productivity (20-24%) in conventional agriculture were the most cited reasons to participate in carbon farming across both male-headed households (MHHs) and female-headed households (FHHs). These were followed by increasing input costs and decreasing profitability, each of which was mentioned by around 10% of farmers. A smaller share also pointed to declining water levels and cost reduction as reasons for participation.

Beyond these reactive motivations, some farmers also highlighted more opportunity-driven reasons. Environmental consciousness was reported by over half of both MHHs and FHHs. Interestingly, a slightly higher proportion of FHHs (50%) cited yield benefits as motivation compared to MHHs (41%), and this difference is statistically significant at 10% (χ^2 $p = 0.059$). Further, around 16-18% of respondents across both groups perceived participation in carbon credit programs as a potential way to generate additional income. Overall, motivations were similarly distributed across genders, suggesting shared challenges in conventional farming and a growing interest in climate-smart practices.

Extension agents were the most common channels through which farmers learned about carbon farming programs (37-40%), followed by group meetings (24-28%) in both groups (Figure 5b, Table 3.1b). NGOs/agricultural companies are reported as a source of information by 15% of respondents in both groups. Notably, FHHs (14%) were more reliant on peer networks than MHHs (10%), with a higher share reporting of fellow farmers as their main source of information, but this difference was not statistically significant. Other sources, including county government, project proponents, radio, group meetings and agricultural shows, were each mentioned by fewer than 5% of farmers, showing their relatively limited role in spreading awareness. Radio was a very minor channel, reported by only 2.3% of MHHs and 0.45% of FHHs, but the difference approached statistical significance at 10% (χ^2 $p = 0.098$). Except for radio, none of the other sources is statistically significant.

Most training on carbon farming was provided by NGOs (53% MHH; 51% FHH) and carbon project developers (40% MHH; 44% FHH) (Figure 5c, Table 3.1c). Government extension officers were reported as training providers by fewer than 10% of respondents, while farmer-to-farmer training was nearly absent, reported by less than 0.5% of MHHs and none of the FHHs. None of these training provision patterns showed significant gender differences.

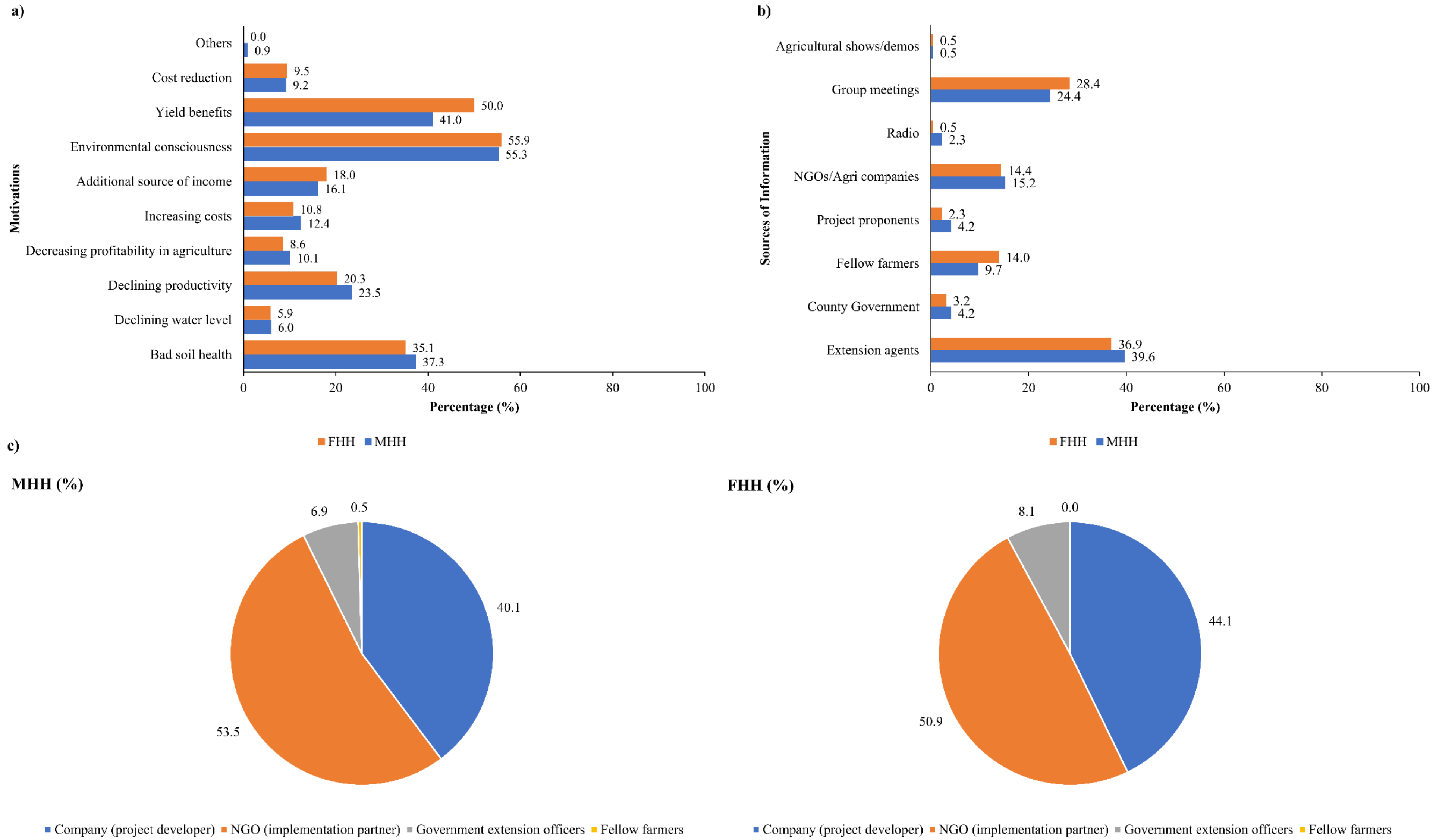

Figure 5. (a) Motivational drivers for participation in carbon farming programs, (b) sources of information received by farmers, and (c) organizers of carbon farming training, disaggregated by gender of the household head

5.1.2 Enabling Conditions

The carbon companies provided various types of support to farmers for engaging in carbon farming programs (Figure 6a, Table 3.2a). In all reported support packages, carbon credits (CC) formed the core component. The most common support package was a combination of carbon credits and technical information, received by 55% of MHHs and 59% of FHHs. Carbon credits alone were the second most common type, reported by 28% of MHHs and 26% of FHHs.

Some farmers also received additional support, including farm inputs, machinery, and livestock. Around 12% of MHHs and 10% of FHHs received carbon credits along with farm inputs. While carbon credits were central to all packages, only a minority of farmers received material support like farm inputs, livestock or equipment alongside them. No support package distribution showed a statistically significant gender difference.

Farmers' engagement with carbon companies through trainings, payment receipt, and their awareness of carbon credit ownership varied among household heads (Figure 6b, Table 3.2b). Most respondents reported having received carbon farming training, accounting for 89% of MHHs and 93% of FHHs, though the difference was not significant. However, fewer had signed formal contracts with the company (38% MHH; 36% FHH), and received payment at the time of the survey (8% MHH; 28% FHH). When asked about ownership of carbon credits, 61% of MHHs and 56% of FHHs said that they knew who owned the credits generated on their land. From this, it is understood that only a moderate level of awareness exists about benefit-sharing among the trained households. However, the results are statistically insignificant.

The farmers were paid for undertaking carbon farming activities at different time frequencies (Figure 6c, Table 3.2c). Yearly payments were the most common, reported by 57% of MHHs and 63% of FHHs. Seasonal payments were reported by about 10% of farmers in both groups. Monthly payments were rare and only reported by a small number of FHHs (2%). In addition, a notable share of farmers indicated receiving payments through "other arrangements" (33% MHH; 25% FHH), suggesting some variation or uncertainty in how payments are handled.

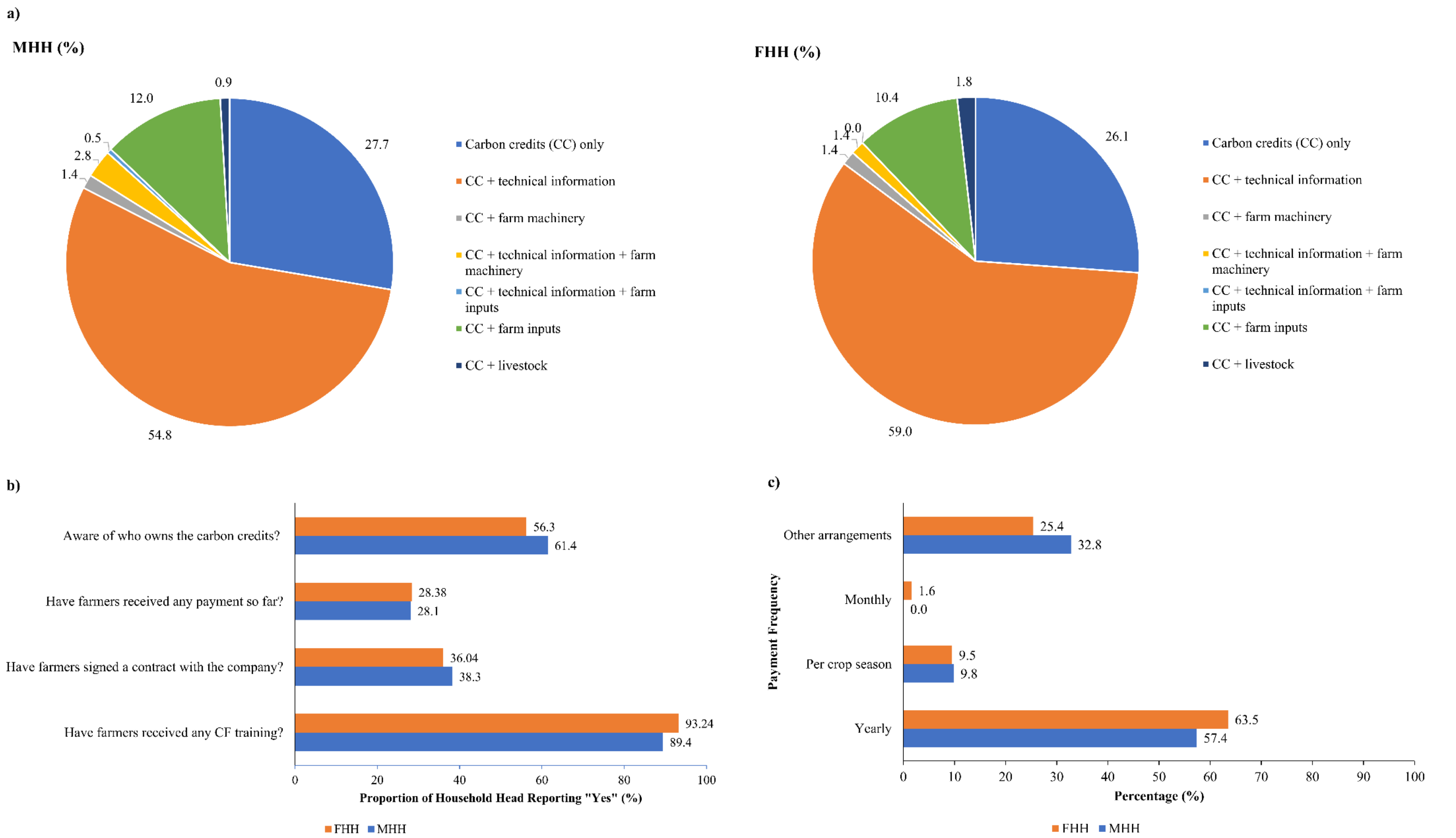

Figure 6. Enabling conditions for carbon farming participation by the gender of the household head. (a) Types of support provided by carbon companies (b) Farmer awareness, engagement, and ownership of carbon credits and (c) Frequency of carbon farming payment

5.1.3 Barriers

Barriers that have prevented non-carbon farmers from joining the carbon farming programs have been reported by the gender of the household head (Figure 7, Table 3.3). The most frequently mentioned barrier was lack of awareness about carbon farming, reported by 53% of MHHs and 55% of FHHs. This indicates a major information gap that affects both household types.

About 30% of MHHs and 23% of FHHs reported that they do not know how to enroll, or nobody approached them, as the second most common barrier. This result is marginally significant at 10% (χ^2 $p = 0.099$). The limitations in the outreach block the entry of interested farmers who otherwise would have joined if they were properly sensitized.

A smaller share (around 8%) reported that they did not have enough land to participate, indicating perceived eligibility constraints. Some others (2% of both groups) expressed that the delay in payments and no payments as a reason for non-participation. These concerns are based on perception and are probably heard from existing carbon farmers.

Notably, around 1% of FHHs reported that the company had rejected their enrollment, an issue not reported by any MHHs. Additionally, 6% of MHHs and 10% of FHHs selected “other” reasons, which may reflect unlisted or gender-specific barriers not captured by the predefined categories.

Overall, the results indicate that while motivations, information sources, and support types were largely similar across genders, certain patterns, such as yield benefits as a motivation, radio as an information source, lack of enrollment opportunities, and payment receipts showed emerging gender-related differences worth exploring further in the discussion.

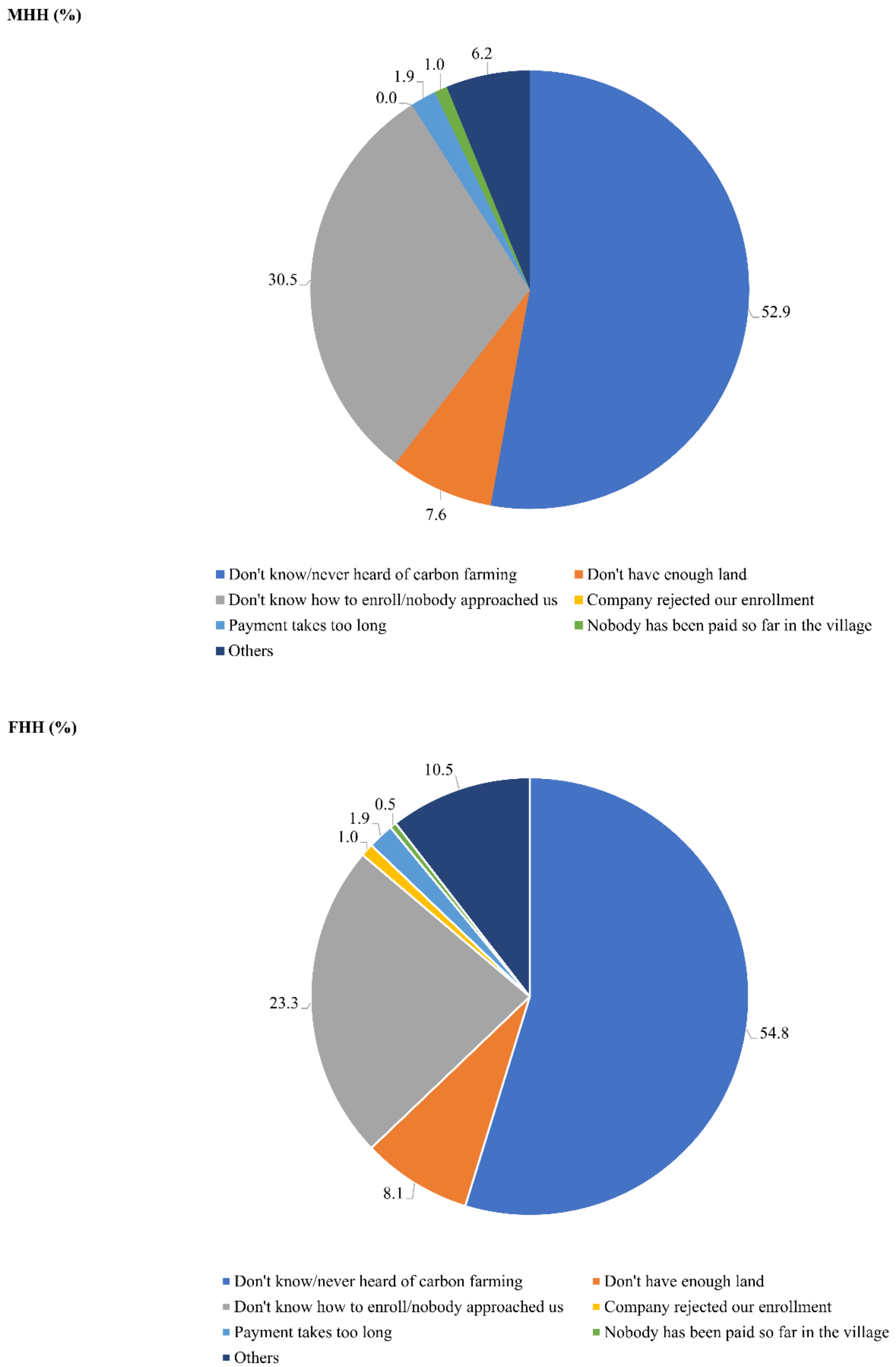

Figure 7. Farmer-reported barriers to participation in carbon farming programs, disaggregated by gender

5.2 Adoption of Carbon Farming Practices

Having examined motivations and barriers to carbon farming participation, this section presents the findings of gender differences in the adoption of specific practices and the socio-demographic and institutional factors influencing agroforestry adoption and carbon payment receipt.

5.2.1 Adoption Patterns

Adoption rates of carbon farming practices showed remarkable differences across practices, but only subtle differences between MHHs and FHHs (Figure 8, Table 4.1). Out of 23 practices reported, organic fertilizer use (47% MHHs, 48% FHHs), agroforestry (41% for both groups), and intercropping (30% MHHs, 29% FHHs) were the three most widely adopted practices. Practices such as mulching, crop rotation, and cover cropping were also implemented by about 18-22% of households. Water harvesting structures like terracing were adopted by fewer than 10% of farmers. The adoption of a few other CFPs, such as zero tillage, minimum tillage, soil amendments, precision irrigation, and biopesticides, has dropped sharply, with their rates falling below 5% in both groups.

Overall, no statistically significant gender differences have been observed for any practice. A slightly higher percentage difference was observed between MHHs and FHHs for tree nursery establishment (MHH 3.2%; FHH 4.5%). However, the result was insignificant. The similarity in adoption rates across genders would be due to the equitable resource provision and training for both households.

Despite higher adoption rates of organic fertilizer use, the factors influencing agroforestry adoption will be analyzed because of its significant role in long-term carbon sequestration in the above and below-ground biomass and providing co-benefits (e.g., shade, biodiversity, soil fertility). This is a prerequisite for higher credit issuance under results-based methodologies, and agroforestry has been recognized as a core activity in many carbon credit projects.

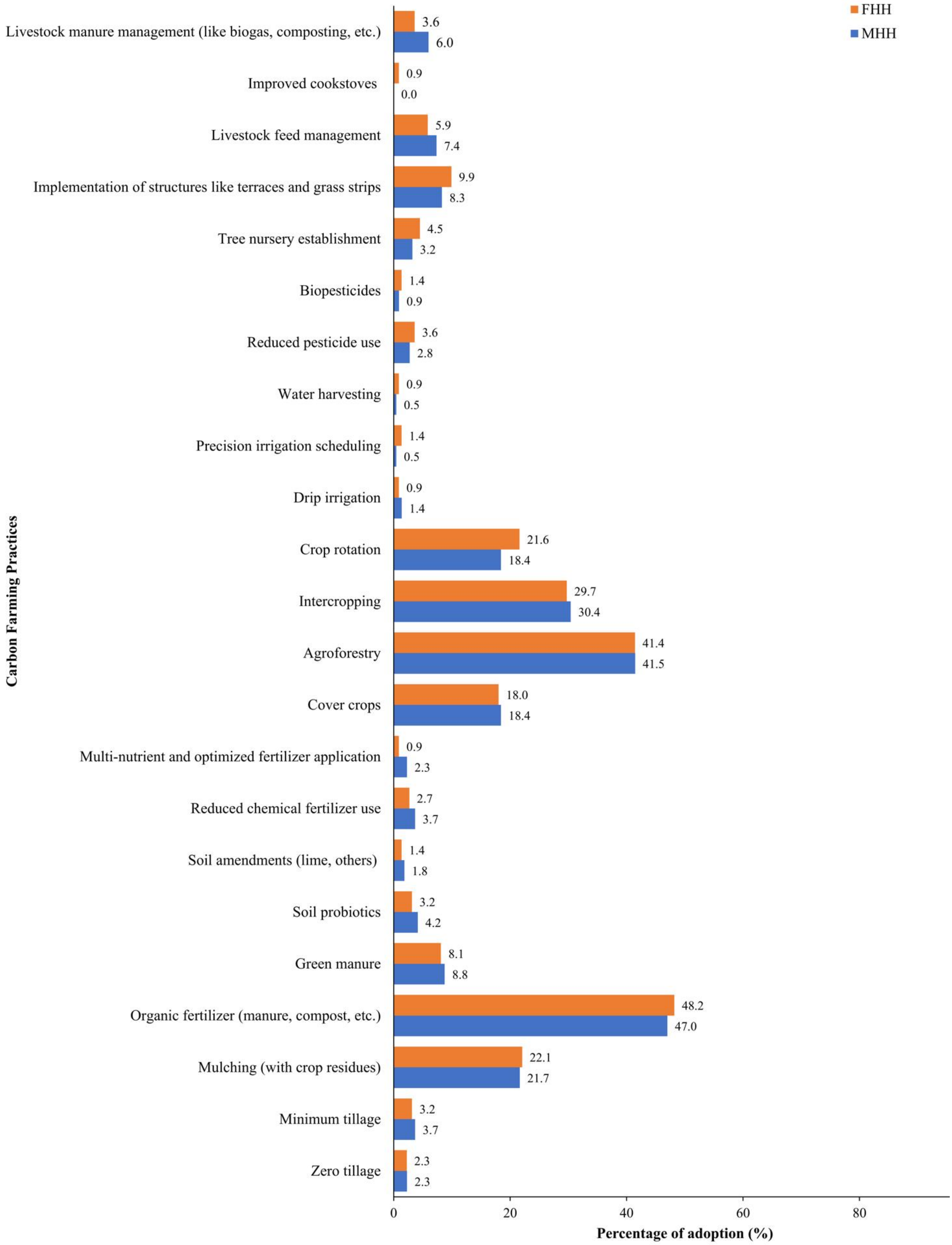

Figure 8. Adoption of carbon farming practices under carbon credit programs, disaggregated by gender of household head

5.2.2 Determinants of Agroforestry Adoption

Carbon farmers cultivated a larger land area than non-carbon farmers in the last 12 months (Figure 9, Table 5.1). From the t-test results, MHH carbon farmers (Mean: 0.717 ha) cultivated 31.8% more land than MHH non-carbon farmers (0.544 ha), and the differences were statistically significant ($t = –2.96$, $p < 0.01$). Similarly, FHH carbon farmers (Mean: 0.595 ha) cultivated 19% more land than MHH non-carbon farmers (0.544 ha). Though the difference was small, it is statistically significant ($t = –1.98$, $p < 0.05$).

The regression results show that the odds ratio (OR) of land size was negatively associated with AF adoption in both groups and statistically insignificant (MHH = 0.827; FHH = 0.844). However, the average marginal effects show an increasingly positive trend. Among MHHs, predicted probability declined from 44.3 pp at zero hectares to 25.4 pp at five hectares. In FHHs, the decline was weaker (41.9 pp to 39.5 pp), suggesting that land constraints may be less influential for women farmers in this context (Figure 12, Table 5.20).

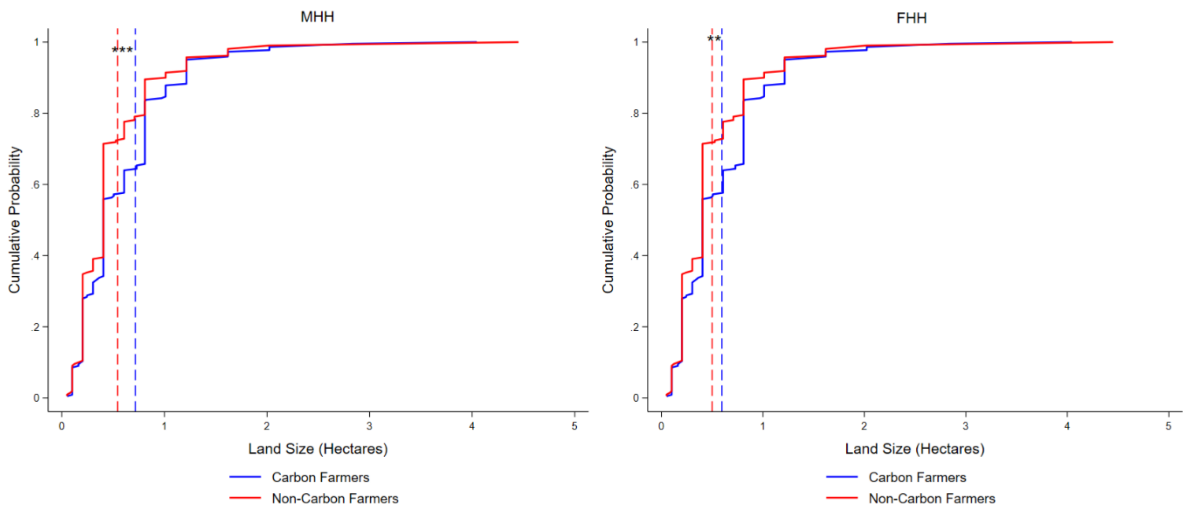

Figure 9. Cumulative distribution functions (CDFs) of cultivated land size among carbon and non-carbon farmers, disaggregated by gender

Project-level differences in the adoption of agroforestry have been noticed, and the adoption rates varied across projects and households. Each project has been implemented by different entities (project developers/implementers) in different counties (Table 10).

Table 10. Project classification, implementing entities, and associated counties

Project	County	Entity
1	Kisumu or Bungoma	ViAgroforestry
	-	Livelihoods Carbon Fund
2	Kakamega	Soil Carbon Certification Services, GIZ
3	-	ViAgroforestry
4	-	YaraEA, Farm to Market Alliance, Kenyan Organic Agriculture Network

Note: A dash (-) indicates that the project is not restricted to a specific county.

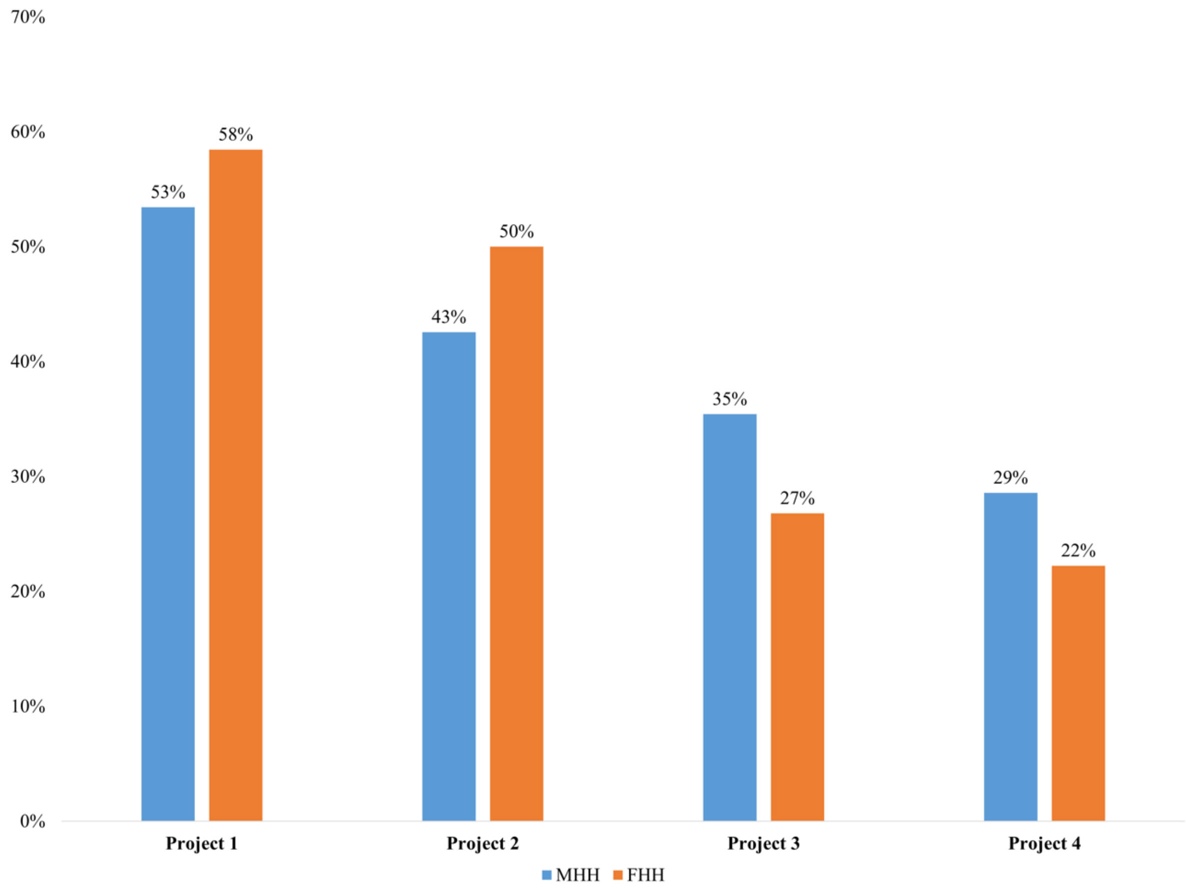

Figure 10. Project-wise share of farmers who adopted agroforestry, disaggregated by gender

FHHs showed a higher rate of adoption in projects 1 and 2, whereas in projects 3 and 4, MHHs displayed higher rates of adoption. Within MHHs, the proportionate difference is greater between projects, i.e., 29% in Project 4 and 53% in Project 1. Similarly, the range was from 22% in Project 4 to 58% in Project 1 among FHHs (Figure 10, Table 5.3). These patterns indicate the heterogeneity between project sites. However, the present analysis does not dive deep into this aspect.

The logistic regressions further confirmed these differences (Figure 11, Table 5.5). Farmers in Project 3 had 59% lower odds of adoption (OR = 0.41, $p < 0.01$) compared to Project 1. This corresponds to an 18.3 percentage point lower probability ($p < 0.01$). The negative influence persisted for both MHHs and FHHs. However, the effect was significant for FHHs (OR = 0.33, $p < 0.05$).

Ethnicity significantly influenced the adoption of agroforestry. The likelihood of agroforestry adoption is twice for Kalenjin farmers (OR = 2.10, $p < 0.10$), with the higher probability of 16.4 percentage points. Conversely, Luo farmers in pooled and FHH samples are significantly less likely to adopt ($p < 0.05$), with 21.4 pp and 26.4 pp lower probabilities, respectively. “Other” ethnic groups comprising Kamba, Kikuyu and Kisii showed three times higher probability of AF adoption in the pooled sample, but the result was only marginally significant (OR = 3.02; $p < 0.1$).

Organizational membership increased the likelihood of adopting agroforestry by nearly two times in the pooled sample (OR = 1.84, $p < 0.05$) and the MHH sample (OR = 2.22, $p < 0.10$). Although FHHs showed slightly increased likelihood of adoption, the results are not significant (OR = 1.34, $p = 0.480$). AMEs revealed that membership in an organization positively increased adoption probability from 28.1 pp to 44.9 pp for MHHs and from 35 pp to 43.2 pp for FHHs, equivalent to a 60% and 23% relative increase, respectively (Figure 12, Table 5.21)

Age and household size did not influence the probability of agroforestry adoption in all the models. But, average marginal effects of age (39.7 pp at 18 years to 42.7 pp at 80 years for MHHs; 32.4 pp to 48.6 pp for FHHs over the same range) and household size (39.1 pp with one household to 46.1 pp with 15 households for MHHs; 32.9 pp to 58.6 pp for FHHs over the same range) on AF adoption indicate that an increase in age and household size enormously raises the rate of adoption of agroforestry among both household heads (Figure 12, Tables 5.17 and 5.18).

Education effects were not significant in the pooled or gender-specific regressions, but marginal effects revealed some contrasts. In MHHs, the probability of AF adoption increased steadily from 33.33 percentage points with no formal education to 61.3 with university education. An increasing pattern has been observed among FHHs until vocational/diploma education (65.2 pp), but a sudden decrease was observed with university education (24.3 pp). The lower adoption among university-educated FHHs with a wide 95% confidence interval (–21.7 to 70.2 pp) and no significance may reflect small sample sizes and imprecise estimates (Figure 12, Table 5.19).

Overall, ethnicity, project affiliation, and organizational membership were the most consistent predictors of agroforestry adoption. Age and household size showed gradual positive associations in marginal effects, landholding size was negatively associated, and education patterns differed by gender.

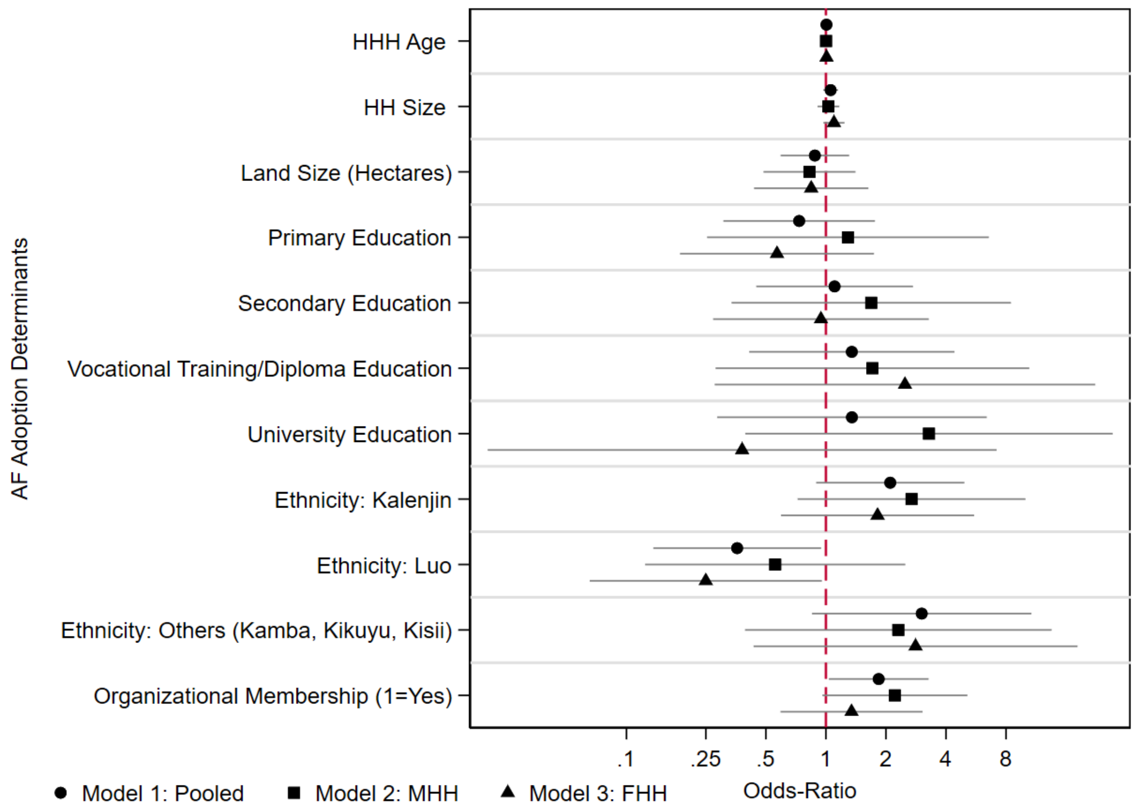

Figure 11. Socio-demographic and institutional determinants of agroforestry adoption

Note: The regression models adjust for project-level effects, which are not shown in the plot.

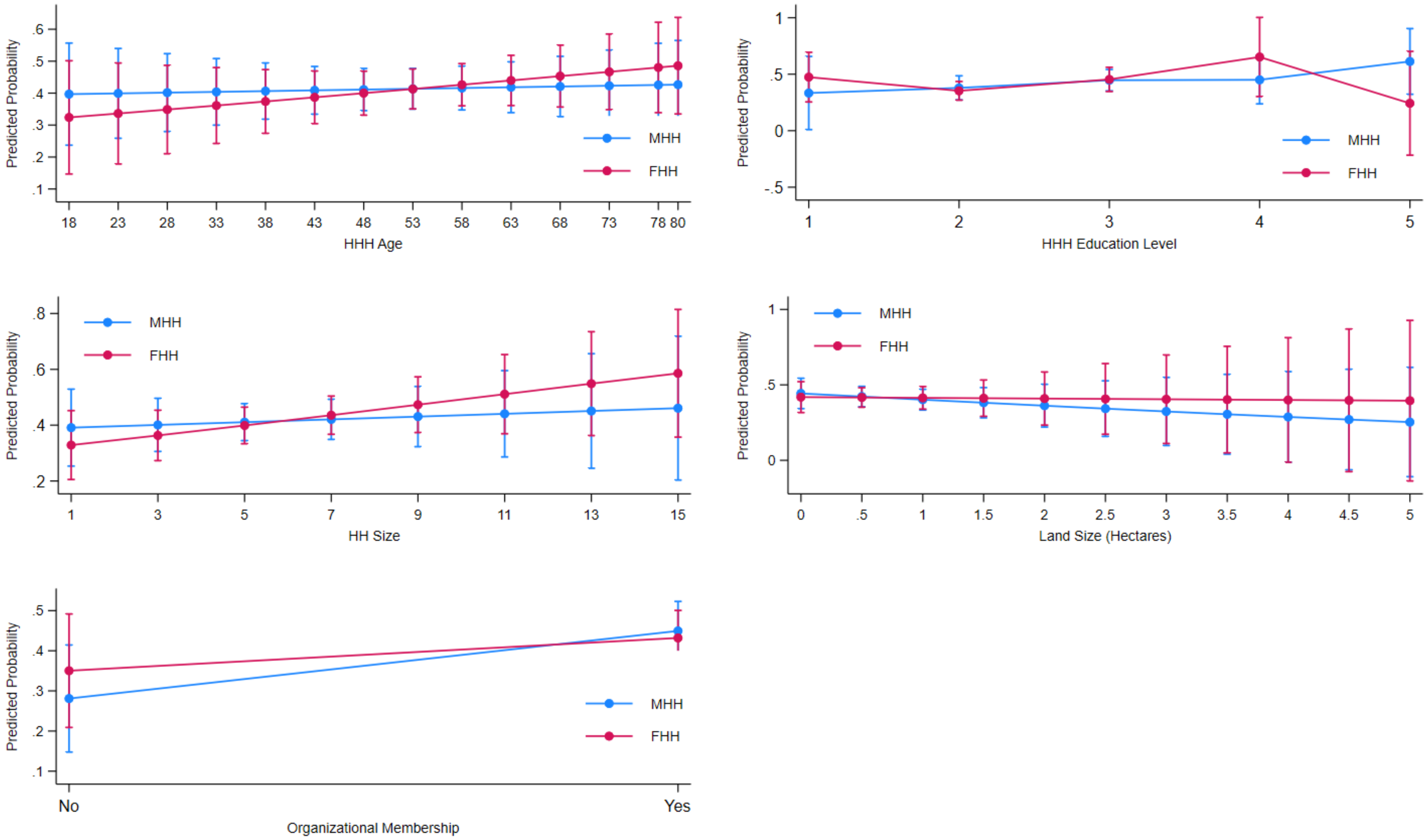

Figure 12. Average marginal effects of (a) age, (b) education, (c) household size, (d) land size and (e) organizational membership on agroforestry adoption by gender of household head

5.2.3 Determinants of Carbon Payment Receipt

Descriptive results for carbon credit payment receipt (Figure 13, Table 6.1) also show marked between-project variation. Among MHHs, payment rates ranged from 0% in Projects 3 and 4 to 74% in Project 2. Among FHHs, rates ranged from 2% in Projects 3 and 4 to 64% in Project 2. In Project 1, a higher proportion of FHHs (43%) than MHHs (36%) received payments, whereas in Project 2, the pattern was inverse. The complete or near absence of payments in Projects 3 and 4 contrasts sharply with the high rates in Project 2, indicating strong project-level determinants.

Regression results further confirmed the strong project effects (Figure 14, Table 6.3). Farmers affiliated with Project 3 (OR = 0.010, $p < 0.01$; AME = –36.2 pp) and Project 4 (OR = 0.027, $p < 0.05$; AME = –35.1 pp) significantly received too minimal payments. Project 2 had a high OR of 5.131, but the result was not significant. But the AME has a marginally positive effect (+34.1 pp, $p < 0.10$). These patterns were consistent across both genders.

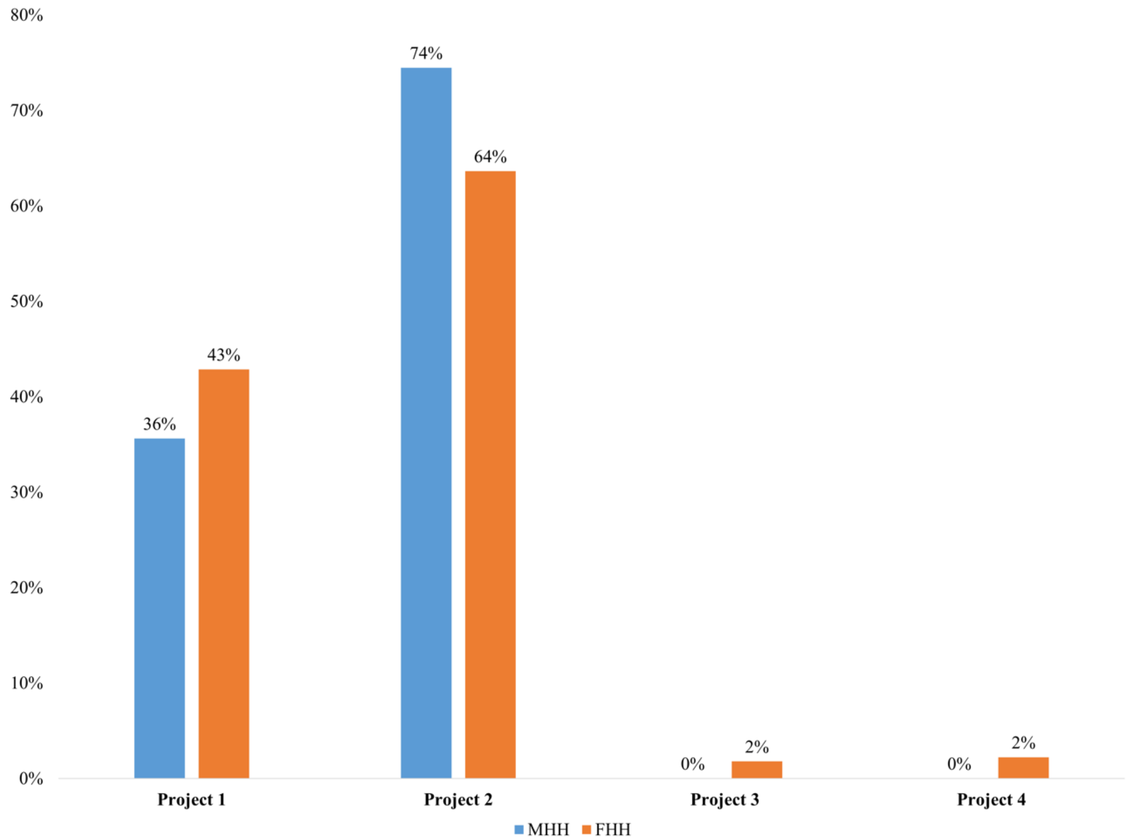

Figure 13. Project-wise share of farmers who received carbon payments, disaggregated by gender

Ethnicity strongly influenced payment receipt. In the pooled model, belonging to the Kalenjin group reduced the odds by 71% (OR = 0.287, $p < 0.05$; AME = –14.2 pp), and belonging to the "Others" category reduced odds by 89% (OR = 0.108, $p < 0.01$; AME = –22.9 pp) compared to the Luhya reference group. The Luo ethnicity showed no significant difference. Gender-specific results indicated similar negative effects for Kalenjin and "Others" across both MHHs and FHHs (Figure 15).

Membership in a farmer organization had a marginally positive association (OR = 1.95, $p < 0.10$; AME = +7.95 pp). Marginal effects showed that membership increased payment probability from 24.3 pp to 30 pp for MHHs and from 17.8 pp to 29.1 pp for FHHs, corresponding to a 23% and 63% relative increase, respectively (Figure 15, Table 6.17).

Land size was not a significant predictor of carbon farming payment, despite positive odds (OR = 1.304, p = 0.249). However, marginal analysis revealed a steady increase in payment probability with larger landholdings. For MHHs, the probability rose by 17.9 pp and for FHHs by 10.2 pp over zero to five hectares of land size (Figure 15, Table 6.16).

Age was not a significant factor influencing the CF payment (OR = 1.012, $p = 0.27$), but marginal effects showed a clear positive trend for both genders (Figure 15, Table 6.13). For MHHs, predicted payment probability increased from 24 pp at 18 years to 32.5 pp at 80 years (35% relative increase). For FHHs, the increase was from 22.1 pp to 30.8 pp (39% relative increase).

Education effects were mixed, and farmers with vocational training/diploma education were negatively associated with payment receipt (OR = 0.173, $p < 0.05$; AME = –19.4 pp). Marginal effects showed that for MHHs, payment probability declined from 48.8 pp for those with no formal education to 11.6 pp for those with vocational training/diploma education ($p < 0.10$), corresponding to a 76% relative decrease. Among FHHs, the highest probability was for primary education (29.5 pp), while university education showed a lower probability (23.3 pp) but with a wide confidence interval (–7.6 to +54.2 pp), reflecting small sample sizes (Figure 15, Table 6.15).

Adoption of agroforestry showed an increased likelihood of CF payment receipt with insignificant odds (OR = 1.224, $p = 0.48$; AME = +2.35 pp). However, the interaction effects with gender positively predicted payment receipt for MHHs (32.6 pp for adopters vs. 25.6 pp for non-adopters), equivalent to a 27% relative increase. Contrastingly, there is a slightly negative probability for FHHs (26.3 pp for adopters vs. 28.6 pp for non-adopters), equivalent to an 8% relative decrease (Figure 15, Table 6.14).

Overall, these results confirm that socio-demographic and institutional factors such as project affiliation, ethnicity, and organizational membership were significantly associated with carbon farming payment receipt. On the other hand, the age of the household head and land size positively predicted the payment receipt in both genders. Education effects were mixed, showing MHHs with no formal education and primarily educated FHHs having higher payment probabilities. Among both households, vocational training/diploma-qualified farmers have a lower probability of receiving carbon payments. Notably, agroforestry adoption did not guarantee payment receipt, indicating that other eligibility, performance, or project-specific criteria may be decisive.

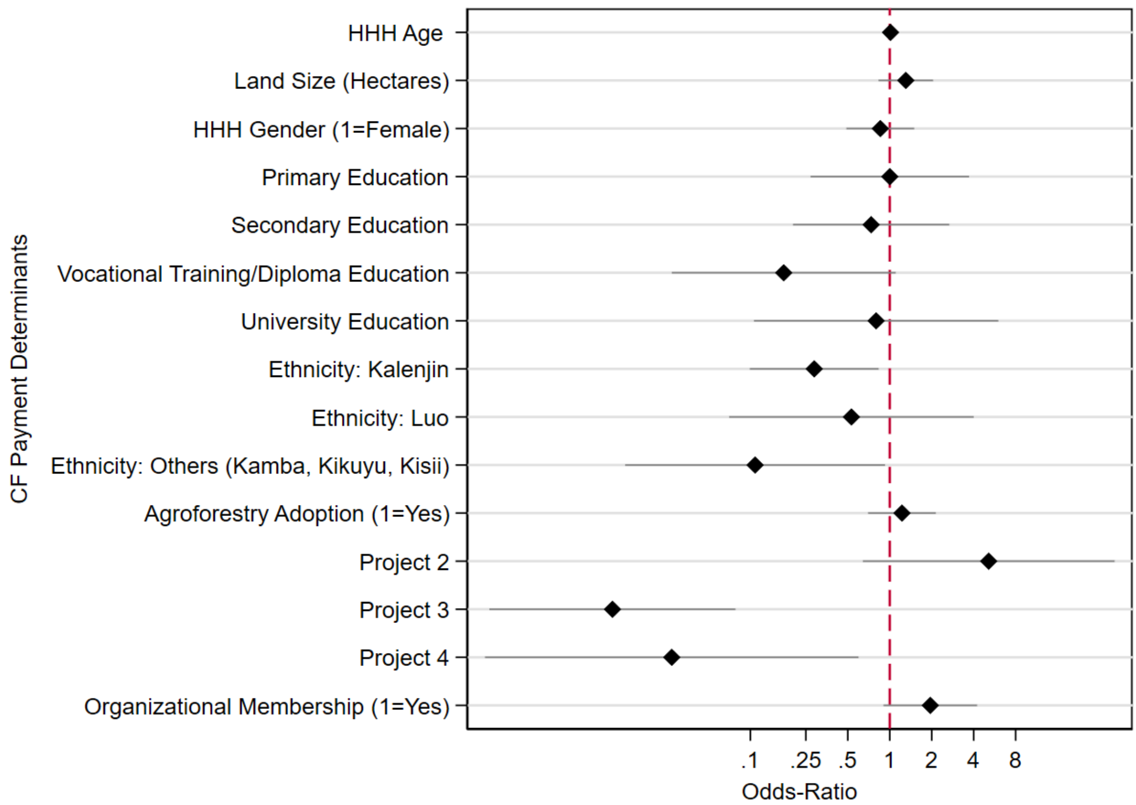

Figure 14. Determinants of carbon farming payment receipt, including socio-demographic, institutional and contextual factors

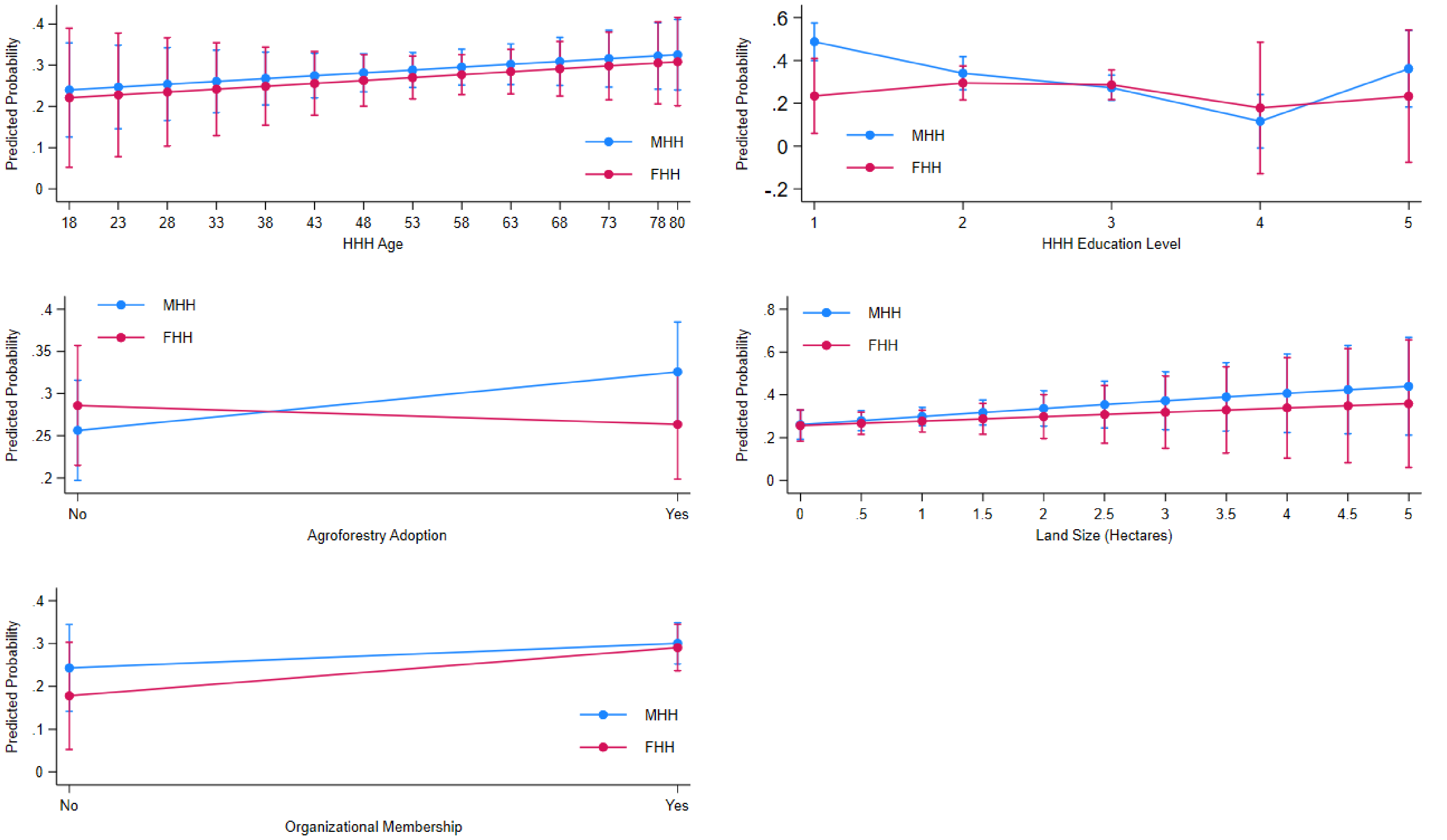

Figure 15. Average marginal effects of (a) age, (b) education, (c) agroforestry adoption, (d) land size and (e) organizational membership on carbon farming payment by gender of household head

5.3 Determinants of Carbon Farming Participation

Socio-demographic and institutional factors influencing participation in the carbon farming program across pooled, male- and female-headed households are presented in this section. Results from the logistic regression (Figure 16, Table 7.2) and average marginal analysis (Figure 17) indicate notable differences between the genders of the household heads.

Age of the household head was the most consistent and robust predictor across all models. From the results, it is understood that an increase in age increased the odds of participation by 4.9% (OR = 1.049, $p < 0.01$). In gender-specific regressions, the effect remained strong for MHHs (OR = 1.037, $p < 0.01$) and even stronger for FHHs (OR = 1.065, $p < 0.01$). Additionally, the average marginal effects positively predicted the probability of participation for both genders (Figure 17, Table 7.14). In MHHs, the probability increased from about 31 pp at 18 years to 70 pp at 80 years, equivalent to a 125% relative increase. The effect was much stronger for FHHs, corresponding to a 350% relative increase (from about 18 pp to over 83 pp).

Education level, particularly secondary education, had a strong prediction over CF participation in the pooled sample (OR = 2.46, $p < 0.05$) and among MHHs (OR = 3.58, $p < 0.05$), while only marginally significant for FHHs (OR = 2.31, $p < 0.10$). AMEs notably showed a significant decreasing trend for FHHs with vocational training/diploma education (46.35 pp) before rising again with university education (60.57 pp). It is vice versa for MHHs, where vocational training/diploma education (57.39 pp) showed the highest probability and subsequently dropped for university qualification (52.37 pp) (Figure 17, Table 7.16).

Having membership in the farmer group or organization strongly predicted the participation across all models (Pooled OR = 6.23, $p < 0.01$; MHH OR = 5.80, $p < 0.01$; FHH OR = 6.96, $p < 0.01$). Membership increased the likelihood of CF participation by nearly six times (OR = 6.23, $p < 0.01$) in the pooled sample, compared to non-members. Further, marginal effects showed that membership raised participation probability by the difference of 36 and 38 percentage points for MHHs and FHHs, respectively (Figure 17, Table 7.18).

Pooled (OR = 6.38, 95% CI = 2.04-19.96) and male-headed households (OR = 8.75, 95% CI = 2.13-35.88) in Kisumu County showed significantly higher participation odds compared to Trans Nzoia. Despite nearly five times the increased odds of participation, the result was not significant for FHHs. But the average marginal effect was marginally significant for FHHs in Kisumu with 27 percentage points ($p < 0.1$).

Ethnicity effects were negative for some groups. Kalenjin and Luo farmers decreased the odds of participation in carbon farming compared to the Luhya. Pooled sample (OR = 0.36, $p < 0.1$), Kalenjin MHHs (OR = 0.41, $p < 0.1$) and Luo MHHs (OR = 0.30, $p < 0.1$) showed marginal significance. None of the ethnic groups showed significance for FHHs.

Household size and land size were not statistically significant in the regressions. However, marginal effects displayed gradual positive associations with an increase in household members and land availability (Figure 17, Tables 7.15 and 7.17). For example, in MHHs, participation probability surged from 48 pp at 0.5 ha to 70 pp at 5 ha, corresponding to a 46% relative increase and for FHHs, a 25.5% increase has been observed over the same range of land area. Furthermore, the main source of income from agriculture marginally influenced the likelihood of participation in CF programs among pooled households (OR = 1.69, $p < 0.1$) and MHHs (OR = 2.41, $p < 0.1$).

In summary, age and organizational membership showed positive odds and strongly influenced the carbon farming participation across all the models, whereas education effects were mixed and varied based on the level and gender. County of residence, especially Kisumu, positively influenced the outcome, except for FHHs. Ethnicity mattered more for men than women, with negative associations for Kalenjin and Luo farmers. Landholding and household size showed only gradual effects visible in marginal analysis, and agricultural income source effects were limited to MHHs.

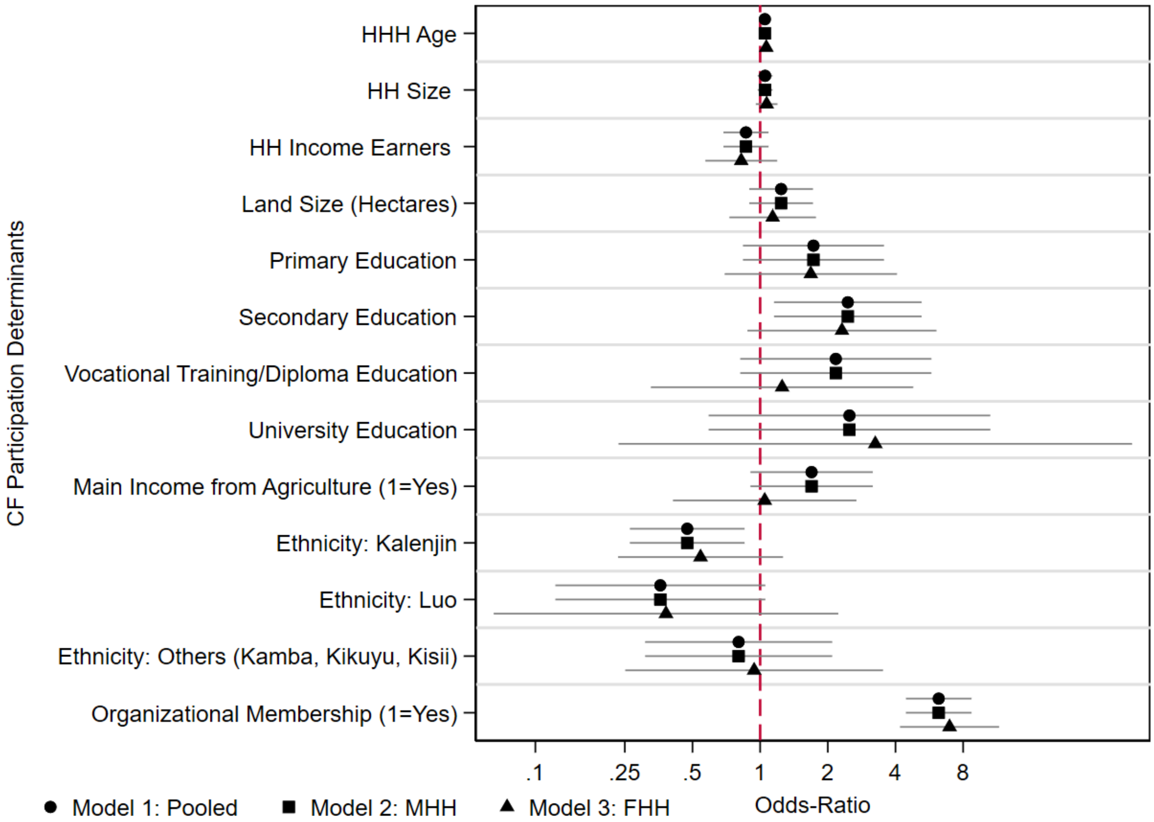

Figure 16. Socio-demographic and institutional determinants of carbon farming participation

Note: The regression models adjust for county-level effects, which are not shown in the plot.

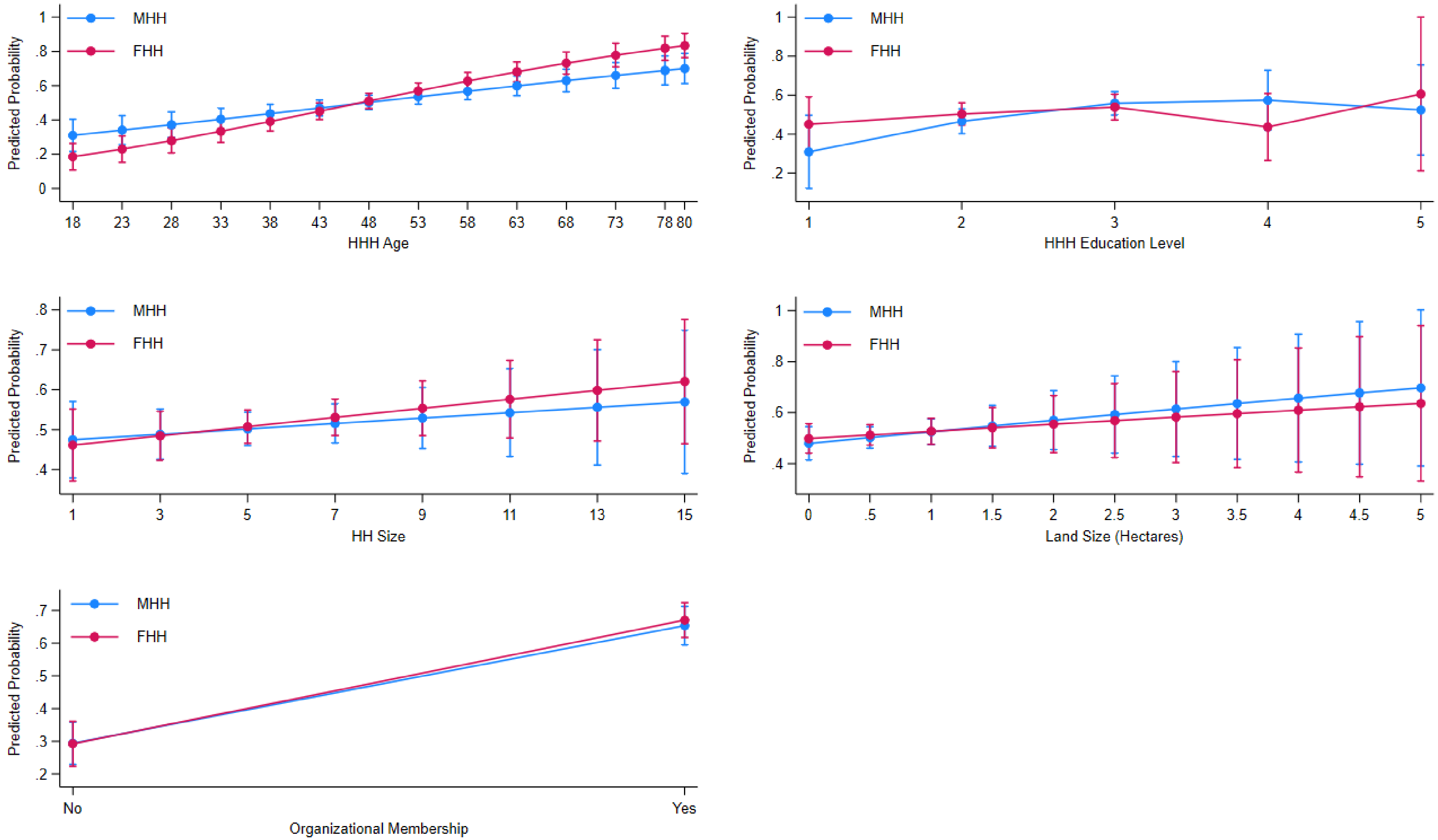

Figure 17. Average marginal effects of (a) age, (b) education, (c) household size, (d) land size and (e) organizational membership on carbon farming participation by gender of household head

6. Discussion

6.1 Motivations and Barriers Influencing Carbon Farming Participation

6.1.1 Motivations

The results of this research indicate that production and environmental concerns are the major drivers for farmers to participate in carbon farming programs. Poor soil health (35-37%) and declining productivity (20-24%) are the most cited reasons for participation by both households. Furthermore, increasing input costs and decreasing profitability in conventional agriculture motivated 10% of them to shift to carbon farming by joining the programs. These results are aligned with studies highlighting that smallholder farmers are motivated by ecosystem services such as improved soil quality, offered by carbon farming practices, which reduces the burden of using additional inputs while enhancing agricultural productivity and profits (Antwi-Agyei et al. 2021; Buck & Palumbo-Compton 2022; Ogisi & Begho 2023; Schilling et al. 2023; Figueredo 2024). For instance, the Kenya Agricultural Carbon Project (KACP) reported that agroforestry and terracing practices addressed the soil degradation problem and boosted maize yields by 30-50%. This resulted in higher food self-sufficiency and input cost savings compared to those who do not practice carbon farming (Öborn et al. 2017; Nyberg et al. 2020). The climate reports from the county government and research studies in Western Kenya further support the existence of the above risks, affecting the livelihoods of farmers (MoALF 2018a, 2018b; De Giusti et al. 2019; Reppin et al. 2020; MoALFC 2021a, 2021b). Therefore, the study farmers' emphasis on soil health, agricultural productivity, and decline in profitability as a driver to join the CF programs reflects the significant role of carbon farming in addressing livelihood challenges imposed by the effects of soil degradation due to climate change, high population density, and intensive land use in Western Kenya (De Giusti et al. 2019; Karanja & Jalango 2019; Reppin et al. 2020).

The percentage of FHHs (50%) who reported yield benefits as a motivation was higher than that of MHHs (41%), and a statistically significant gender difference (χ^2 $p = 0.059$) was observed. This finding is consistent with a case study of KACP, where female farmers prioritized practices providing short-term tangible benefits, such as for household food security (Lee 2017). Farmers' identities would also have shaped these motivations because most of the male households identified themselves as sugarcane farmers (in Kitale) or fishermen (in Kisumu), occupations linked to the market sphere of the economy. Such identities reduced their interest in interventions aimed at boosting food crop productivity. Contrastingly, more women were willing to adopt practices that directly enhance subsistence crop yields and food security, linked to the household sphere (Lee 2017). This gendered pattern suggests that carbon farming programs could increase participation rates by tailoring interventions that address women's priorities, such as household food security.

Financial incentives for carbon sequestration are a key driver in countries like Kenya, where agricultural incomes are often unpredictable (Nandakishor et al. 2022; Jassim et al. 2022; Schilling et al. 2023; Figueredo 2024). However, carbon farming as an opportunity for additional income motivated only 16-18% of MHHs and FHHs, with no statistically significant difference between the groups. For instance, the KACP paid an average of USD 1.97 per hectare annually for sequestering carbon in the soil. But deductions and low carbon prices substantially reduced direct payment benefits (Lee 2017; Öborn et al. 2017). In contrast, projects such as WKCP do not pay carbon revenues to farmers, instead investing it in the project to cover the costs of advisory services and inputs for 30 years (Tennigkeit et al. 2023). From this study, it is understood that farmers value co-benefits such as yield improvements, which are more immediate and certain than carbon payments. The interview answers provided by KACP farmers also revealed that only 10% prioritized carbon payments, while many described them as *"kidogo kidogo"* (very small) (Lee 2017). This reflects a similar trend to our study, highlighting the need to emphasize co-benefits to strengthen participation, as ecological and production-related motivations outweigh direct economic incentives for resource-constrained farmers in Western Kenya.

The channels through which farmers learned about carbon farming and who trained them play an influential role in motivating participation. Extension agents (37-40%) and group meetings (24-28%) are the primary information sources for both MHHs and FHHs. The empirical evidence from Western Kenya, Cameroon, and Ethiopia shows that regular contact with extension agents significantly influenced the adoption of CFPs such as cover cropping, soil and water conservation, farmyard manure application, and crop diversification (Diro et al. 2022; Musafiri et al. 2022; Ngaiwi et al. 2023). However, their effectiveness at the practice level is still a question, with limited competence noted in certain practices like animal manure application and terracing (Karanja & Jalango 2019; Musafiri et al. 2022).

Notably, FHHs (14%) were more reliant on fellow farmers than MHHs (10%) for the information, though this difference was not statistically significant. Women in Kenya often depend on homogenous social groups (women-based) that facilitate information exchange due to their limited access to formal channels like extension services (Ngigi & Muange 2022). Such reliance on peer networks among FHHs suggests that social capital plays a crucial role in their engagement with carbon farming, mainly due to the limited access to other information sources, such as extension officers or print media, which are more utilized by MHHs (Ngigi et al. 2017; Ngigi & Muange 2022). However, the limited role of radio (2.3% MHHs, 0.45% FHHs) as an information channel, despite approaching statistical significance (χ^2 p = 0.098), contradicts studies indicating that Kenyan women rely more on radio and social groups for information (Ngigi et al. 2017; Ngigi & Muange 2022). This discrepancy may reflect the dominance of in-person channels within carbon farming programs, where technical knowledge transfer is effective and radio may be less effective.

NGOs (51-53%) and carbon project developers (40-44%) were the main organizers of carbon farming training. The prominence of NGOs underscores their role as key implementation partners in most carbon projects, because of their local knowledge and good rapport with farmers for capacity building, as seen in initiatives such as KACP, WKCP, TBGF, and Boomitra (Öborn et al. 2017; Tennigkeit et al. 2023; Boomitra Inc 2025; Verra 2025). Farmer-to-farmer training was nearly absent (<0.5%), as seen in a study by Lee (2017), who found that only five out of 205 farmers in KACP supported each other in implementing SALM practices. This limited potential of peer-to-peer knowledge sharing presses the need for leveraging social capital and using this as a complementary channel for scaling adoption.

6.1.2 Enabling Conditions

Carbon company support, their engagement, and raising awareness about carbon credit ownership among farmers enable increased participation in carbon farming programs through extrinsic motivation. This study reveals that most farmers received a combination of carbon credits and technical information support (55% MHHs, 59% FHHs) from the carbon company (also known as the carbon project developer) to carry out the package of practices. Providing technical assistance other than carbon payments has been a widely adopted approach in KACP and WKSACFP, implemented by Vi Agroforestry. The result-based payments are disbursed after a successful MRV, while technical services are disseminated continuously to engage farmers in the project seamlessly (Shames et al. 2012; Öborn et al. 2017; Nyberg et al. 2020; Raina et al. 2024). In some cases, such as WKCP, carbon revenues are invested in the project to cover technical advisory costs instead of paying farmers directly (Tennigkeit et al. 2023). Interestingly, a notable share of farmers reported receiving only carbon credits as support (28% MHHs, 26% FHHs). This approach is neither usual nor supported by much of the literature, except in a study on Costa Rica's Regional Integrated Silvo-pastoral Ecosystem Management Project (RISEMP), which highlights that cash payments alone are insufficient to guarantee the permanence of land-use (Rasch et al. 2021). Further, no significant gender differences in support package distribution signify relatively equitable access to program resources for both MHHs and FHHs, which is important for addressing gendered adoption barriers. However, only a low proportion of farmers receiving material support like farm inputs or livestock (10–12%) indicates a reliance on carbon credits as the primary incentive. This may limit participation among resource-constrained farmers, particularly FHHs. For example, KACP did not provide free tools, seedlings, cash, or credit (Lee 2017). Expanding material support could enhance participation, especially for women, who often face greater socio-economic and cultural constraints limiting access to productive resources.

The farmers enrolled in carbon farming programs were engaged by providing training through various extension agents, and 89% MHHs and 93% FHHs acknowledged that they received training. However, fewer farmers had signed contracts (36-38%) and received payments (8% MHHs, 28% FHHs). The higher payment receipt among FHHs is notable but not statistically significant and may reflect targeted inclusion efforts in programs like KACP and WKSACFP, which prioritize women in empowerment-focused initiatives (Shames et al. 2012; Lee 2017; Öborn et al. 2017). The low proportion of payment receipts display concerns of payment delays and deductions, as in KACP, where only 90% of sequestered carbon is paid out to account for uncertainties (Lee 2017; Öborn et al. 2017; Raina et al. 2024).

Yearly payments were the most frequent arrangement (57% MHHs, 63% FHHs), consistent with the annual monitoring of the project and the long-term nature of carbon sequestration contracts. A similar approach has been noticed in the TGB program in Uganda and the Emiti Nibwo Bulora (ENB) program in Tanzania, where payments were disbursed every year once the project had been initiated (Lee et al. 2016; Öborn et al. 2017). Nearly a quarter of farmers (25-33%) revealed the presence of "other arrangements", which may create uncertainty or confusion among farmers due to variability in payment structures. This is a rising concern observed in studies on volatile carbon markets and complex scheme designs (Lee et al. 2016; Raina et al. 2024). To overcome this payment-related uncertainty, flexible schedules that combine upfront and performance-based payments would be ideal to increase smallholder participation by lowering financial risks and fulfilling the needs of farmers in Western Kenya (Raina et al. 2024).

The farmers had moderate awareness of who owns the carbon credits (56–61%), which necessitates the need for enhanced transparency and sensitization regarding the benefit-sharing mechanism (Mayr et al. 2025). Such a clear understanding of land rights and carbon credit ownership is vital for companies developing nature-based projects and farmers, ensuring both project continuity and long-term risk mitigation. Current policy uncertainties in Kenya further exacerbate these issues, pressing the significant requirement for regulatory clarity (Alliance 2024).

6.1.3 Barriers

Despite various intrinsic and extrinsic motivations among farmers, the lack of awareness about carbon farming emerged as the most significant barrier to participation (53% MHHs, 55% FHHs). This finding is corroborated by studies emphasizing that many farmers are unfamiliar with carbon farming benefits and market processes, necessitating robust extension services and capacity-building (Lee 2017; Lal 2020; Wongpiyabovorn et al. 2021; Schilling et al. 2023; Kashyap et al. 2024; Raina et al. 2024; Awazi et al. 2025;

Mayr et al. 2025). The lack of significant gender differences in awareness suggests that informational constraints exist irrespective of gender. Limited outreach would likely be a cause, and in WKCP, a major share (76%) of costs for extension services illustrates the importance of strengthening outreach (Tennigkeit et al. 2023). Further, the hindrance of not knowing how to enroll in the program or lack of approach by the project staff (30% MHHs, 23% FHHs), with a near-significant gender difference (χ^2 $p = 0.099$), highlights the limited outreach efforts by the project team. Sufficient assistance with the enrollment process otherwise would have attracted farmers to join the carbon farming programs. This is consistent with observations that complex scheme designs, and bureaucratic hurdles discourage participation (Lee 2017; Sharma et al. 2021; Figueredo 2024; Pudasaini et al. 2024; Mayr et al. 2025). In particular, the company rejected the enrolment of 1% FHHs. Although the percentage is minimal, the scope for potential gender-specific barriers, possibly linked to cultural norms or resource constraints, would limit women's eligibility (Ogisi & Begho 2023).

Constraints, such as insufficient land size (8%), align with the identification of small farm sizes (<1 ha) as an eligibility barrier to carbon farming participation in Western Kenya. For example, farmers who have more than 0.5 hectares were eligible to participate in the KACP (Lee 2017). Though only a few farmers mentioned payment delays and lack of any payments in the village, these concerns reflect uncertainties and risks associated with volatile carbon markets and non-permanence that may deter participation (Lee 2017; Öborn et al. 2017; McDonald et al. 2021; Sharma et al. 2021; Schilling et al. 2023; Tennigkeit et al. 2023). A considerable number of farmers (6% MHHs, 10% FHHs) cited "other" reasons, which may include unlisted barriers like cultural restrictions, low social status or personal interests (Ogisi & Begho 2023). The path dependency of existing government policies, which favour traditional farming, can also hinder the shift towards carbon farming, particularly for women (Kashyap et al. 2024).

6.1.4 Implications and Recommendations

The research findings highlight that motivations for participating in carbon farming programs are almost similar across genders. But subtle differences, such as FHHs' greater emphasis on yield benefits and their reliance on peer networks, point to opportunities for more gender-responsive program design. Also, the limited salience of carbon credits, often overshadowed by tangible benefits such as higher yields and improved soil health, implies that promoting ecological co-benefits is as important as economic incentives for increased participation. Extension services and group-based trainings should be strengthened through a "training for trainers" program to address persistent awareness gaps and increase grassroots-level knowledge of trainers. It is important to expand material support, such as inputs, seedlings or tools, alongside carbon credits to reduce financial barriers, especially for resource-constrained FHHs. Equally, simplifying enrolment processes, increasing transparency around carbon credit ownership and delivering timely payments, while leveraging hybrid payment models, could mitigate both outreach and uncertainty-related barriers.

Future studies need to delve into the "other" barriers reported to identify possible gender-specific constraints attributed to cultural norms, decision-making within the household, or access to assets, which could be hindering equitable participation. Longitudinal studies would also be useful in determining the long-term effect of various payment arrangements on participation, with implications for how inclusive and scalable carbon farming programs can be developed. Such initiatives are particularly urgent for FHHs, as they still experience distinct challenges at the enrolment and implementation phases, despite receiving higher carbon payments.

6.2 Adoption of Carbon Farming Practices

6.2.1 Adoption Patterns

From earlier studies, it is obvious that farmers in Western Kenya widely adopt carbon farming practices in response to severe soil fertility degradation and due to the initiatives of pioneer carbon farming programs (De Giusti et al. 2019; Karanja & Jalango 2019; Nyberg et al. 2020; Reppin et al. 2020; Musafiri et al. 2022; Schilling et al. 2023; Raina et al. 2024). Such practices not only improve soil health but also contribute to higher household income and food security (Nyuma et al. 2025). However, the extent of adoption varies from region to region, depending on the physiographic features and household objectives (Karanja & Jalango 2019; Buleti et al. 2023 & Nyuma et al. 2025).

This research revealed that organic fertilizer use (47% MHHs, 48% FHHs), agroforestry (41% for both groups), and intercropping (30% MHHs, 29% FHHs) were the three most widely adopted practices out of 23 among carbon farmers, with no statistically significant gender differences (χ^2 $p > 0.05$). While this result mimics broader trends in Western Kenya (Buleti et al. 2023), the adoption rates in this study are substantially lower than those reported elsewhere. For instance, the adoption of agroforestry and intercropping ranged between 62-73% and 74-76% respectively, in Vihiga and Kakamega counties of Western Kenya, which is much higher than in our study (Karanja & Jalango 2019; Buleti et al. 2023). In the same way, mulching, crop rotation, and cover cropping were adopted by only 18-22% of farmers, compared to much higher rates in previously published studies. This pattern is not consistent with published evidence that crop rotation and intercropping (e.g. legume-maize) are practiced by nearly all farmers in Western Kenya (Karanja & Jalango 2019) and mulching by around 60% of KACP participants (Nyberg et al. 2020). However, a mixed effect has been observed in KACP for cover cropping as the adoption increased from 10% in 2009 to 55% in 2011 before falling again to 10% in 2012 (Nyberg et al. 2020).

Water harvesting structures like terracing were adopted by fewer than 10% of farmers despite their importance in reducing the vulnerability to soil erosion in the region. In other studies, 60% of KACP farmers (Bungoma and Kisumu) and 67% of Murang’a farmers (Nyberg et al. 2020; Irungu et al. 2024). Further, Karanja & Jalango (2019) found that terracing was prevalent in Vihiga (78%) due to its hilly terrain and higher erosion risk than in Kakamega (62%).

The adoption of CFPs like zero tillage, minimum tillage, soil amendments, precision irrigation, and biopesticides has dropped sharply, with its adoption rates falling below 5%. In a study carried out in Embu County, only 14% of farmers adopted conservation tillage practices, such as zero and minimum tillage (Jena 2022). Nyberg et al. (2020) also reported that farmers affiliated with KACP rarely applied them. The adoption inconsistencies would be due to high upfront costs, specialized equipment needs, knowledge constraints, and a greater preference for practices that provide immediate, visible benefits (e.g., organic fertilizers) over those with long-term benefits (e.g., zero/minimum tillage). In resource-constrained settings, the scalability of capital-intensive practices is a critical question. This urges the need to balance long-term climate goals with farmers' short-term livelihood priorities.

In this study, there is an absence of major differences in adoption rates among household heads, compared to published studies that documented gendered inequalities in resource access, decision-making, and practice choice (Bernier et al. 2015; Lee 2017; Mungai et al. 2017; McDonald et al. 2021; Ngigi & Muange 2022; Li et al. 2023; Ogisi & Begho 2023; Schilling et al. 2023; Hailemariam et al. 2024). For example, the literature found that women tend to favour crop-based practices like intercropping for food security, whereas men prefer agroforestry due to greater land ownership and tenure rights (Lee 2017; Karanja & Jalango 2019; Waaswa et al. 2022; Ngaiwi et al. 2023). Such gender neutrality observed here may be a result of standardized training and resource provision in carbon programs, which mitigate barriers such as unequal credit access and knowledge gaps.

Nonetheless, the slightly higher adoption of tree nursery establishment among FHHs (4.5% vs. 3.2% for MHHs) suggests subtle gendered preferences, likely driven by women's focus on household-oriented benefits such as fuelwood and fodder. This pattern resonates with evidence that women incline toward agroforestry practices with lower commercial value, shaped by cultural norms and empowerment-oriented interventions (Musafiri et al. 2022; Li et al. 2023). In many cases, trees are planted primarily for shade, fodder, or fuelwood, which is of women's household interests, rather than for nutrient cycling or yield enhancement. This tendency is due to limited management knowledge (e.g., pruning for green manure), long time lags in benefits, or competing household priorities (Nyuma et al. 2025).

6.2.2 Determinants of Agroforestry Adoption

Agroforestry's high adoption among carbon farmers in Western Kenya reflects its centrality in carbon credit methodologies, such as the Verified Carbon Standard (VCS), due to its capacity for long-term carbon sequestration in both above and below-ground biomass, as well as co-benefits like biodiversity, shade, and improved soil health (De Giusti et al. 2019; Nyberg et al. 2020; Reppin et al. 2020; Santhyami et al. 2023; Awazi et al. 2025; Mayr et al. 2025). To identify the socio-demographic factors influencing agroforestry adoption, the logistic regression analysis has been performed for pooled, MHH and FHH samples. From the results, ethnicity, project affiliation, and organizational membership were recognized as significant predictors in the pooled model. For MHHs, organizational membership had a positive influence on adoption, whereas FHHs belonging to the Luo ethnic group and those in Project 3 had a significant negative influence. Further, factors such as age, education, land size, and household size showed increasingly positive marginal effects with gender.

The likelihood of agroforestry adoption is twice for Kalenjin farmers (OR = 2.10, $p < 0.10$), with the higher probability of 16.4 percentage points. Conversely, Luo farmers in pooled and FHH samples are significantly less likely to adopt ($p < 0.05$), with 21.4 pp and 26.4 pp lower probabilities, respectively. These results are in contradiction with the findings of Mungai et al. (2017), who found that Luo communities adopt a higher rate of agroforestry than Kalenjin in Kisumu and Kericho counties of Western Kenya. From Mungai et al. (2017), it is evident that the farmers in the Kalenjin group hold larger land sizes than the Luo, encouraging them to adopt land-intensive practices like agroforestry. The reason for Luo FHH's non-adoption would be attributed to the socio-cultural norms, such as intra-household conflicts among women (e.g. mother-in-law vs daughter-in-law) over agricultural activities, interest towards early maturing crop varieties and resistance towards the new practices. This is a major problem, especially if the FHHs are younger, as most of the decisions are taken in accordance with the eldest family member (Mungai et al. 2017). Additionally, women in some cultures of SSA are restricted from adopting agroforestry, perceiving it as a culturally inappropriate action (Ogisi & Begho 2023). Further, the other ethnic groups, such as Kamba, Kikuyu and Kisii, altogether have a three times higher probability of adoption of agroforestry in the pooled sample, and the result is marginally significant (OR = 3.02; $p < 0.1$). This shows that ethnicity and accompanying gender dynamics play an important role in the uptake of agroforestry practices.

The adoption of agroforestry is negatively influenced by the project affiliation in pooled and FHH samples, and farmers participating in Project 3 are significantly less likely to adopt agroforestry ($p < 0.05$). The variation in adoption rates across projects (e.g., 53% MHHs and 35% FHHs in Project 1 vs. 35% MHHs and 27% FHHs in Project 3 also reveals the influence of program design operated by different entities in different locations. Thus, the lower adoption of agroforestry in Project 3 may reflect weaker extension services by project implementers or unsuitable biophysical conditions in the project region, as the literature identified these as critical constraints (Reppin et al. 2020; Awazi et al. 2025). The more negative effect for FHHs in Project 3 (OR = 0.33, $p < 0.05$) implies that women face greater obstacles in projects where there is less support, perhaps because of less access to training or inputs. This is an equity concern, as programs could be unintentionally favouring resource-rich farmers or male-headed groups, and a more inclusive design is needed to secure the participation of women.

Households with organizational membership increased the likelihood of adopting agroforestry by nearly two times in the pooled sample (OR = 1.84, $p < 0.05$) and MHH sample (OR = 2.22, $p < 0.10$). Although FHHs showed slightly increased likelihood of adoption, the results are not significant (OR = 1.34, $p = 0.480$). Further, an interaction with gender highlighted that households having membership in an organization typically have higher chances of adopting AF. This finding corroborates Pello et al. (2021) that group membership in Kenya increased the likelihood of AF adoption. The increase in likelihood would be because being members of organizations or associations provides greater proximity to extension services and credit that influence adoption (Syano et al. 2022). The stronger effect for men may be that women rely more on informal homogenous social groups due to less access to formal channels and low participation in mixed groups (Ngigi et al. 2017; Ngigi & Muange 2022). This iterates the need for gender-inclusive group structures so that women and less influential groups can also benefit, thereby increasing the AF adoption.

Land size has substantial effects on agroforestry adoption. A one-hectare increase in land reduced the odds of adopting agroforestry across pooled, MHH and FHH samples by 2.77%, 4.23% and 3.46%, respectively. This does not reflect the findings from other studies, such as Pello et al. (2021) and Syano et al. (2022), which showed that land size positively influenced AF adoption in Kenya. This discrepancy may arise from the intensive management and higher capital required for agroforestry, which could deter farmers with larger plots facing labour and financial constraints (Awoke et al. 2025). The literature identified that farmers who have leased land with insecure land tenure are discouraged from making long-term investments as required in agroforestry (Kurgat et al. 2020; Awoke et al. 2025). Unfortunately, this study did not classify the type of land ownership during the survey and suggests further investigation, including the land tenure factor as a predictor.

The smaller average marginal effect among FHHs suggests that women find agroforestry more feasible, as noted by Musafiri et al. (2022). From the t-test, it is understood that FHHs manage a mean land size of 0.595 ha compared to MHHs, who own an average of 0.717 ha, as also found by Awoke et al. (2025) and Cariappa & Krishna (2025). This highlights an interlinkage between gender, land size, and suitability of practices, thus suggesting that stakeholders must consider household land ownership in the design of agroforestry interventions specific to smallholder situations (Syano et al. 2022).

Age and household size did not influence the probability of agroforestry adoption in all the models. Nevertheless, average marginal effects of age (39.7 pp to 42.7 pp for MHHs; 32.4 pp to 48.6 pp for FHHs) and household size (39.1 pp to 46.1 pp for MHHs; 32.9 pp to 58.6 pp for FHHs) on AF adoption indicate that an increase in age and household size enormously raises the rate of adoption of agroforestry among both household heads. This concurs with the literature that older farmers adopt agroforestry owing to experience and risk aversion (Mogaka et al. 2021; Syano et al. 2022; Musafiri et al. 2022; Ngaiwi et al. 2023), and larger families supply adequate labour from household members to conduct intensive agroforestry activities (Syano et al. 2022). However, the effect of AMEs contradicts Mungai et al. (2017), who found that farmers over age 50 adopted a lower proportion of agroforestry than younger farmers in Western Kenya. Stronger effects for FHHs suggest that older women would have been exposed to more technical information (Pello et al. 2021), and larger families overcome resource shortages by the availability of labour, considering women's greater dependency on family labour under resource-scarce conditions. This underscores the importance of considering household dynamics in program design to take advantage of labour availability for women.

Education levels show a positive effect on the AF adoption of MHHs and FHHs, respectively. This shows that higher education levels enable households to access information on AF technology and increase the awareness of its benefits, ultimately enhancing the probability of adopting it (Mungai et al. 2017; Syano et al. 2022).

In MHHs, the intensity of AF adoption increased steadily from 33.33 pp with no formal education to 61.3 pp with university education. An increasing trend has been observed among FHHs in vocational/diploma education (65.2 pp). However, a sudden decrease occurred in university education. The lower adoption among university-educated FHHs (24.3 pp, with wide CI and no significance) may reflect small sample sizes or migration to urban areas in search of jobs; hence, they do not undertake farming (Mungai et al. 2017). Therefore, education's impact varies by gender and practice complexity, requiring targeted extension to bridge knowledge gaps for women.

6.2.3 Determinants of Carbon Payment Receipt

Despite farmers' participation in carbon farming programs and adoption of various climate-smart practices, do smallholders really enjoy the benefits from carbon credits is a question. The logistic regression analysis has been performed to explore what factors determine the receipt of carbon farming payments. The results show that project affiliation, ethnicity, and organizational membership were the most consistent predictors of carbon payment receipt, with land size and age showing positive marginal effects and education exhibiting mixed patterns.

Only a few FHHs (2%) involved in projects 3 and 4 reported that they received carbon payments, compared to the highest share in project 2 (74% MHHs and 64% FHHs) and project 1 (36% MHHs, 43% FHHs). The odds of farmers receiving payments in Projects 3 and 4 are almost zero, and the results are significant at 1% and 5%, respectively. This stark variation in payment receipt would be due to the influence of project-specific factors such as project start date, payment mechanisms and high verification costs. For example, the KACP uses result-based payments, with farmers receiving USD 1.97/ha after deductions, while WKCP focuses on advisory services rather than direct payments (Öborn et al. 2017; Nyberg et al. 2020; Tennigkeit et al. 2023; Raina et al. 2024). The low carbon revenues for farmers are further aggravated by high MRV costs (e.g., EUR 2000/farm/5 years), as highlighted in McDonald et al. (2021). Although Project 2 showed a higher likelihood of receiving carbon payments, the results are insignificant with a wider confidence interval (OR = 5.131, $p = 0.123$, 95% CI = 0.641-41.082), likely due to a smaller sample size and variability.

Kalenjin (OR = 0.287, $p < 0.05$) and other communities (Kamba, Kikuyu and Kisii) (OR = 0.108, $p < 0.01$) have 71% and 89% lower odds of receiving carbon farming payments compared to the Luhya group. While literature does not directly address the influence of ethnicity on payment receipt, it notes that socio-cultural factors drive participation (Lee 2017; Rois-Díaz et al. 2018; Figueredo 2024). Although these ethnic groups neighbour one another, their adaptive capacities and landholdings differ, as mentioned in Mungai et al. (2017).

The farmers having organizational membership are more likely to receive CF payments; however, the result is marginally significant (OR = 1.95, $p < 0.10$). The AME interactions with gender present that higher membership in organizations significantly increases the receipt of CF payments among MHHs and FHHs ($p < 0.01$) than those with no membership. This is because an association with farmer organizations accelerates the farmers' capacity to build technical knowledge of CFPs, as farmer groups act as an easy platform for extension officers to organize trainings (Li et al. 2023; Ogisi & Begho 2023; Kioko et al. 2024). In Makueni County, group membership improved the productivity of pulses through knowledge sharing (Kioko et al. 2024). In other words, the higher the carbon sequestration, the higher the payments. Particularly, the stronger effect for FHHs in marginal analysis (17.8 pp to 29.1 pp) suggests that women have the probability to derive more benefits from social capital to navigate complex payment systems. This underscores the farmer organization’s ability to construct gender gaps in payment access inclusively.

The ORs of land size and age are insignificant with the carbon farming payment receipt. But the positive AMEs of land size (26.1 pp to 44.0 pp for MHHs; 25.7 pp to 35.9 pp for FHHs) and age (24.0 pp to 32.5 pp for MHHs; 22.1 pp to 30.8 pp for FHHs) with household head gender reflect that land availability and experience facilitate CSA participation (Li et al. 2023; Kioko et al. 2024). In contrast, a study by Nyang’au et al. (2021) in Kisii County negatively correlated farmers’ experience with CSA adoption. Larger landholdings enable greater adoption of CFPs, thus increasing carbon sequestration potential and eligibility for payments, while older farmers are better equipped to implement CFPs and have better access to established networks, reaping greater project benefits. The weaker effect for FHHs in land size suggests that FHH carbon farmers manage smaller plots compared to MHH carbon farmers, a critical constraint for limited payments.

Education attained exerts a nuanced and gender-differentiated influence on carbon farming payment receipt. Among MHHs, payment receipt is highest for those without formal education (48.8 pp, $p < 0.01$), declines with primary and secondary education, but rises again at the university level (36.2 pp, $p < 0.01$). For FHHs, adoption is lower among those without schooling (23.4%, $p < 0.01$) yet stabilizes across primary (29.5%) and secondary (28.7%) education, indicating that even modest education equips women to participate, though higher education does not yield additional gains. The marginally significant negative association with vocational training/diploma education (OR = 0.173, $p < 0.1$) is surprising and contradicts earlier findings that education enhances CFP adoption and hence the CF payments (Karanja & Jalango 2019; Mogaka et al. 2021; Musafiri et al. 2022; Kioko et al. 2024; Awoke et al. 2025). Although marginally significant, the wide confidence intervals suggest caution due to uncertainty around the estimate, but cultural barriers limiting women's engagement in complex practices may also play a role, or the shift of more educated farmers, particularly women, toward off-farm activities (Mungai et al. 2017; Ogisi & Begho 2023). Overall, the results suggest a threshold effect of education that primary and secondary schooling favour receipt of carbon payments, but vocational and higher education do not add much. This implies that education alone is insufficient, and programs need to provide practical training, peer learning, and inclusive extension services to ensure equitable participation while exploring the off-farm opportunities.

The lack of a significant association between odds of agroforestry adoption and CF payment receipt (OR = 1.224, $p = 0.48$) is striking, despite agroforestry's prominence in study areas and carbon credit methodologies (De Giusti et al. 2019; Reppin et al. 2020; Wanjira & Muriuki 2020). This indicates that payment distribution mechanisms may not always reward the practices most critical for long-term carbon sequestration.

Slightly lower marginal effects for FHHs (26.3 pp for adopters vs. 28.6 pp for non-adopters) raise concerns about gender equity, where women's adoption efforts may not translate into financial rewards due to verification or eligibility barriers. This pattern points to payment distribution systems prioritizing project-specific targets or verification outcomes rather than AF adoption alone. Risks such as non-permanence and non-additionality could also exclude some adopters from receiving payments, as mentioned in the literature (Jackson Hammond et al. 2021; Schilling et al. 2023; Figueredo 2024; Raina et al. 2024).

6.2.4 Implications and Recommendations

These results provide important insights for carbon farming in Western Kenya. While adoption of carbon farming practices is apparent, the overall rates are lower than in comparable studies. The influence of project design, resource limitations, and local context could be decisive factors for varied rates. Socio-demographic and institutional factors such as ethnicity, project affiliation, and organizational membership significantly influence both agroforestry adoption and carbon farming payment receipt. Worth observing is that agroforestry adoption is not significantly linked to carbon farming payment receipt, despite the key role of AF in carbon markets. This discrepancy highlights that current payment schemes might not properly reward farmers adopting AF that has long-term climate advantages. The lack of significant gender differences in overall adoption suggests that training and resource support within carbon projects can restrict traditional barriers. Yet, subtle differences, such as FHHs' slightly greater preference towards tree nursery establishment than MHHs, point to the importance of promoting gender-responsive practices, considering the cultural norms and livelihood priorities. Marginal effects further reveal that age, land size, household size, organizational membership, and agroforestry adoption positively affect AF adoption and payment receipt for both genders. This implies that a one-size-fits-all approach in program design may obscure important subgroup dynamics. Moreover, the negative prediction of university education of FHHs on AF adoption and the mixed effects of education on CF payment receipt in both MHHs and FHHs suggest that formal education alone does not guarantee the expected outcome, and further exploration is needed to understand how education interacts with underlying factors such as off-farm activities and household priorities.

Programs need to enhance extension services and employ more female agents, especially to eliminate the constraints faced by women. Further, the carbon farming training should be context-specific, focusing on both short-term activities like organic fertilizer application and long-term ones like agroforestry, keeping in mind the farmers' household dynamics. Promoting inclusiveness in farmer organizations can also increase access to knowledge, credit, and networks, irrespective of gender, enhancing both adoption and payment access. Meanwhile, the farmers should be supported with necessary inputs to adopt capital-intensive practices like agroforestry, and payment structures should better capture the value of practices with the greatest carbon sequestration contribution. While designing program interventions, it is indispensable to focus on disseminating low-cost and workable technologies to address the smallholder constraints. Most importantly, simplifying verification procedures and reducing transaction costs would offer a higher and equitable share of carbon revenues. These actions would enable carbon farming programs to deliver climate goals and uplift farmer livelihoods more effectively and inclusively.

6.3 Factors Influencing Carbon Farming Participation

6.3.1 Determinants of Carbon Farming Participation

The participation in carbon farming among smallholder farmers in Western Kenya is determined by socio-demographic factors that farmers innately possess and institutional factors. Understanding key factors influencing the decisions of male- and female-headed farmers is imperative to increasing participation (Bernier et al. 2015; Mungai et al. 2017; Ngigi & Muange 2022; Li et al. 2023; Ogisi & Begho 2023; Hailemariam et al. 2024). Logit results identified age, education, county, ethnicity, and organizational membership as significant predictors, while land size, household size, and income from agriculture depicted subtle or gender-specific effects.

The age of the household head significantly increased the likelihood of practicing carbon farming across pooled, MHH, and FHH samples, with stronger effects among FHHs. This suggests that accrued experience and risk-aversion behaviour in older farmers encourage them to adopt CFPs to mitigate the production risks (Li et al. 2023, 2024; Kioko et al. 2024). However, CFPs cannot be generalized solely by age, as physical constraints of older farmers determine their willingness to choose specific types of practices. Evidence from Western Kenya supports that older farmers practice agroforestry, cover crops, zero tillage, and animal manure application, whereas young farmers use more intercropping, crop rotation, and mulching in Western Kenya (Mogaka et al. 2021; Musafiri et al. 2022; Ngaiwi et al. 2023). Similar studies in Vietnam and Nigeria also revealed that labour-intensive practices like crop diversification and mulching are less likely to be adopted by older farmers due to less physical function and high-risk sensitivity (Tran et al. 2020; Mailumo et al. 2021).

Interestingly, these findings contradict the view that older farmers are more resistant to change and prefer to stick to the already-known practices instead of trying out new exploits due to their long-standing, local attitudes, values, and beliefs (Negera et al. 2022; Jassim et al. 2022; Ogisi & Begho 2023; Pudasaini et al. 2024). Mungai et al. (2017) also found that farmers over age 50 adopted a lower proportion of labour-intensive practices such as agroforestry and terracing in Western Kenya. In contrast, our marginal analysis shows that the predicted probability of carbon farming participation increases sharply with age, from 31 pp at 18 years to 70 pp at 80 years among MHHs, and much more strongly from 18.5 pp to 83 pp among FHHs. The stronger effect of age for FHHs indicates that older women would gain greater household authority after widowhood or separation, leveraging their experience to overcome gender-based barriers, which supports the notion that women's empowerment enhances CFP adoption (Musafiri et al. 2022; Li et al. 2023).

Education level, particularly secondary education, had a strong prediction over CF participation in the pooled sample and among MHHs, while it was only marginally significant for FHHs ($p < 0.1$). This is consistent with previous studies that formal education positively influences the adoption of CFPs in Western Kenya, as literate farmers have better knowledge to apply appropriate methods and understand the benefits for soil and crop management than illiterate ones (Karanja & Jalango 2019; Mogaka et al. 2021; Musafiri et al. 2022). Also, evidence from Indonesia, Turkey, Nigeria, and Ethiopia shows that higher education levels tend to increase willingness to adopt CFPs, as educated farmers are in a better position to access and apply information from diverse sources such as extension services and the Internet (Saptutyningsih et al. 2020; Everest 2021; Mashi et al. 2022; Negera et al. 2022). However, it contrasts with a study in Tanzania by Awoke et al. (2025), who emphasized the role of education in increasing the effectiveness of CFPs, particularly among FHHs. The weaker effects for FHHs may stem from the fact that it is more difficult for women in developing countries to access formal and non-formal education (Dabkiene 2025). The marginal effects notably showed a significant decreasing trend for FHHs with vocational training/diploma education (46.35 pp) before rising again with university education (60.57 pp). In one way, this result is consistent with the findings of Mungai et al. (2017) that households with post-secondary level education showed reduced uptake of CFPs in Western Kenya. On the other hand, it conflicts with (Awoke et al. (2025) that each additional year of increase in education positively influences the CFPs adoption intensity in Tanzania, especially among FHHs.

Organizational membership showed a more pronounced influence, increasing participation odds across all three samples, and the effects were slightly higher for FHHs than MHHs. This highlights the significant role of membership in farmer organizations/groups in the uptake of carbon farming interventions. Membership enhances participation by facilitating knowledge sharing and collective action, ultimately increasing bargaining power, access to markets, and risk resilience (Ma et al. 2018; Li et al. 2023; Ogisi & Begho 2023; Zhou et al. 2024; Awoke et al. 2025). This is evident from the research in Makueni County of Kenya, which showed improved green gram productivity among 54.6% of farmers in groups. Further, Haldar & Damodaran (2022) and Zhou et al. (2024) highlighted that participation in agricultural organizations or cooperatives significantly improves the adoption of organic and CSA practices among farmers in India and China, respectively. The increased participation among members in farmer groups is mainly because extension officers utilize organizations as a platform for providing training and disseminating information. However, this finding is inconsistent with Bernier et al. (2015), who reported that information from farmers' organizations does not significantly increase the awareness of CFPs.

The stronger significant probability of organizational membership among FHHs (67 pp) than MHHs (65 pp) is noteworthy, as women rely more on social groups, unlike men, who prefer extension officers and print media for information (Ngigi et al. 2017; Ngigi & Muange 2022). But our finding refutes a study in Tanzania by Awoke et al. (2025), who reported that the effect was higher in MHHs than FHHs due to the lack of land ownership documents with women, which are prerequisites for accessing group membership and credit. Therefore, even with a female as the household head, the legal document stating ownership is important to fully benefit from the social capital.

Pooled (OR = 6.38, 95% CI = 2.04-19.96) and male-headed households (OR = 8.75, 95% CI = 2.13-35.88) in Kisumu County showed significantly higher participation odds compared to those in other counties. Although the confidence interval is wide, the lower bound still accounts for more than a two-fold increase in odds of participation. The stronger influence observed among MHHs could be due to the greater access to resources and mobility of men in the Kisumu region, which facilitates program uptake. These results reflect contextual advantages such as agro-ecological suitability, program availability, and increased climate risks in the region. Kisumu's proximity to Lake Victoria provides a greater water source, while the historical presence of carbon farming initiatives like KACP and WKCP in the region may foster greater awareness and participation (Lee 2017; County Government of Kisumu 2023a; Tennigkeit et al. 2023). Furthermore, the significant crop loss in the region due to extreme climate risks pushes farmers to adopt climate-smart technologies to cope with the risks (MoALF 2018a; County Government of Kisumu 2023b).

Ethnicity decreased the odds of participation in carbon farming among the Kalenjin and Luo farmers compared to the Luhya. The effects were marginally significant for MHHs of both the Kalenjin and Luo groups. The findings of Mungai et al. (2017) also reported that the adoption rate of CFPs is lower among Kalenjin than Luo households in Western Kenya. This illustrates the influence of cultural practices and norms within ethnic groups, and regional influence cannot be underestimated. The gender specificity suggests further exploration of whether the MHHs from communities other than Luhya are excluded from program participation.

Household size and land size were not statistically significant in the regressions. However, marginal effects displayed gradual positive associations with an increase in household members and land availability, suggesting that larger families and holdings provide labour and scale for carbon farming implementation. This aligns with the studies that interpreted large farm size (Mogaka et al. 2021; Negera et al. 2022; Musafiri et al. 2022; Li et al. 2023; Ogisi & Begho 2023; Ngaiwi et al. 2023; Kioko et al. 2024) and household size as a positively influencing factor in the adoption of CFPs (Bernier et al. 2015; Nyang'au et al. 2021). For instance, farmers with larger land adopted practices such as agroforestry and cover cropping in Western Kenya and Cameroon, respectively (Musafiri et al. 2022; Ngaiwi et al. 2023). Similarly, households with more family members adopted labour-intensive practices like soil conservation, mixed cropping, and application of manure (Nyang'au et al. 2021).

In contrast, some studies found that a smaller farm size can positively influence the uptake of carbon farming due to rapid decision-making and the ability to quickly adapt to new practices that would increase productivity and climate-resilience (Bernier et al. 2015; Issahaku & Abdulai 2020; Azumah et al. 2022; Ogisi & Begho 2023), while a larger family size could limit participation in CF activities due to a higher dependency ratio within the household (Karanja & Jalango 2019; Musafiri et al. 2022). The direction of the effect is dependent on the type of carbon farming practice and the location (Ogisi & Begho 2023).

The main source of income from agriculture slightly influenced the likelihood of participation in CF programs among pooled households and MHHs. As mentioned in the past studies (García de Jalón et al. 2018; Negera et al. 2022; Kassa & Abdi 2022; Ogisi & Begho 2023), the higher income from agriculture increases the level of adoption of

CFPs. The effect on MHHs specifically might be due to the greater control of men over income streams and markets. Further, it could be argued that farmers who depend on farm income for livelihoods will have an urge to adopt technologies such as carbon farming that can mitigate risks from the conventional system and provide an additional source of income in the form of carbon credits.

6.3.2 Implications and Recommendations

The study highlights that socio-demographic, institutional, and contextual factors shaped carbon farming participation among smallholders in Western Kenya with notable gender differences. Age had a significant effect on adopting CFPs, particularly among FHHs, implying the crucial role of risk-aversion and household authority in older women. Higher education increased participation rates, with a strong influence on MHHs, whereas organizational membership was as a strong predictor for both genders. This reflects the importance of social capital in knowledge sharing, collective support, and access to input and credit resources. Contextual factors, such as regional effects, agroecological suitability, existing carbon projects and climate risks, further determine the farmers' willingness to shift towards carbon farming. On the flip side, ethnic norms can either enable or constrain participation. The farm and family size, as well as dependence on agricultural income, indicate that the carbon farming decisions are based on labour availability, land availability, and livelihood reliance, respectively.

As a recommendation, CF programs should promote labour-appropriate practices, considering the physical capacity of participants (based on age), gender preferences, and household dependency ratio. Strengthening extension services by adopting gender-sensitive approaches, such as recruiting more female extension workers, using diverse communication channels, and strengthening social organizations, will uplift the awareness of carbon farming programs, resolve the women-faced constraints, and boosts participation. The carbon farming interventions must be designed based on micro-level evidence (subcounty/village level) rather than just the broader context (county level) for the successful implementation of the project. As there are limited studies available on the influence of ethnicities on carbon farming adoption, future research should explore adoption using an ethnic lens and its interaction with gender. Also, the case-by-case analysis of education is suggested to identify what level of education favours participation in carbon farming programs, along with their interaction with off-farm opportunities.

7. Conclusion

This study provides a gender-differentiated analysis of carbon farming among smallholders in Western Kenya, exploring motivations, barriers, adoption patterns and determinants of agroforestry adoption, carbon payment receipt and overall participation. The findings of this study provided critical insights for carbon project developers and policymakers in designing gender-responsive carbon programs. This aligns well with broader tropical contexts, where smallholder agriculture is vital.

Production concerns, such as poor soil health and lowering agricultural productivity, and environmental awareness, rather than carbon incentives, primarily motivated households to shift towards carbon farming. Women value higher yield benefits from carbon farming practices than men, emphasizing their role in food security. Unlike many tropical countries, where carbon credits are perceived to be a major driver, the farmers in Western Kenya prioritized ecological benefits over financial incentives. This can be since carbon payments are often too little and delayed, as evidenced in the Kenya Agricultural Carbon Project. Extension agents and group meetings are the main sources of information to learn about carbon farming, while most of the farmers are trained by NGOs and project developers in both groups. Female-headed households have a higher reliance on peer networks and a lower response to extension agents than male-headed households, which underscores their limited access to formal channels. Despite farmers' engagement in carbon programs, a few farmers signed formal contracts and were aware of carbon credit ownership, which questions the efficiency of knowledge transfer, especially to FHHs. The farmers reported that a lack of awareness and limited outreach by the implementer as major barriers to enrollment in CF programs. Particularly, women require greater assistance to join the carbon programs.

Carbon farming practices such as organic fertilizer use, agroforestry and intercropping were the most widely adopted under the carbon credit program. However, the extent of adoption is much lower than that reported in other studies of Kenya. This can be linked to the result that carbon companies offer limited support for inputs such as seedlings, tools or credit that restricts the extent of carbon farming practices adoption. Notably, subtle gender differences in the adoption patterns might be because of indiscriminate training and extension support in carbon programs, which mitigate traditional gender inequalities.

Recognizing the climate mitigation and livelihood importance of agroforestry in Western Kenya and recognition in carbon credit methodologies, the factors influencing its adoption were investigated. Ethnicity, project affiliation, and organizational membership determined agroforestry adoption and carbon payment outcomes. Kalenjin farmers and households in farmer groups were more likely to adopt agroforestry, while Luo female-headed households and farmers in Project 3 faced adoption constraints. AF adoption itself did not significantly affect carbon payment receipt, but ethnicity and participation in Projects 3 and 4 reduced the likelihood of receiving payments. Older farmers with greater experience, MHHs with secondary education and members of farmer groups have higher chances of participating in carbon farming. Ethnicity (Kalenjin and Luo) and main income from agriculture also showed near significance, mainly for MHHs.

Overall, carbon farming is gaining attention among both male and female-headed households, driven by shared motivations and well-established outreach mechanisms. But who benefits still depends heavily on landholding, project-level differences, and socio-demographic factors that affect men and women differently. To ensure the effectiveness and widespread adoption of CF, it is necessary to tailor interventions considering the gender priorities. Supporting farmers with agricultural inputs reduces the upfront cost burden, crucial for scaling up carbon farming practices. The policymakers and carbon project developers should focus on strengthening extension services, education, land access, and supporting social networks by empowering female extension workers.

This study has a few limitations, and future research should address the unspecified barriers for non-participation through a qualitative study. The mixed effects of education reflect the need to study the influence of different education levels and off-farm work on CF adoption across genders. Also, the type of land ownership is a significant factor to be studied to understand the influence of land tenure on agroforestry adoption. There is a limited data available on the influence of ethnicity on carbon farming, leaving scope for future research through an ethnic lens. By addressing these challenges, the carbon farming programs, and the agricultural sector can become more equitable, resilient and result-oriented, contributing to the sustainable development goals.

8. References

Adhikari J, Timsina J. 2022. Regenerative Agriculture for Sustainable Food Security and Livelihoods in Nepal: A Proposal for Multi-scalar Planning Framework. Pages 177–194 in Timsina J, Maraseni TN, Gauchan D, Adhikari J, Ojha H, editors. Agriculture, Natural Resources and Food Security: Lessons from Nepal. Springer International Publishing, Cham. Available from https://doi.org/10.1007/978-3-031-09555-9_11.

Akanmu AO, Akol AM, Ndolo DO, Kutu FR, Babalola OO. 2023. Agroecological techniques: adoption of safe and sustainable agricultural practices among the smallholder farmers in Africa. Frontiers in Sustainable Food Systems **Volume 7-2023**. Available from https://www.frontiersin.org/journals/sustainable-food-systems/articles/10.3389/fsufs.2023.1143061.

Al-Amin AKMA, Akhter T, Islam AHMdS, Jahan H, Hossain MJ, Prodhan MdMH, Mainuddin M, Kirby M. 2019. An intra-household analysis of farmers' perceptions of and adaptation to climate change impacts: empirical evidence from drought prone zones of Bangladesh. Climatic Change **156**:545–565. Available from https://doi.org/10.1007/s10584-019-02511-9.

Ali MdM, Ahmad B, Bari MS, Pal AC, Rahman MdL, Sarmin IJ. 2024. An assessment of agroforestry as a climate-smart practice: Evidences from farmers of northwestern region of Bangladesh. Agrosystems, Geosciences & Environment **7**:e20501. John Wiley & Sons, Ltd. Available from https://doi.org/10.1002/agg2.20501.

Alliance KPS. 2024. A Carbon Market Guidebook for Kenyan Enterprises. Washington, DC: World Bank.

Almaraz M, Wong MY, Geoghegan EK, Houlton BZ. 2021. A review of carbon farming impacts on nitrogen cycling, retention, and loss. Annals of the New York Academy of Sciences **1505**:102–117. John Wiley & Sons, Ltd. Available from https://doi.org/10.1111/nyas.14690.

Amede T, Konde AA, Muhinda JJ, Bigirwa G. 2023. Sustainable Farming in Practice: Building Resilient and Profitable Smallholder Agricultural Systems in Sub-Saharan Africa. Sustainability 2023, Vol. 15, Page 5731 **15**:5731. Multidisciplinary Digital

Publishing Institute. Available from https://www.mdpi.com/2071-1050/15/7/5731/htm (accessed May 31, 2025).

Andati P, Majiwa E, Ngigi M, Mbeche R, Ateka J. 2022. Determinants of adoption of climate smart agricultural technologies among potato farmers in Kenya: Does entrepreneurial orientation play a role? Sustainable Technology and Entrepreneurship **1**:100017. Elsevier España. Available from https://www.sciencedirect.com/science/article/pii/S2773032822000177?via%3Dihub (accessed August 15, 2025).

Antwi-Agyei P, Abalo EM, Dougill AJ, Baffour-Ata F. 2021. Motivations, enablers and barriers to the adoption of climate-smart agricultural practices by smallholder farmers: Evidence from the transitional and savannah agroecological zones of Ghana. Regional Sustainability **2**:375–386. Elsevier. Available from https://www.sciencedirect.com/science/article/pii/S2666660X22000056?via%3Dihub (accessed August 15, 2025).

Assèdé ESP, Othoo CO, Ly A, Bayisa G, Tarkegn TG, Zohoun M, N'goran A-J. 2025. Research progress on climate change adaptation strategies to control invasive crop pest in sub-Saharan Africa: a bibliometric and systematic review. Frontiers in Climate **Volume 7-2025**. Available from https://www.frontiersin.org/journals/climate/articles/10.3389/fclim.2025.1478721.

Autio A, Johansson T, Motaroki L, Minoia P, Pellikka P. 2021. Constraints for adopting climate-smart agricultural practices among smallholder farmers in Southeast Kenya. Agricultural Systems **194**:103284. Elsevier. Available from https://www.sciencedirect.com/science/article/pii/S0308521X21002377?via%3Dihub (accessed August 16, 2025).

Awazi NP, Alemagi D, Ambebe TF. 2025. Promoting the carbon market in agroforestry systems: the role of global, national and sectoral initiatives. Discover Forests **1**:9. Springer.

Awoke MD, Löhr K, Kimaro AA, Lana M, Soh Wenda BD, Buabeng K, Hafner JM, Sieber S. 2025. Exploring gender dynamics in climate-smart agriculture adoption: a study in semi-arid Dodoma, Tanzania. Frontiers in sustainable food systems **8**:1507540. Frontiers Media SA.

Azumah S, Zakaria A, Yegbemey R, Apalogta P, Mahama A, Dagar V. 2022. Climate Smart Production, Gross Income, and Downstream Risk Characterization of Rice Farmers in Ghana. Journal of Agricultural Studies **10**:13–35.

Barbato CT, Strong AL. 2023. Farmer perspectives on carbon markets incentivizing agricultural soil carbon sequestration. npj Climate Action **2**:26. Available from https://doi.org/10.1038/s44168-023-00055-4.

Baumber A, Metternicht G, Cross R, Ruoso LE, Cowie AL, Waters C. 2019. Promoting co-benefits of carbon farming in Oceania: Applying and adapting approaches and metrics from existing market-based schemes. Ecosystem Services **39**:100982. Elsevier. Available from https://www.sciencedirect.com/science/article/pii/S2212041619302396 (accessed June 18, 2025).

Beacham JD, Jackson P, Jaworski CC, Krzywoszynska A, Dicks L V. 2023. Contextualising farmer perspectives on regenerative agriculture: A post-productivist future? Journal of Rural Studies **102**:103100. Pergamon. Available from https://www.sciencedirect.com/science/article/pii/S0743016723001663 (accessed June 26, 2025).

Bernier Q, Meinzen-Dick RS, Kristjanson PM, Haglund E, Kovarik C, Bryan E, Ringler C, Silvestri S. 2015. Gender and institutional aspects of climate-smart agricultural practices: evidence from Kenya. CGIAR Research Program on Climate Change, Agriculture and Food Security.

BirdLife Europe, EEB. 2022. CAP Strategic Plans: Insufficient Action on Soil and Carbon Farming. European Environmental Bureau, Belgium. Available from https://policycommons.net/artifacts/2641634/soil-and-carbon-farming-in-the-new-cap/.

Boomitra Inc. 2025. Boomitra Carbon Farming in East Africa through Soil Enrichment. California, USA. Available from https://registry.verra.org/app/projectDetail/VCS/3774 (accessed August 14, 2025).

Brown G. 2018. Dirt to soil: One family's journey into regenerative agriculture. Chelsea Green Publishing.

Buck HJ, Palumbo-Compton A. 2022. Soil carbon sequestration as a climate strategy: what do farmers think? Biogeochemistry **161**:59–70. Available from https://doi.org/10.1007/s10533-022-00948-2.

Buleti SI, Kuyah S, Olagoke A, Gichua M, Were S, Chidawanyika F, Martin EA. 2023. Farmers' perceived pathways for further intensification of push-pull systems in Western Kenya. Frontiers in Sustainable Food Systems **Volume 7-2023**. Available from https://www.frontiersin.org/journals/sustainable-food-systems/articles/10.3389/fsufs.2023.1191038.

Cariappa AAG, Krishna V V. 2025. Carbon farming in India: are the existing projects inclusive, additional, and permanent? Climate Policy **25**:756–771. Taylor & Francis.

Carmichael J, Cran A, Hrvatin F, Matthews J. 2023. "We are stewards and caretakers of the land, not exploiters of resources": A qualitative study exploring Canadian farmers' perceptions of environmental sustainability in agriculture. PLOS ONE **18**:e0290114-. Public Library of Science. Available from https://doi.org/10.1371/journal.pone.0290114.

Coherent MI. 2025. Kenya Carbon Credit Market Size YoY Growth Rate, 2025-2032. Available from https://www.coherentmi.com/industry-reports/kenya-carbon-credit-market (accessed August 16, 2025).

County Government of Bungoma. 2023. Bungoma County Integrated Development plan 2023-2027. County Government of Bungoma. Available from https://repository.kippra.or.ke/handle/123456789/4569 (accessed July 13, 2025).

County Government of Kakamega. 2023a. Kakamega County Integrated Development Plan 2023-2027. Available from https://kakamega.go.ke/kakamega-county-integrated-development-plan-2023-2027/ (accessed July 13, 2025).

County Government of Kakamega. 2023b. Kakamega County Climate Change Action Plan 2023-2027.

County Government of Kisumu. 2023a. Kisumu County Integrated Development Plan 2023-2027. County Government of Kisumu. Available from https://repository.kippra.or.ke/handle/123456789/4375 (accessed July 13, 2025).

County Government of Kisumu. 2023b. Kisumu Climate Change Action Plan 2023-2027.

County Government of Trans Nzoia. 2023. Trans Nzoia County Integrated Development Plan 2023-2027. County Government of Trans Nzoia. Available from https://repository.kippra.or.ke/handle/123456789/4357 (accessed July 13, 2025).

Dabkiene V. 2025. Gender, Women's Barriers and Innovation in Agriculture: A Systemic Literature Review. European Countryside **17**:1–26.

Das P. 2019. Analysis of collinear data: multicollinearity. Pages 137–151 Econometrics in Theory and Practice: Analysis of Cross Section, Time Series and Panel Data with Stata 15.1. Springer.

De Giusti G, Kristjanson P, Rufino MC. 2019. Agroforestry as a climate change mitigation practice in smallholder farming: evidence from Kenya. Climatic Change **153**:379–394. Available from https://doi.org/10.1007/s10584-019-02390-0.

Denny DMT, Cerri CEP, Cherubin MR, Burnquist HL. 2023. Carbon farming: nature-based solutions in Brazil. Green and Low-Carbon Economy **1**:130–137.

Diro S, Tesfaye A, Erko B. 2022. Determinants of adoption of climate-smart agricultural technologies and practices in the coffee-based farming system of Ethiopia. Agriculture & Food Security **11**:1–14. Springer.

Djido A, Zougmoré RB, Houessionon P, Ouédraogo M, Ouédraogo I, Seynabou Diouf N. 2021. To what extent do weather and climate information services drive the adoption of climate-smart agriculture practices in Ghana? Climate Risk Management **32**:100309. Elsevier. Available from https://www.sciencedirect.com/science/article/pii/S2212096321000383?via%3Dihub (accessed August 16, 2025).

Dow WH, Norton EC, Donahoe JT. 2019. Stata tip 134: multiplicative and marginal interaction effects in nonlinear models. The Stata Journal **19**:1015–1020. SAGE Publications Sage CA: Los Angeles, CA.

EIA. 2020, May 5. U.S. energy-related carbon dioxide fell by 2.8% in 2019, slightly below 2017 levels. Available from https://www.eia.gov/todayinenergy/detail.php?id=43615 (accessed May 31, 2025).

Ellis K, Lemma A, Mutimba S, Wanyoike R. 2013. Low carbon competitiveness in Kenya: Policy brief. ODI. Available from http://www.jstor.org/stable/resrep50495.

ENRD. 2022. Upscaling carbon farming in the EU. Brussels. Available from https://eu-cap-network.ec.europa.eu/publications/upscaling-carbon-farming-eu_en (accessed May 31, 2025).

Everest B. 2021. Farmers' adaptation to climate-smart agriculture (CSA) in NW Turkey. Environment, Development and Sustainability **23**:4215–4235. Springer.

FAO. 2021. Land use statistics and indicators (Global, regional and country trends 1990–2019). Available from https://www.fao.org/statistics/highlights-archive/highlights-detail/New-FAOSTAT-data-release-Land-use-statistics-and-indicators-(Global-regional-and-country-trends-1990-2019)/ (accessed May 31, 2025).

Figueredo A. 2024. A review of research on farmers' perspectives and attitudes towards carbon farming as a climate change mitigation strategy. Urban and rural reports. Available from https://res.slu.se/id/publ/139340 (accessed May 31, 2025).

García de Jalón S, Iglesias A, Neumann MB. 2018. Responses of sub-Saharan smallholders to climate change: Strategies and drivers of adaptation. Environmental Science & Policy **90**:38–45. Elsevier. Available from https://www.sciencedirect.com/science/article/pii/S1462901118307652?via%3Dihub (accessed August 15, 2025).

Ghajarzadeh M. 2025. Interpretation of results in the forest plot. Pages 153–156 Systematic Review and Meta-Analysis. Elsevier.

Griscom BW, Adams J, Ellis PW, Houghton RA, Lomax G, Miteva DA, Schlesinger WH, Shoch D, Siikamäki J V, Smith P. 2017. Natural climate solutions. Proceedings of the National Academy of Sciences **114**:11645–11650. National Academy of Sciences.

Günther P, Garske B, Heyl K, Ekardt F. 2024. Carbon farming, overestimated negative emissions and the limits to emissions trading in land-use governance: the EU carbon removal certification proposal. Environmental Sciences Europe **36**:72. Springer.

Hailemariam A, Kalsi J, Mavisakalyan A. 2024. Gender gaps in the adoption of climate-smart agricultural practices: Evidence from sub-S aharan A frica. Journal of Agricultural Economics **75**:764–793. Wiley Online Library.

Haldar T, Damodaran A. 2022. Can cooperatives influence farmer's decision to adopt organic farming? Agri-decision making under price volatility. Environment, Development and Sustainability **24**:5718–5742. Springer.

Haya BK, Bernard T, Abayo A, Rong X, So IS, Elias M. 2025. Voluntary Registry Offsets Database v2025-06. Page Berkeley . Available from https://gspp.berkeley.edu/berkeley-carbon-trading-project/offsets-database (accessed August 14, 2025).

Hayduk D, Satoyama S, Vafadari K. 2015. Soils Help to Combat and Adapt to Climate Change by Playing a Key Role in the Carbon Cycle. Food and Agriculture Organization of the United Nations: Rome, Italy:1–4.

Irungu I, Yegon R, Muniale F. 2024. Determinants for rainwater harvesting adoption: a case study of smallholder farmers in Murang'a County, Kenya. Sustainable Water Resources Management **10**.

Issahaku G, Abdulai A. 2020. Adoption of climate-smart practices and its impact on farm performance and risk exposure among smallholder farmers in Ghana. Australian Journal of Agricultural and Resource Economics **64**:396–420. John Wiley & Sons, Ltd. Available from https://doi.org/10.1111/1467-8489.12357.

Jackson Hammond AA, Motew M, Brummitt CD, DuBuisson ML, Pinjuv G, Harburg D V, Campbell EE, Kumar AA. 2021. Implementing the soil enrichment protocol at scale: Opportunities for an agricultural carbon market. Frontiers in Climate **3**:686440. Frontiers Media SA.

Jann B. 2013. Predictive margins and marginal effects in Stata. Page 11th German Stata Users Group Meeting, Potsdam, Germany.

Jassim D, Witt B, Evans MC. 2022. Community perceptions of carbon farming: A case study of the semi-arid Mulga Lands in Queensland, Australia. Journal of Rural Studies **96**:78–88. Pergamon. Available from https://www.sciencedirect.com/science/article/pii/S0743016722002479 (accessed June 26, 2025).

Jena PR. 2022. Extension services as key determining factor for adoption of minimum tillage practice in Kenya: A plot level analysis. Journal of Public Affairs **22**:e2724. John Wiley & Sons, Ltd. Available from https://doi.org/10.1002/pa.2724.

John K, Joel S, Paul O. 2025. Significance of Carbon Farming for Improved Household Incomes in Baringo County, Kenya. African Journal of Education, Science and Technology (AJEST) **8**.

Kaewkungwal J. 2025. The Grammar of Science: How “Robust” Are Your Study Results? Outbreak, Surveillance, Investigation & Response (OSIR) Journal **18**:127–132.

Kalungu JW, and Leal Filho W. 2018. Adoption of appropriate technologies among smallholder farmers in Kenya. Climate and Development **10**:84–96. Taylor & Francis. Available from https://doi.org/10.1080/17565529.2016.1182889.

Kanyenji GM, Oluoch-Kosura W, Onyango CM, Ng’ang’a SK. 2022. Does the adoption of soil carbon enhancing practices translate to increased farm yields? A case of maize yield from Western Kenya. Heliyon **8**:e09500. Elsevier. Available from https://www.sciencedirect.com/science/article/pii/S2405844022007885 (accessed April 26, 2025).

Karanja S, Jalango D. 2019. Adoption of soil carbon enhancing practices and their impact on farm output in Western Kenya.

Kashyap N, Hussain HM, Mohanty AK, Pathak PK, Pandey A, Devi K. 2024. Carbon Farming. Pages 343–368 in Babu S, Singh R, Rathore SS, Das A, Singh VK, editors. Agricultural Diversification for Sustainable Food Production. Springer Nature Singapore, Singapore. Available from https://doi.org/10.1007/978-981-97-7517-0_14.

Kassa Bamlaku Ayenew, Abdi Abera Tilahun. 2022. Factors Influencing the Adoption of Climate-Smart Agricultural Practice by Small-Scale Farming Households in Wondo Genet, Southern Ethiopia. SAGE Open **12**:21582440221121604. SAGE Publications. Available from https://doi.org/10.1177/21582440221121604.

Khalikova VR, Jin M, Chopra SS. 2021. Gender in sustainability research: Inclusion, intersectionality, and patterns of knowledge production. Journal of Industrial Ecology **25**:900–912. Wiley Online Library.

Khangura R, Ferris D, Wagg C, Bowyer J. 2023. Regenerative Agriculture - A Literature Review on the Practices and Mechanisms Used to Improve Soil Health. Sustainability 2023, Vol. 15, Page 2338 **15**:2338. Multidisciplinary Digital

Publishing Institute. Available from https://www.mdpi.com/2071-1050/15/3/2338/htm (accessed May 31, 2025).

Kioko M, Ndirangu S, Nyarindo W. 2024. Evaluating effect of climate smart agricultural practices adoption on productivity of drought-tolerant pulses: Insights from dryland areas of Makueni County, Kenya. J. Glob. Innov. Agric. Sci **12**:803–813.

Kiran BR, Prasad MNV, Mohan SV. 2023. Farm to fork: Sustainable agrifood systems. Pages 25–38 Sustainable and circular management of resources and waste towards a green deal. Elsevier.

Kurgat BK, Lamanna C, Kimaro A, Namoi N, Manda L, Rosenstock TS. 2020. Adoption of Climate-Smart Agriculture Technologies in Tanzania. Frontiers in Sustainable Food Systems **Volume 4-2020**. Available from https://www.frontiersin.org/journals/sustainable-food-systems/articles/10.3389/fsufs.2020.00055.

Lal R. 2020. The role of industry and the private sector in promoting the "4 per 1000" initiative and other negative emission technologies. Geoderma **378**:114613. Elsevier. Available from https://www.sciencedirect.com/science/article/pii/S0016706120305693?via%3Dihub (accessed August 18, 2025).

Lal R, Smith P, Jungkunst HF, Mitsch WJ, Lehmann J, Nair PKR, McBratney AB, de Moraes Sá JC, Schneider J, Zinn YL. 2018. The carbon sequestration potential of terrestrial ecosystems. Journal of soil and water conservation **73**:145A-152A. Taylor & Francis.

Lamanna C, Steward P, Kamau HN, Nowak A, Rosenstock TS. 2020. Data Atlas for Climate-Smart Agriculture in Kenya. Copenhagen, Denmark. Available from https://ccafs.cgiar.org/resources/publications/data-atlas-climate-smart-agriculture-kenya (accessed June 14, 2025).

Leakey RRB. 2017. Definition of agroforestry revisited. Pages 5–6 Multifunctional Agriculture – Achieving Sustainable Development in Africa. Academic Press, San Diego, California, USA.

Lee J. 2017. Farmer participation in a climate-smart future: Evidence from the Kenya Agricultural Carbon Project. Land use policy **68**:72–79. Elsevier.

Lee J, Ingalls M, Erickson JD, Wollenberg E. 2016. Bridging organizations in agricultural carbon markets and poverty alleviation: An analysis of pro-Poor carbon market projects in East Africa. Global Environmental Change **39**:98–107. Elsevier.

Li J, Ma W, Wang P, Meng X. 2024. Farmers' willingness to transform untreated livestock manure into organic fertilizer: does information technology adoption make a difference? Environment, Development and Sustainability **26**:5025–5045. Springer.

Li J, Ma W, Zhu H. 2023. A systematic literature review of factors influencing the adoption of climate-smart agricultural practices. Mitigation and Adaptation Strategies for Global Change **29**:2. Available from https://doi.org/10.1007/s11027-023-10098-x.

Liu X. 2012. Classification accuracy and cut point selection. Statistics in medicine **31**:2676–2686. Wiley Online Library.

Ma W, Abdulai A, Goetz R. 2018. Agricultural cooperatives and investment in organic soil amendments and chemical fertilizer in China. American Journal of Agricultural Economics **100**:502–520. Wiley Online Library.

Mailumo SS, Onuwa GC, Oyewole S. 2021. Adoption of climate smart agriculture among food crop farmers in Birnin-Kudu Local Government Area, Jigawa State, Nigeria. Russian Journal of Agricultural and Socio-Economic Sciences **110**:168–176. Редакция журнала Russian Journal of Agricultural and Socio-Economic Sciences.

Marks AB. 2020. (Carbon) Farming Our Way out of Climate Change. Denver Law Review **97**:497–556. Available from https://heinonline.org/HOL/P?h=hein.journals/denlr97&i=515.

Mashi SA, Inkani AI, Oghenejabor OD. 2022. Determinants of awareness levels of climate smart agricultural technologies and practices of urban farmers in Kuje, Abuja, Nigeria. Technology in Society **70**:102030. Elsevier.

Matis M, Saatkamp HW. 2023. Carbon Farming: Conceptual Framework and Bioeconomic Modelling Approach, Applied at Dutch Intensive Arable Farms. [Netherlands]:[publisher not identified].

Mayr S, Pokorny B, Montero-de-Oliveira F-E, Reinecke S. 2025. Scaling agroforestry through payments for ecosystem services: a scoping review. Climate Policy:1–20. Taylor & Francis. Available from https://doi.org/10.1080/14693062.2025.2490205.

McDonald H, Frelih-Larsen A, Lóránt A, Duin L, Pyndt Andersen S, Costa G, Bradley H. 2021. Carbon farming – Making agriculture fit for 2030. European Parliament.

Mills J, Ingram J, Dibari C, Merante P, Karaczun Z, Molnar A, Sánchez B, Iglesias A, Ghaley BB. 2020. Barriers to and opportunities for the uptake of soil carbon management practices in European sustainable agricultural production. Agroecology and Sustainable Food Systems **44**:1185–1211. Taylor & Francis.

Mnukwa L, Mdoda L, Mudhara M. 2025. Assessing the adoption and impact of climate-smart agricultural practices on smallholder maize farmers' livelihoods in Sub-Saharan Africa: a systematic review. Frontiers in Sustainable Food Systems **9**.

MoALF. 2018a. Climate Risk Profile for Kisumu County. Kenya County Climate Risk Profile Series. Available from https://ccafs.cgiar.org/resources/publications/climate-risk-profile-kisumu-county-kenya-county-climate-risk-profile (accessed July 14, 2025).

MoALF. 2018b. Climate Risk Profile for Kakamega County. Kenya County Climate Risk Profile Series. Available from https://ccafs.cgiar.org/resources/publications/climate-risk-profile-kakamega-county-kenya-county-climate-risk-profile (accessed July 13, 2025).

MoALFC. 2021a. Climate Risk Profile for Trans Nzoia County. Kenya County Climate Risk Profile Series. Nairobi. Available from https://www.cgiar.org/research/publication/kenya-climate-risk-profile-trans-nzoia-county/ (accessed July 13, 2025).

MoALFC. 2021b. Climate Risk Profile for Bungoma County. Kenya County Climate Risk Profile Series. Available from https://www.cgiar.org/research/publication/kenya-county-climate-risk-profile-bungoma-count/ (accessed July 13, 2025).

Mogaka BO, Bett HK, Ng'ang'a SK. 2021. Socioeconomic factors influencing the choice of climate-smart soil practices among farmers in western Kenya. Journal of Agriculture and Food Research **5**:100168. Elsevier. Available from https://www.sciencedirect.com/science/article/pii/S2666154321000703?via%3Dihub (accessed July 10, 2025).

Montagnini F, Nair PKR. 2004. Carbon sequestration: an underexploited environmental benefit of agroforestry systems. Agroforestry systems **61**:281–295. Springer.

Mungai C, Opondo M, Outa G, Nelson V, Nyasimi M, Kimeli P. 2017. Uptake of climate-smart agriculture through a gendered intersectionality lens: experiences from Western Kenya. Pages 587–601 Climate change adaptation in Africa: fostering resilience and capacity to adapt. Springer.

Musafiri CM, Kiboi M, Macharia J, Ng'etich OK, Kosgei DK, Mulianga B, Okoti M, Ngetich FK. 2022. Adoption of climate-smart agricultural practices among smallholder farmers in Western Kenya: do socioeconomic, institutional, and biophysical factors matter? Heliyon **8**. Elsevier. Available from https://doi.org/10.1016/j.heliyon.2021.e08677.

Mutimba S, Mayieko S, Olum P, Wanyatma K. 2010. Climate Change Vulnerability and Adaptation Preparedness in Kenya. Kenya. Available from www.boell.or.ke.

Mutombo P, Musarandega H. 2023. Unpacking the determinants of climate-smart agriculture adoption by smallholder farmers in Ward 10, Zvimba District, Zimbabwe. European Journal of Development Studies **3**:74–84.

Nandakishor TM, Gopi G, Champatan V, Sukesh A, Aravind P V. 2022. Agroforestry in Shade Coffee Plantations as an Emission Reduction Strategy for Tropical Regions: Public Acceptance and the Role of Tree Banking. Frontiers in Energy Research **Volume 10-2022**. Available from https://www.frontiersin.org/journals/energy-research/articles/10.3389/fenrg.2022.758372.

Nchanji EB, Kabuli H, Nyamolo VO, Cosmas L, Chisale V, Matumba A. 2022. Gender differences in climate-smart adaptation practices amongst bean-producing farmers in Malawi: The case of Linthipe Extension Planning Area. Frontiers in Sustainable Food Systems **6**:1001152. Frontiers Media SA.

Negera M, Alemu T, Hagos F, Haileslassie A. 2022. Determinants of adoption of climate smart agricultural practices among farmers in Bale-Eco region, Ethiopia. Heliyon **8**. Elsevier.

Newton P, Civita N, Frankel-Goldwater L, Bartel K, Johns C. 2020. What Is Regenerative Agriculture? A Review of Scholar and Practitioner Definitions Based on Processes and Outcomes. Frontiers in Sustainable Food Systems **Volume 4-2020**. Available from https://www.frontiersin.org/journals/sustainable-food-systems/articles/10.3389/fsufs.2020.577723.

Ngaiwi ME, Molua EL, Sonwa DJ, Meliko MO, Bomdzele EJ, Ayuk JE, Castro-Nunez A, Latala MM. 2023. Do farmers' socioeconomic status determine the adoption of conservation agriculture? An empirical evidence from Eastern and Southern Regions of Cameroon. Scientific African **19**:e01498. Elsevier. Available from https://www.sciencedirect.com/science/article/pii/S2468227622004021?via%3Dihub (accessed July 10, 2025).

Ngigi MW, Muange EN. 2022. Access to climate information services and climate-smart agriculture in Kenya: a gender-based analysis. Climatic Change **174**:21. Springer.

Ngigi MW, Mueller U, Birner R. 2017. Gender Differences in Climate Change Adaptation Strategies and Participation in Group-based Approaches: An Intra-household Analysis From Rural Kenya. Ecological Economics **138**:99–108. Elsevier. Available from https://www.sciencedirect.com/science/article/pii/S0921800915302275?via%3Dihub (accessed August 16, 2025).

Njue PN, Isaboke HN, Migose SA. 2023. Contribution of dairy goat farming to household dietary diversity among smallholder farmers in the Central Highlands of Kenya. Journal of Agriculture and Rural Development in the Tropics and Subtropics (JARTS) **124**:1–11.

Nyang'au JO, Mohamed JH, Mango N, Makate C, Wangeci AN. 2021. Smallholder farmers perception of climate change and adoption of climate smart agriculture practices in Masaba South Sub-county, Kisii, Kenya. Heliyon **7**. Elsevier. Available from https://doi.org/10.1016/j.heliyon.2021.e06789.

Nyberg Y, Musee C, Wachiye E, Jonsson M, Wetterlind J, Öborn I. 2020. Effects of agroforestry and other sustainable practices in the Kenya agricultural carbon project (KACP). Land **9**:389. MDPI.

Nyuma HT, Njoroge R, Otinga AN. 2025. Agroforestry adoption and its influence on soil quality under smallholder maize production systems in western Kenya. PLOS ONE **20**:e0313385-. Public Library of Science. Available from https://doi.org/10.1371/journal.pone.0313385.

Öborn I, Wekesa A, Natongo P, Kiguli L, Wachiye E, Musee C, Kuyah S, Neves B. 2017. Who enjoys smallholder generated carbon benefits. Co-Investment in Ecosystem Services: Global Lessons from Payment and Incentive Schemes; Namirembe, S., Leimona, B., van Noordwijk, M., Minang, P., Eds:1–10.

Ogisi OD, Begho T. 2023. Adoption of climate-smart agricultural practices in sub-Saharan Africa: A review of the progress, barriers, gender differences and recommendations. Farming System **1**:100019. Elsevier.

Otieno S, Nzuma J, Ritho C, Muriithi B. 2025. Impact of adoption of Integrated Pest Management practices on the control of fruit fly infestation among smallholder mango farmers in Kenya. International Journal of Pest ManagementDOI: 10.1080/09670874.2025.2516474.

Owuor Odhiambo JK. 2025, February 18. Kenya's Carbon Market Evolution: Bridging Climate Action and Economic Development - The Mount Kenya Times. Available from https://www.mountkenyatimes.co.ke/kenyas-carbon-market-evolution-bridging-climate-action-and-economic-development/ (accessed August 2, 2025).

Pachauri RK, Allen MR, Barros VR, Broome J, Cramer W, Christ R, Church JA, Clarke L, Dahe Q, Dasgupta P. 2014. Climate change 2014: synthesis report. Contribution of Working Groups I, II and III to the fifth assessment report of the Intergovernmental Panel on Climate Change. Ipcc.

Paul C, Bartkowski B, Dönmez C, Don A, Mayer S, Steffens M, Weigl S, Wiesmeier M, Wolf A, Helming K. 2023. Carbon farming: are soil carbon certificates a suitable tool for climate change mitigation? Journal of Environmental Management **330**:117142. Elsevier.

Pello K, Okinda C, Liu A, Njagi T. 2021. Factors affecting adaptation to climate change through agroforestry in Kenya. Land **10**:371. MDPI.

Pennynar M. 2025, June 16. How FLLoCA is driving county-led climate resilience in Kenya. Available from https://newsday.co.ke/county-led-climate/ (accessed August 14, 2025).

Petropoulos T, Benos L, Busato P, Kyriakarakos G, Kateris D, Aidonis D, Bochtis D. 2025. Soil Organic Carbon Assessment for Carbon Farming: A Review. Agriculture 2025, Vol. 15, Page 567 **15**:567. Multidisciplinary Digital Publishing Institute. Available from https://www.mdpi.com/2077-0472/15/5/567/htm (accessed May 31, 2025).

Phelan L, Chapman PJ, Ziv G. 2024. The emerging global agricultural soil carbon market: the case for reconciling farmers' expectations with the demands of the market. Environmental Development **49**:100941. Elsevier.

Pudasaini K, Bhattarai T, Rolfe J. 2024. Exploring the barriers to farmer participation in soil carbon projects under the Australian Carbon Credit Unit Scheme. Australasian Journal of Environmental Management:1–19. Taylor & Francis.

QCI. 2024, June 20. What are the options when considering a project to sequester carbon in the soil? Available from https://www.qcintel.com/carbon/article/feature-what-are-the-options-when-considering-a-project-to-sequester-carbon-in-the-soil-25943.html (accessed August 14, 2025).

Raina N, Zavalloni M, Viaggi D. 2024. Incentive mechanisms of carbon farming contracts: A systematic mapping study. Journal of Environmental Management **352**:120126. Elsevier.

Rasch S, Wünscher T, Casasola F, Ibrahim M, Storm H. 2021. Permanence of PES and the role of social context in the Regional Integrated Silvo-pastoral Ecosystem Management Project in Costa Rica. Ecological Economics **185**:107027. Elsevier. Available from https://www.sciencedirect.com/science/article/pii/S0921800921000859?via%3Dihub (accessed August 18, 2025).

Reppin S, Kuyah S, de Neergaard A, Oelofse M, Rosenstock TS. 2020. Contribution of agroforestry to climate change mitigation and livelihoods in Western Kenya. Agroforestry Systems **94**:203–220. Available from https://doi.org/10.1007/s10457-019-00383-7.

Richardson K, Steffen W, Lucht W, Bendtsen J, Cornell SE, Donges JF, Drüke M, Fetzer I, Bala G, Von Bloh W. 2023. Earth beyond six of nine planetary boundaries. Science advances **9**:eadh2458. American Association for the Advancement of Science.

Rios-Avila F. 2021. Estimation of marginal effects for models with alternative variable transformations. The Stata Journal **21**:81–96. SAGE Publications Sage CA: Los Angeles, CA.

Rois-Díaz M et al. 2018. Farmers' reasoning behind the uptake of agroforestry practices: evidence from multiple case-studies across Europe. Agroforestry Systems **92**:811–828. Available from https://doi.org/10.1007/s10457-017-0139-9.

Saha SK, Stein T V, Nair PKR, Andreu MG. 2011. The Socioeconomic Context of Carbon Sequestration in Agroforestry: A Case Study from Homegardens of Kerala, India. Pages 281–298 in Kumar BM, Nair PKR, editors. Carbon Sequestration Potential of Agroforestry Systems: Opportunities and Challenges. Springer Netherlands, Dordrecht. Available from https://doi.org/10.1007/978-94-007-1630-8_16.

Sanderman J, Hengl T, Fiske GJ. 2017. Soil carbon debt of 12,000 years of human land use. Proceedings of the National Academy of Sciences **114**:9575–9580. National Academy of Sciences.

Sands B, Machado MR, White A, Zent E, Gould R. 2023. Moving towards an anti-colonial definition for regenerative agriculture. Agriculture and Human Values **40**:1697–1716. Available from https://doi.org/10.1007/s10460-023-10429-3.

Santhyami S, Roziaty E, Suparti S. 2023. Trade-off between carbon offset and economic benefit: Potential of cocoa-based agroforestry system implemented in voluntary carbon market. Journal of Agriculture and Rural Development in the Tropics and Subtropics (JARTS) **124**:101–114.

Saptutyningsih E, Diswandi D, Jaung W. 2020. Does social capital matter in climate change adaptation? A lesson from agricultural sector in Yogyakarta, Indonesia. Land use policy **95**:104189. Elsevier.

Schilling F, Baumüller H, Ecuru J, von Braun J. 2023. Carbon farming in Africa: Opportunities and challenges for engaging smallholder farmers. University of Bonn, Center for Development Research (ZEF), Bonn. Available from https://hdl.handle.net/10419/278420.

Schreefel L, Schulte RPO, de Boer IJM, Schrijver AP, van Zanten HHE. 2020. Regenerative agriculture – the soil is the base. Global Food Security **26**:100404. Available from https://www.sciencedirect.com/science/article/pii/S2211912420300584.

Seddon N, Daniels E, Davis R, Chausson A, Harris R, Hou-Jones X, Huq S, Kapos V, Mace GM, Rizvi AR. 2020. Global recognition of the importance of nature-based solutions to the impacts of climate change. Global Sustainability **3**:e15. Cambridge University Press.

Seddon N, Smith A, Smith P, Key I, Chausson A, Girardin C, House J, Srivastava S, Turner B. 2021. Getting the message right on nature-based solutions to climate change. Global change biology **27**:1518–1546. Wiley Online Library.

Shahzad A, Ullah S, Dar AA, Sardar MF, Mehmood T, Tufail MA, Shakoor A, Haris M. 2021. Nexus on climate change: Agriculture and possible solution to cope future climate change stresses. Environmental Science and Pollution Research **28**:14211–14232. Springer.

Shames S, Wollenberg EK, Buck LE, Kristjanson PM, Masiga M, Biryahwaho B. 2012. Institutional innovations in African smallholder carbon projects. CGIAR Research Program on Climate Change, Agriculture and Food Security.

Shan H, Gubin EI. 2019. Data cleaning for data analysis. Pages 387–388 Молодежь и современные информационные технологии: сборник трудов XVI Международной научно-практической конференции студентов, аспирантов и молодых учёных, 3-7 декабря 2018 г., г. Томск.—Томск, 2019.

Sharma M, Kaushal R, Kaushik P, Ramakrishna S. 2021. Carbon farming: Prospects and challenges. Sustainability **13**:11122. MDPI.

Shaw BP. 2022. Effect sizes for contrasts of estimated marginal effects. The Stata Journal **22**:134–157. SAGE Publications Sage CA: Los Angeles, CA.

Singh S, Kiran BR, Mohan SV. 2024. Carbon farming: a circular framework to augment CO2 sinks and to combat climate change. Environmental Science: Advances **3**:522–542. RSC. Available from http://dx.doi.org/10.1039/D3VA00296A.

Sithole A, Olorunfemi OD. 2024. Sustainable Agricultural Practices in Sub-Saharan Africa: A Review of Adoption Trends, Impacts, and Challenges Among Smallholder Farmers. Sustainability 2024, Vol. 16, Page 9766 **16**:9766. Multidisciplinary Digital Publishing Institute. Available from https://www.mdpi.com/2071-1050/16/22/9766/htm (accessed July 12, 2025).

Sommer R, Paul BK, Mukalama J, Kihara J. 2018. Reducing losses but failing to sequester carbon in soils – the case of Conservation Agriculture and Integrated Soil Fertility Management in the humid tropical agro-ecosystem of Western Kenya. Agriculture, Ecosystems & Environment **254**:82–91. Available from https://www.sciencedirect.com/science/article/pii/S0167880917304863.

Srinivasan K, and Yadav VK. 2024. An empirical investigation of barriers to the adoption of smart technologies integrated urban agriculture systems. Journal of Decision Systems **33**:878–912. Taylor & Francis. Available from https://doi.org/10.1080/12460125.2023.2189652.

StataCorp. 2025. Why Stata? Available from https://www.stata.com/why-use-stata/ (accessed August 5, 2025).

Steenkamp L, Thebuho W. 2022. Understanding smallholder farmers' perceptions of and adaptations to climate change: the case of the Zambezi Region, Namibia. Climate Change and Agriculture: Perspectives, Sustainability and Resilience:443–464. Wiley Online Library.

Streck C. 2012. Towards Policies for Climate Change Mitigation: Incentives and benefits for smallholder farmers. CGIAR Research Program on Climate Change, Agriculture and Food Security.

Syano NM, Nyangito MM, Wasonga OV, Kironchi G. 2022. Agroforestry practices and factors influencing their adoption by communities in the drylands of Eastern Kenya. Agroforestry Systems **96**:1225–1235. Available from https://doi.org/10.1007/s10457-022-00782-3.

Tamba Y, Wafula J, Magaju C, St-Jacques B, Stiem-Bhatia L, Arias-Navarro C, Aynekulu E, Winowiecki L. 2021. A review of the participation of smallholder farmers in land-based carbon payment schemes. TMG Research gGmbH.

Tang K, He C, Ma C, Wang D. 2019. Does carbon farming provide a cost-effective option to mitigate GHG emissions? Evidence from China. Australian Journal of Agricultural and Resource Economics **63**:575–592. John Wiley & Sons, Ltd. Available from https://doi.org/10.1111/1467-8489.12306.

Tec M. 2025. ROC Analysis for Classification and Prediction in Practice. Journal of the American Statistical Association **120**:585–586. ASA Website. Available from https://doi.org/10.1080/01621459.2024.2423434.

Tennigkeit T, Okoli A, Brakhan A. 2023. Best practice for Agricultural carbon project development targeting Voluntary Carbon Markets (VCM). Germany. Available from https://www.unique-landuse.de/en/news/2023/guidebook-for-project-developers/ (accessed August 14, 2025).

Tran NLD, Rañola Jr RF, Ole Sander B, Reiner W, Nguyen DT, Nong NKN. 2020. Determinants of adoption of climate-smart agriculture technologies in rice production in Vietnam. International journal of climate change strategies and management **12**:238–256. Emerald Publishing Limited.

Umweltbundesamt. 2025, April 15. The 1.5°C goal of the Paris Agreement . Available from https://www.umweltbundesamt.de/en/topics/climate-energy/the-15degc-goal-of-the-paris-agreement#undefined (accessed May 31, 2025).

Velev V. 2024, February 23. Microsoft Buys 350,000 Nature-Based Carbon Credits From Kenyan Agroforestry Project. Available from https://carbonherald.com/microsoft-buys-350000-nature-based-carbon-credits-from-kenyan-agroforestry-project/ (accessed August 16, 2025).

Verra. 2025. Verra Project Registry. Available from https://registry.verra.org/app/search/VCS/All%20Projects (accessed August 2, 2025).

Vidaller C, Dutoit T. 2022. Ecosystem services in conventional farming systems. A review. Agronomy for Sustainable Development **42**:22. Springer.

Vistarte L, Kubule A, Rozentale L, Pubule J. 2024. Carbon Farming: A Systematic Literature Review on Sustainable Practices. Environmental and Climate Technologies **28**. Available from https://doi.org/10.2478/rtuect-2024-0068.

Von Braun J, Afsana K, Fresco LO, Hassan MHA. 2023. Food systems: seven priorities to end hunger and protect the planet. Science and innovations for food systems transformation:3–9. Springer International Publishing Cham.

Waaswa A, Oywaya Nkurumwa A, Mwangi Kibe A, Ngeno Kipkemoi J. 2022. Climate-Smart agriculture and potato production in Kenya: review of the determinants of practice. Climate and Development **14**:75–90. Taylor & Francis.

Wanjira E, Muriuki J. 2020. Review of the Status of Agroforestry Practices in Kenya. Background study for preparation of Kenya National Agroforestry Strategy (2021-2030).

Wekesa BM, Ayuya OI, Lagat JK. 2018. Effect of climate-smart agricultural practices on household food security in smallholder production systems: micro-level evidence from Kenya. Agriculture & Food Security **7**:80. Available from https://doi.org/10.1186/s40066-018-0230-0.

Wekesah FM, Mutua EN, Izugbara CO. 2019. Gender and conservation agriculture in sub-Saharan Africa: a systematic review. International Journal of Agricultural Sustainability **17**:78–91. Taylor & Francis.

White H. 1980. A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. Econometrica: journal of the Econometric Society:817–838. JSTOR.

Wollenberg EK, Richards MB, Costa C, Sapkota TB, Wilkes A, Reddy RC, Cheng Z, Tao N. 2021. Unlocking crediting opportunities in climate-smart agriculture.

Wongpiyabovorn O, Plastina A, Crespi J. 2021. US agriculture as a carbon sink: From international agreements to farm incentives.

Wooldridge JM. 2020, October 14. Introductory Econometrics: A Modern Approach, 7th Edition. Copyright Clearance Center, Beaverton. Available from http://search.proquest.com.infozdroje.czu.cz/other-sources/introductory-econometrics-modern-approach-7th/docview/2450823121/se-2?accountid=26997.

Zhou X, Ma W, Zheng H, Li J, Zhu H. 2024. Promoting banana farmers' adoption of climate-smart agricultural practices: the role of agricultural cooperatives. Climate and Development **16**:301–310. Taylor & Francis.

Appendices

List of Appendix Tables:

List of Appendix Figures:

Appendix 1: Household Survey Questionnaire

Carbon Farming in Kenya: Assessing Women's Participation, Gendered Impacts, and Best Practices for Global Application

ENUMERATOR, please introduce yourself and the study.

Greetings! “Enumerator name”, I have come as a member of a research team to collect information on your participation in carbon farming projects, the sustainable agricultural practices you follow, and their impact. This study is conducted by the non-profit organization International Maize and Wheat Improvement Center (CIMMYT), which has its headquarters in Mexico and offices in Africa and South Asia. We would like to briefly introduce our work before asking you whether you are willing to participate.

In this project, we will try to know the type of farmers participating in carbon farming projects, their awareness and motivation, sustainable agriculture practices followed, and their impact on GHG emissions and income, among others. The information collected through this survey is important for policymakers, researchers, the carbon market, and other stakeholders to make better decisions towards the promotion of carbon farming among the farmers in the region. While there may not be any immediate and visible benefits from your participation in this study, your responses would contribute to enhancing agricultural policies and practices from which you may also benefit in the future.

If you participate in this study, we will ask you questions about your household and farm characteristics, input use, sustainable agricultural practices followed, awareness and perception about carbon farming, crop residue management, and some additional information on resource conservation. Our team will be interviewing the head of the households (who makes farming decisions most of the time). It will take about 45 minutes of your time. You or other household members will neither be exposed to any risks by participating in this study nor will you be identified personally in any study report or publication. All information about your household will be kept strictly confidential. Data may be shared with other CIMMYT researchers, but we are committed to ensuring absolute confidentiality.

Participation in this study is voluntary. If you choose to participate, you have the right to stop at any time or to not answer individual questions in the questionnaire without any consequences. You may ask any questions you have about the study. If you have questions later, they can be directed to Dr. Adeeth Cariappa (+91 8455683780; a.adeeth@cgiar.org), who is an economist at CIMMYT-India.

I. Are you willing to participate in the study as a respondent? __________ (1= yes/ 0 = no)

(If the respondent answered “no” for the above question, please do not activate the rest of the questionnaire and replace this household with another farmer household).

1. General Household Information

1.1. Household Identification

1. GPS coordinates of the main dwelling	
2. Date of the Interview	
3. Supervisor name (select from the drop-down list)	
4. Interviewer name (select from the drop-down list)	
5. County name (select from the drop-down list)	
6. Subcounty name (select from the drop-down list)	
7. Ward name (select from the drop-down list)	
8. Village name (Enter the name of the village)	
9. Household ID	
10. Is this a male-headed household or female-headed household (1 = female; 0 = male)	
11. Enter the name of the household head	
12. Mobile phone number of HH	
13. Is HH available for an interview? (1= yes/ 0 = no) [If *yes*, go to section 1.2]	
14. Name of respondent, if HH not available for the interview (Please ensure that the respondent belongs to the study household and is above 18 years old)	
15. Relation of the respondent to HH head (Code 1)	
16. Gender of the respondent, if not HH (1 = female; 0 = male)	
17. Mobile phone number of the respondent if he/she is not the HH	

1.1. Farmer Characteristics

Characteristics	Head	Respondent
1. Name of the farmer		
2. What is your age?		
3. For how many years have you been engaged in farming?		
4. What is the highest level of education you have? **(Code 2)**		
5. What is […]'s read and write ability? **(Code 3)**		
6. How many people live in your household? ("Include only the long-term occupants. Do not include short-term guests". Short-term guests refer to individuals who stay for a brief period, typically ranging from a few days to a maximum of one month.)		
7. How many children under age 15 are in the household?		
8. How many of these children (under 15) are school age?		
9. How many of these school-age children under 15 attend school?		
10. Is agriculture the household's main source of income? (Yes = 1/No = 0)		
11. What is the main religion of the household **(Code 4)**		
12. What is the household's ethnic group **(Code 5)**		
13. How many members of the household earn an income?		

14. Are any of the household members a member of a registered farmers'/social organization? (Yes-1, no-0)	
15. If yes to Q16, which one? **(Code 6)**	
16. What is a household member's most important activity? (enumerator: do not prompt) **(Code 7)**	
17. What is the household total cultivated land coverage in acres in the last 12 months (please include land inherited, purchased rented)? Record the responses in acres.	

Code 1: Respondent is HH head's ……

1= Myself (Household head)

2= Wife

3=Husband

4= Father

5=Mother

6=Son/Daughter;

7= Other relative;

8= Non-family resident

2. Question: Are farmers participating in carbon farming? Details of carbon farming

Description: Carbon farming means farmers practicing sustainable agricultural practices like direct seeded rice (DSR), alternative wetting and drying (AWD), zero-till, crop residue management, less chemical fertilizer application, use of organic fertilizer, biochar, *etc*., in collaboration with Agtech companies and NGOs to earn carbon credits. The companies usually sell these carbon credits and promise some payments to the farmers. For this, your plots' GPS coordinates are recorded, and data is collected on the practices you are following and the start date of these practices to measure and monitor GHG emissions reductions and carbon sequestered.

1. **Are you practicing carbon farming?** Yes/No *(If no, skip to question 3)*
2. If yes, how did you get to know about carbon farming? **Code 8** _________
3. If no, why are you not participating in carbon farming?
    - Do not know/never heard of carbon farming
    - Do not have enough land
    - Don't know how to enroll/nobody approached us
    - Company rejected our enrollment
    - Payment takes too long
    - Nobody has been paid so far in the village
    - Others

4. With which entity are you working (Carbon program you are registered with)? (Multiple options)
    - Vi Agroforestry
    - UNIQUE land use

- JOANNEUM RESEARCH
- Livelihoods Fund SICAF SIV
- Soil-Carbon Certification Services Ltd (SCCS)
- GIZ
- Boomitra Inc
- Yara East Africa
- Farm To Market Alliance
- Kenya Organic Agriculture Network

5. How did the company or the implementation partner approach you? (Multiple options)
   a) Directly
   b) Through village leaders
   c) Through farmer collectives
   d) Through other farmers
   e) Through friends
   f) Through relatives
   g) Awareness programs, meetings, workshops, etc.
   h) Others (please mention)

6. What motivated you to get involved in carbon farming? (Multiple options)
   a) Bad soil health
   b) Declining water level
   c) Decreasing productivity
   d) Decreasing profitability of agriculture
   e) Increasing costs
   f) Another source of income (Extra income)
   g) Environmental consciousness/sustainability (saving soil, water, and other resources for future generations)
   h) Yield benefits
   i) Cost reduction
   j) Others (Mention)

7. What new sustainable agriculture practices have you started because of the carbon credit program?

Practices	Do you follow the practice in the project? Yes=1/No=0 (If No, go to the next practice)	If yes, area under technology (LLU)	Were you doing this before the project? Yes=1/No=0	If yes, for how many years?
Zero tillage				
Minimum tillage				
Mulching (with crop residues)				
Organic fertilizer (manure, compost, etc.)				
Green manure				
Soil probiotics				
Soil amendments (lime, others)				
Reduced chemical fertilizer use				
Multi-nutrient and optimized fertilizer application				
Cover crops				
Agroforestry				
Intercropping				
Crop rotation				
Drip irrigation				
Precision irrigation scheduling				
Water harvesting				
Reduced pesticide use				
Biopesticides				
Tree nursery establishment				
Implementation of structures like terraces and grass strips.				
Livestock feed management				
Improved cookstoves				
Livestock manure management (like biogas, composting, etc.)				
Others (Please mention the specific practice. Do not enter a generic term like nutrient management)				

8. Have you received any training to practice carbon farming? (Yes/No)
9. If yes, who conducted the training? (Multiple options)
    I. Company (project developer)
    II. NGO (implementing partner)
    III. Government extension officers
    IV. Others (Specify)

10. Has the company contacted/interacted with you after you agreed to join the carbon farming project? Yes/No
11. If yes, how often does the company contact you/interact with you?
    I. Once every week
    II. Once every month
    III. Once in two months
    IV. Once in three months
    V. Once in >3 months
    VI. Never
    VII. Others
12. What does the company offer?
    I. Carbon credits (CC) only
    II. CC + technical information
    III. CC + farm machinery
    IV. Both II & III
    V. CC + others (Please mention)
13. Have you received any payment so far? Yes=1/No=0
    I. If yes, how much? (Kenyan Shilling per Acre) ___________
    II. If not, did they promise to offer any payment? Yes=1/No=0
    III. If yes, how much have they promised? (KSH per LLU) _ (9999 if not promised)
14. How often do you get paid?
    I. Yearly
    II. Per crop season
    III. Monthly
    IV. Other arrangements (please elaborate)
15. Have you signed a contract with the company? Yes/No
    If yes, do you own carbon credits?
    I. Not aware
    II. Yes
    III. No, the company owns it
16. If yes to Q.15, when did you sign the contract (Year)?
17. Are you continuing carbon farming? Yes/no
18. If not, why?
    - Did not receive carbon credits
    - Loss in yield
    - Increased costs
    - Others, specify

Code 2: Highest level of education

1. No formal education
2. Some primary
3. Completed primary
4. Some lower secondary
5. Completed lower secondary
6. High school
7. Completed high school
8. Vocational/Technical
9. College/Diploma (Certificate) Completed
10. College/Diploma (drop out)
11. University graduate
12. University drop out
13. Postgraduate and above
14. alternative/Informal specify

Code 3: Literate

1. Read only
2. Write only
3. Read and write
4. Neither

Code 4: Religion

0. No religion
1. Catholic
2. Protestant/Other Christian
3. Muslim
4. Hindu

Code 5: Social group

1. Kalenjin
2. Kamba
3. Kikuyu
4. Kisii
5. Luhya
6. Luo
7. Masai
8. Meru/Embu
9. Mijikenda/Swahili
10. Somali
11. Taita/Taveta
12. Other (specify)

Code 6: Group membership

1. Horticultural
2. Coffee
3. Tea
4. Welfare
5. Women's Group
6. Other (specify)

Code 7: Most important activity

1. Farming
2. Agricultural trading
3. Food processing
4. Animal raising
5. Fishing
6. Construction
7. Manufacturing
8. Service/employee
9. Unemployed
10. Student
11. Retired/not working
12. Unpaid housework
13. Other (specify)

Code 8: Source of information

1. Extension agents /Farmer
2. County government
3. Fellow farmers
4. Project proponents
5. NGOs/Agri Companies
6. Radio
7. Group meetings
8. Agricultural shows/Demos

END NOTE:

Thank you very much for your time and participation in this survey. That was the last of our questions for today. As mentioned earlier, you will receive a small token of appreciation, Ksh 400, via M-Pesa within the next three days as a thank you for your involvement. Before we finish, I would like to confirm your M-Pesa number, and the name registered on it.

1. Confirm the Respondent's name registered in M-Pesa
2. Confirm the Respondent's M-Pesa Number

1. Record the GPS point of the household
2. Select the result of the interview
    1) Complete
    2) Incomplete
    3) Ineligible household
    4) Refuse to participate
    5) 96. Other (Specify)

Is there anything else or a comment you would like to add regarding this interview? If you have no comment, please write “OK.”

Appendix 2: Study Locations in Western Kenya

Table 2.11. Study locations in Western Kenya

County	Sub-county	Ward	Village
Kakamega	Malava	Chemuche	Kimangeti
			Lugusi
			Machemo
			Shibiriri
			Shitirira
	Khwisero	Kisa Central	Ebukondosi
			Elukaka
			Emung'Weso
			Emunyanza
			Eshirali
Kisumu	Seme	Central Seme	Kabondo
			Kajagongo
			Kajauga
			Kamonye
			Kanam
			Kanyadwera
			Kaswaga
			Kochiel
			Kogila
			Koliech
			Kolunje
			Komolo
			Konyango
			Kosea
			Kwayumba
	Nyakach	South Nyakach	Kabete
			Kamnwa
			Kochia
			Soko Kahawa
Bungoma	Bumula	Kimaeti	Kamurumba
			Kimaeti
	Sirisia	Malakisi/South Kulisiru	Bisunu
			Busikhe
			Butonge B
			Chebukutumi
			Chongoi
			Florida
			Lukala
			Lutaso
			Nabululi
			Namawanga

			Tunyo
			Wasekese
			Wokape
		Lwandanyi	Habakoya
			Kabendo
			Kabrot
			Kapkara
			Kapsitet
			Kibindoi
			Machakha
			Mayekwe
			Njobosi
			Wamanje
Trans Nzoia	Kaminini	Kaminini	Binyenye
			Kananachi
			Kiminini
			Mbayi
			Midodo
			Murram
			Nyamira
	Saboti	Kinyoro	Cheporokia
			Kipyoywan
			Maji Chafu
			Mogoywet
		Saboti	Sukwo
	Cherangany	Sitatunga	Sitatunga
		Sinyereri	Furaha
			Jamii
			Mitoto
			Musemwa
	Endebess	Matumbei	Adc
			Chepkoilel
			Kenya Seed Village
			Kundos
			Tobo

Appendix 3: Motivations and Barriers for Carbon Farming Participation

Table 3.1. (a) Motivational drivers for participation in carbon farming programs, (b) sources of information received by farmers, and (c) organizers of carbon farming training, disaggregated by household head gender

Category	Variable	MHH (%)		FHH (%)		Chi² p
		No	Yes	No	Yes	
(a) Motivations	Bad soil health	62.7	**37.3**	64.9	**35.1**	0.633
	Declining water level	94.0	**6.0**	94.1	**5.9**	0.952
	Declining productivity	76.5	**23.5**	79.7	**20.3**	0.413
	Decreasing profitability in agriculture	89.9	**10.1**	91.4	**8.6**	0.570
	Increasing costs	87.6	**12.4**	89.2	**10.8**	0.594
	Additional source of income	83.9	**16.1**	82.0	**18.0**	0.599
	Environmental consciousness	44.7	**55.3**	44.1	**55.9**	0.907
	Yield benefits	59.0	**41.0**	50.0	**50.0**	0.059*
	Cost reduction	90.8	**9.2**	90.5	**9.5**	0.930
	Others	99.1	**0.9**	100.0	**0.0**	0.152
(b) Information Sources	Extension agents	–	**39.6**	–	**36.9**	0.668
	County government	–	**4.2**	–	**3.2**	0.597
	Fellow farmers	–	**9.7**	–	**14.0**	0.165
	Project proponents	–	**4.2**	–	**2.3**	0.271
	NGOs/Agri companies	–	**15.2**	–	**14.4**	0.859
	Radio	–	**2.3**	–	**0.5**	0.098*
	Group meetings	–	**24.4**	–	**28.4**	0.352
	Agricultural shows/demos	–	**0.5**	–	**0.5**	0.993
(c) Training Organizers	Company (project developer)	59.9	**40.1**	55.9	**44.1**	0.390
	NGO (implementation partner)	46.5	**53.5**	49.1	**50.9**	0.592
	Government extension officers	93.1	**6.9**	91.9	**8.1**	0.635
	Fellow farmers	99.5	**0.5**	100.0	**0.0**	0.311

Table 3.2. Enabling conditions for carbon farming participation by the gender of the household head. (a) Types of support provided by carbon companies (b) Farmer awareness, engagement, and ownership of carbon credits and (c) Frequency of carbon farming payment

Category	**Variable**	**MHH (%)**		**FHH (%)**		**Chi² p-value**
		No	**Yes**	**No**	**Yes**	
(a) Types of Support Provided by Carbon Companies	Carbon credits (CC) only	–	**27.7**	–	**26.1**	0.790
	CC + technical information	–	**54.8**	–	**59.0**	0.428
	CC + farm machinery	–	**1.4**	–	**1.4**	0.989
	CC + technical information + farm machinery	–	**2.8**	–	**1.4**	0.306
	CC + technical information + farm inputs	–	**0.5**	–	**0.0**	0.314
	CC + farm inputs	–	**12.0**	–	**10.4**	0.629
	CC + livestock	–	**0.9**	–	**1.8**	0.421
(b) Farmer Awareness, Engagement, and Ownership	CF training receipt	10.6	**89.4**	6.8	**93.2**	0.152
	Signed a contract with the company	61.8	**38.3**	64.0	**36.0**	0.631
	Received any payment so far	71.9	**28.1**	71.6	**28.4**	0.950
	Aware of who owns the carbon credits	38.6	**61.4**	43.8	**56.3**	0.249
(c) Frequency of Carbon Farming Payment	Yearly	–	**57.4**	–	**63.5**	0.581
	Per crop season	–	**9.8**	–	**9.5**	0.984
	Monthly	–	**0.0**	–	**1.6**	0.320
	Other arrangements	–	**32.8**	–	**25.4**	0.474

Table 3.3. Farmer-reported barriers to carbon farming participation, by household head gender

Barriers	**MHH (%)**	**FHH (%)**	**Chi² p-value**
Do not know/never heard of carbon farming	52.86	54.76	0.695
Do not have enough land	7.62	8.10	0.856
Don't know how to enroll/nobody approached us	30.48	23.33	0.099*
Company rejected our enrollment	0.00	0.95	0.156
Payment takes too long	1.90	1.90	1.000
Nobody has been paid so far in the village	0.95	0.48	0.562
Others	6.19	10.48	0.112

Appendix 4: Adoption Patterns of Carbon Farming Practices

Table 4.1. Adoption rate of carbon farming practices under the carbon credit program by household head gender

Carbon Farming Practices	**MHH (%)**		**FHH (%)**		**Chi² p-value**
	No	**Yes**	**No**	**Yes**	
Zero tillage	97.7	**2.3**	97.8	**2.3**	0.971
Minimum tillage	96.3	**3.7**	6.9	**3.2**	0.758
Mulching (with crop residues)	78.3	**21.7**	77.9	**22.1**	0.917
Organic fertilizer (manure, compost, etc.)	53.0	**47.0**	51.8	**48.2**	0.802
Green manure	91.2	**8.8**	91.9	**8.1**	0.807
Soil probiotics	95.9	**4.2**	96.9	**3.2**	0.578
Soil amendments (lime, others)	98.2	**1.8**	98.7	**1.4**	0.681
Reduced chemical fertilizer use	96.3	**3.7**	97.3	**2.7**	0.557
Multi-nutrient and optimized fertilizer application	97.7	**2.3**	99.1	**0.9**	0.241
Cover crops	81.6	**18.4**	82.0	**18.0**	0.910
Agroforestry	58.5	**41.5**	58.6	**41.4**	0.994
Intercropping	69.6	**30.4**	70.3	**29.7**	0.876
Crop rotation	81.6	**18.4**	78.4	**21.6**	0.404
Drip irrigation	98.6	**1.4**	99.1	**0.9**	0.634
Precision irrigation scheduling	99.5	**0.5**	98.7	**1.4**	0.326
Water harvesting	99.5	**0.5**	99.1	**0.9**	0.576
Reduced pesticide use	97.2	**2.8**	96.4	**3.6**	0.617
Biopesticides	99.1	**0.9**	98.7	**1.4**	0.671
Tree nursery establishment	96.8	**3.2**	95.5	**4.5**	0.488
Implementation of structures like terraces and grass strips	91.7	**8.3**	90.1	**9.9**	0.557
Livestock feed management	92.6	**7.4**	94.1	**5.9**	0.522
Improved cookstoves	100.0	**0.0**	99.1	**0.9**	0.161
Livestock manure management (like biogas, composting, etc.	94.0	**6.0**	96.4	**3.6**	0.241

Appendix 5: Determinants of Agroforestry Adoption

Table 5.1. Statistics of two-sample t-test of mean land size (hectares) by carbon farming participation and household head gender

Group	MHH			FHH		
	N	Mean (SD)	SE	N	Mean (SD)	SE
Carbon farmers	217	0.717 (0.644)	0.044	222	0.595 (0.500)	0.034
Non-carbon farmers	210	0.544 (0.558)	0.039	210	0.500 (0.491)	0.034
Difference		**0.173 (+31.8%)**	**0.058**		**0.094 (+19%)**	**0.048**
Test statistics:						
t value	-2.9624			-1.9765		
Degrees of freedom	425			430		
p-value	0.0032***			0.0487**		

Note: Mean differences are based on two-sample t-tests. Percentage differences are calculated relative to the respective non-carbon farmer group within each gender category. Positive values indicate higher mean land sizes among carbon farmers. ***p<0.01; **p<0.05

Table 5.2. Kolmogorov-Smirnov test for distributional differences in land size between carbon and non-carbon farmers

Statistic	MHH	FHH
Number of observations	427	432
K-S statistic (D)	0.1651	0.1557
p-value	0.006***	0.011**

Note: The Kolmogorov-Smirnov (K-S) test compares the distributions of land size between carbon and non-carbon farmers, separately for male-headed households (MHH) and female-headed households (FHH). A significant K-S statistic (D) indicates a statistically meaningful difference in the empirical distribution functions of the two groups.

Table 5.3. Project-wise share of farmers who adopted agroforestry by household head gender

Project	MHH	FHH
1	53%	58%
2	43%	50%
3	35%	27%
4	29%	22%

Table 5.4. Variance Inflation Factors (VIF) for predictors of agroforestry adoption

Variable	**Model 1**		**Model 2**		**Model 3**	
	VIF	**1/VIF**	**VIF**	**1/VIF**	**VIF**	**1/VIF**
Age of the household head (in years)	1.34	0.75	1.25	0.80	1.64	0.61
Size of the household	1.11	0.90	1.23	0.81	1.1	0.91
Total cultivated land in hectares in the last 12 months	1.31	0.76	1.38	0.72	1.36	0.73
Education level of the household head						
Primary education	5.77	0.17	8.05	0.12	4.57	0.22
Secondary education	5.95	0.17	8.55	0.12	4.96	0.20
Vocational training/Diploma education	2.51	0.40	4.18	0.24	1.72	0.58
University education	1.54	0.65	2.04	0.49	1.39	0.72
Ethnicity of the household head						
Kalenjin	1.19	0.84	1.2	0.83	1.21	0.82
Luo	6.03	0.17	6.58	0.15	5.96	0.17
Others (Kamba, Kikuyu, Kisii)	1.12	0.89	1.17	0.85	1.16	0.86
Project affiliation						
Project 2	5.06	0.20	5.57	0.18	4.96	0.20
Project 3	1.77	0.56	1.99	0.50	1.85	0.54
Project 4	4.37	0.23	4.58	0.22	4.82	0.21
Organizational membership (1=Yes)	1.13	0.88	1.24	0.80	1.1	0.91
Mean VIF	**2.87**		**3.5**		**2.7**	

Note: VIF values indicate the degree of multicollinearity among predictors, with VIF > 10 suggesting potential multicollinearity issues. Model 1 includes a pooled sample, while Models 2 and 3 analyze male-headed households (MHH) and female-headed households (FHH), respectively.

Table 5.5. Logit results of socio-demographic factors influencing agroforestry adoption

Variable	**Model 1**		**Model 2**		**Model 3**	
	OR (RSE)	**p-value**	**OR (RSE)**	**p-value**	**OR (RSE)**	**p-value**
Age of the household head (in years)	1.006 (0.008)	0.447	1.002 (0.011)	0.854	1.007 (0.014)	0.611
Size of the household	1.056 (0.046)	0.207	1.029 (0.066)	0.653	1.097 (0.068)	0.134
Total cultivated land in hectares in the last 12 months	0.880 (0.178)	0.527	0.827 (0.224)	0.483	0.844 (0.284)	0.615
Education level of the household head						
Primary education	0.734 (0.328)	0.489	1.289 (1.070)	0.759	0.569 (0.325)	0.323
Secondary education	1.105 (0.510)	0.828	1.688 (1.389)	0.525	0.944 (0.600)	0.928
Vocational training/Diploma education	1.349 (0.816)	0.621	1.710 (1.580)	0.561	2.491 (2.792)	0.416
University education	1.350 (1.072)	0.705	3.286 (3.555)	0.272	0.380 (0.570)	0.519
Ethnicity of the household head						
Kalenjin	2.102 (0.918)	0.089*	2.688 (1.804)	0.141	1.815 (1.032)	0.295
Luo	0.359 (0.177)	0.038**	0.557 (0.427)	0.445	0.250 (0.171)	0.042**
Others (Kamba, Kikuyu, Kisii)	3.023 (1.953)	0.087*	2.307 (2.083)	0.355	2.815 (2.686)	0.278
Project affiliation						
Project 2	2.009 (1.100)	0.202	1.071 (0.888)	0.934	3.318 (2.566)	0.121
Project 3	0.407 (0.130)	0.005***	0.446 (0.224)	0.108	0.327 (0.151)	0.015**
Project 4	0.776 (0.393)	0.616	0.641 (0.486)	0.558	0.686 (0.515)	0.616
Organizational membership (1=Yes)	1.840 (0.540)	0.038**	2.218 (0.947)	0.062*	1.344 (0.562)	0.480
Constant	0.395 (0.315)	0.244	0.325 (0.374)	0.329	0.537 (0.694)	0.630

Note: “Constant” estimate baseline odds (Baseline categories are Project 1, No formal education and Luhya ethnic group). OR = Odds Ratio, RSE = Robust Standard Error
Significance stars indicate p-value thresholds: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5.6. 95% confidence intervals of logistic regression estimates for socio-demographic factors influencing agroforestry adoption

Variable	**Model 1**		**Model 2**		**Model 3**	
	95% CI (Lower)	**95% CI (Upper)**	**95% CI (Lower)**	**95% CI (Upper)**	**95% CI (Lower)**	**95% CI (Upper)**
Age of the household head (in years)	0.990	1.023	0.981	1.023	0.980	1.035
Size of the household	0.970	1.150	0.908	1.166	0.972	1.239
Total cultivated land in hectares in the last 12 months	0.593	1.307	0.486	1.406	0.436	1.633
Education level of the household head						
Primary education	0.306	1.762	0.254	6.558	0.186	1.742
Secondary education	0.447	2.732	0.336	8.470	0.272	3.279
Vocational training/Diploma education	0.412	4.412	0.280	10.457	0.277	22.406
University education	0.285	6.403	0.394	27.394	0.020	7.174
Ethnicity of the household head						
Kalenjin	0.893	4.946	0.721	10.014	0.595	5.534
Luo	0.136	0.946	0.124	2.502	0.065	0.954
Others (Kamba, Kikuyu, Kisii)	0.852	10.726	0.393	13.544	0.434	18.266
Project affiliation						
Project 2	0.687	5.874	0.211	5.442	0.729	15.107
Project 3	0.217	0.762	0.166	1.195	0.132	0.808
Project 4	0.287	2.093	0.145	2.835	0.157	2.990
Organizational membership (1=Yes)	1.035	3.272	0.960	5.121	0.592	3.052
Constant	0.083	1.885	0.034	3.110	0.043	6.767

Table 5.7. Logit summary of socio-demographic factors influencing agroforestry adoption

Statistic	Model 1	Model 2	Model 3
Number of observations	439	217	222
Wald chi^2 (14)	42.58	17.44	31.50
Prob > chi^2	0.0001	0.2336	0.0047
Log pseudolikelihood	-273.45295	-137.8162	-132.01588
Pseudo R^2	0.0819	0.0640	0.1235

Note: The Wald chi^2 statistic is reported with degrees of freedom (df). Prob > chi^2 values of 0.0001 provide strong evidence against the null hypothesis that all coefficients are zero.

Table 5.8. Hosmer-Lemeshow goodness-of-fit test of the agroforestry adoption logit model

Statistic	Model 1	Model 2	Model 3
Variable	SA_CCP_Agrofor	SA_CCP_Agrofor	SA_CCP_Agrofor
Number of observations	439	217	222
Number of groups	10	10	10
Hosmer-Lemeshow chi^2 (8)	10.57	5.62	17.05
Prob > chi^2	0.2274	0.6902	0.0296

Note: A high p-value (> 0.05) indicates no significant evidence of poor model fitness, suggesting that the logistic regression models fit the data adequately.

Table 5.9. Classification table of predicted adoption of agroforestry at the default cutpoint

Model	Classified	True D	True ~D	Total
Model 1	+	84	60	144
	-	98	197	295
	Total	**182**	**257**	**439**
Model 2	+	33	20	53
	-	57	107	164
	Total	**90**	**127**	**217**
Model 3	+	51	31	82
	-	41	99	140
	Total	**92**	**130**	**222**

Note: Classified + if predicted $Pr(D) \geq 0.5$; classified – if predicted $Pr(D) < 0.5$. True D is defined as $SA\_CCP\_Agrofor \neq 0$, indicating adoption of agroforestry.

Table 5.10. Classification performance statistics for predicting agroforestry adoption at the default cutpoint

Statistic	Formula	Model 1 (%)	Model 2 (%)	Model 3 (%)
Sensitivity	Pr(+|D)	46.15	36.67	55.43
Specificity	Pr(-|~D)	76.65	84.25	76.15
Positive predictive value	Pr(D|+)	58.33	62.26	62.20
Negative predictive value	Pr(~D|-)	66.78	65.24	70.71
False positive rate for true ~D	Pr(+|~D)	23.35	15.75	23.85
False negative rate for true D	Pr(-|D)	53.85	63.33	44.57
False positive rate for classified +	Pr(~D|+)	41.67	37.74	37.80
False negative rate for classified -	Pr(D|-)	33.22	34.76	29.29
Correctly classified		**64.01**	**64.52**	**67.57**

Note: Metrics are based on a classification threshold of Pr(D) ≥ 0.5, where D indicates adoption of agroforestry (SA_CCP_Agrofor ≠ 0).

Table 5.11. Empirical cutpoint estimation of agroforestry adoption using the Liu method

Statistic	Value
Method	Liu
Reference variable	SA_CCP_Agrofor (0=neg, 1=pos)
Classification variable	phat
Empirical optimal cutpoint	0.40505438
Sensitivity at cutpoint	0.68
Specificity at cutpoint	0.62
Area under ROC curve at cutpoint	0.65

Table 5.12. Classification table of predicted adoption of agroforestry at empirical cutpoint

Model	Classified	True D	True ~D	Total
Model 1	+	124	98	222
	-	58	159	217
	Total	**182**	**257**	**439**
Model 2	+	53	47	100
	-	37	80	117
	Total	**90**	**127**	**217**
Model 3	+	68	49	117
	-	24	81	105
	Total	**92**	**130**	**222**

Note: Classified + if predicted Pr(D) ≥ 0.4050544; classified – if predicted Pr(D) < 0.4051013. True D is defined as SA_CCP_Agrofor ≠ 0, indicating adoption of agroforestry.

Table 5.13. Classification performance statistics for predicting agroforestry adoption at empirical cutpoint

Statistic	Formula	Model 1 (%)	Model 2 (%)	Model 3 (%)
Sensitivity	Pr(+|D)	68.13	58.89	73.91
Specificity	Pr(-|~D)	61.87	62.99	62.31
Positive predictive value	Pr(D|+)	55.86	53	58.12
Negative predictive value	Pr(~D|-)	73.27	68.38	77.14
False positive rate for true ~D	Pr(+|~D)	38.13	37.01	37.69
False negative rate for true D	Pr(-|D)	31.87	41.11	26.09
False positive rate for classified +	Pr(~D|+)	44.14	47	41.88
False negative rate for classified -	Pr(D|-)	26.73	31.62	22.86
Correctly classified		**64.46**	**61.29**	**67.12**

Note: Metrics are based on a classification threshold of Pr(D) ≥ 0.0.4050544, where D indicates adoption of agroforestry (SA_CCP_Agrofor ≠ 0).

Table 5.14. Receiver Operating Characteristic (ROC) analysis of predictive model for agroforestry adoption

No. of observations	ROC area	Standard Error	Asymptotic Normal (95% CI)	
			Lower	Upper
439	0.6900	0.0255	0.63996	0.73999

Note: The area under the ROC curve (AUC) is 0.6900, suggesting **poor to acceptable** discriminative ability. According to the guideline by Hosmer and Lemeshow (2000), AUC values are interpreted as follows: 0.5 = no discrimination; 0.5-0.7 = poor; 0.7-0.8 = acceptable; 0.8-0.9 = excellent; >0.9 = outstanding.

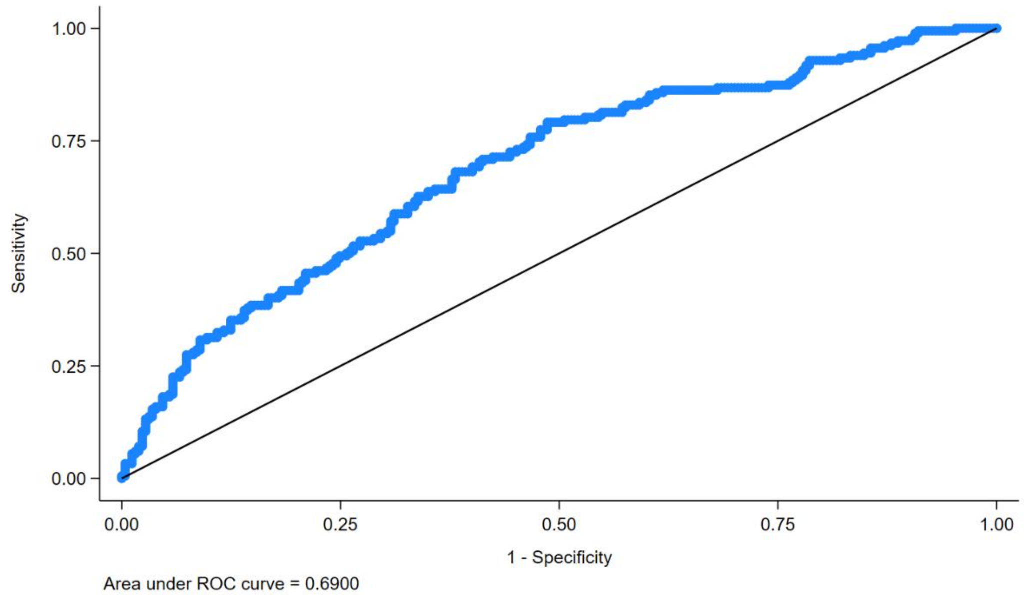

Figure 5.1. ROC curve for predicting the adoption of agroforestry at the empirical cutpoint

Table 5.15. Average marginal effects of socio-demographic determinants influencing agroforestry adoption

Variable	**Model 1**		**Model 2**		**Model 3**	
	AME (RSE)	**p-value**	**AME (RSE)**	**p-value**	**AME (RSE)**	**p-value**
Age of the household head (in years)	0.14 (0.18)	0.446	0.04 (0.24)	0.854	0.15 (0.29)	0.610
Size of the household	1.19 (0.94)	0.204	0.64 (1.42)	0.653	1.89 (1.24)	0.127
Total cultivated land in hectares in the last 12 months	-2.77 (4.36)	0.526	-4.23 (5.99)	0.480	-3.46 (6.85)	0.613
Education level of the household head						
Primary education	-6.67 (9.81)	0.496	5.34 (16.94)	0.753	-11.84 (12.18)	0.331
Secondary education	2.23 (10.24)	0.827	11.34 (16.86)	0.501	-1.23 (13.64)	0.928
Vocational training/Diploma education	6.70 (13.50)	0.620	11.64 (19.38)	0.548	18.98 (22.19)	0.392
University education	6.73 (17.80)	0.705	26.61 (23.11)	0.249	-19.54 (27.86)	0.483
Ethnicity of the household head						
Kalenjin	16.38 (9.36)	0.080*	22.49 (14.39)	0.118	12.35 (11.65)	0.289
Luo	-21.43 (9.30)	0.021**	-13.02 (16.52)	0.431	-26.41 (10.90)	0.015**
Others (Kamba, Kikuyu, Kisii)	23.55 (12.21)	0.054*	19.25 (19.78)	0.330	20.74 (17.36)	0.232
Project affiliation						
Project 2	15.51 (11.20)	0.166	1.59 (19.22)	0.934	24.59 (13.15)	0.062*
Project 3	-18.26 (6.43)	0.005**	-17.64 (10.60)	0.096	-21.05 (8.84)	0.017**
Project 4	-5.54 (11.22)	0.622	-10.08 (17.44)	0.563	-7.73 (15.74)	0.623
Organizational membership (1=Yes)	12.82 (5.84)	0.028**	16.95 (8.34)	0.042**	5.98 (8.34)	0.473

Note: The margin for factor levels represents a discrete change from the base level and is expressed in percentage points. AME = Average Marginal Effect, RSE = Robust Standard Error Significance stars indicate p-value thresholds: * p < 0.10, ** p < 0.05, *** p < 0.01.

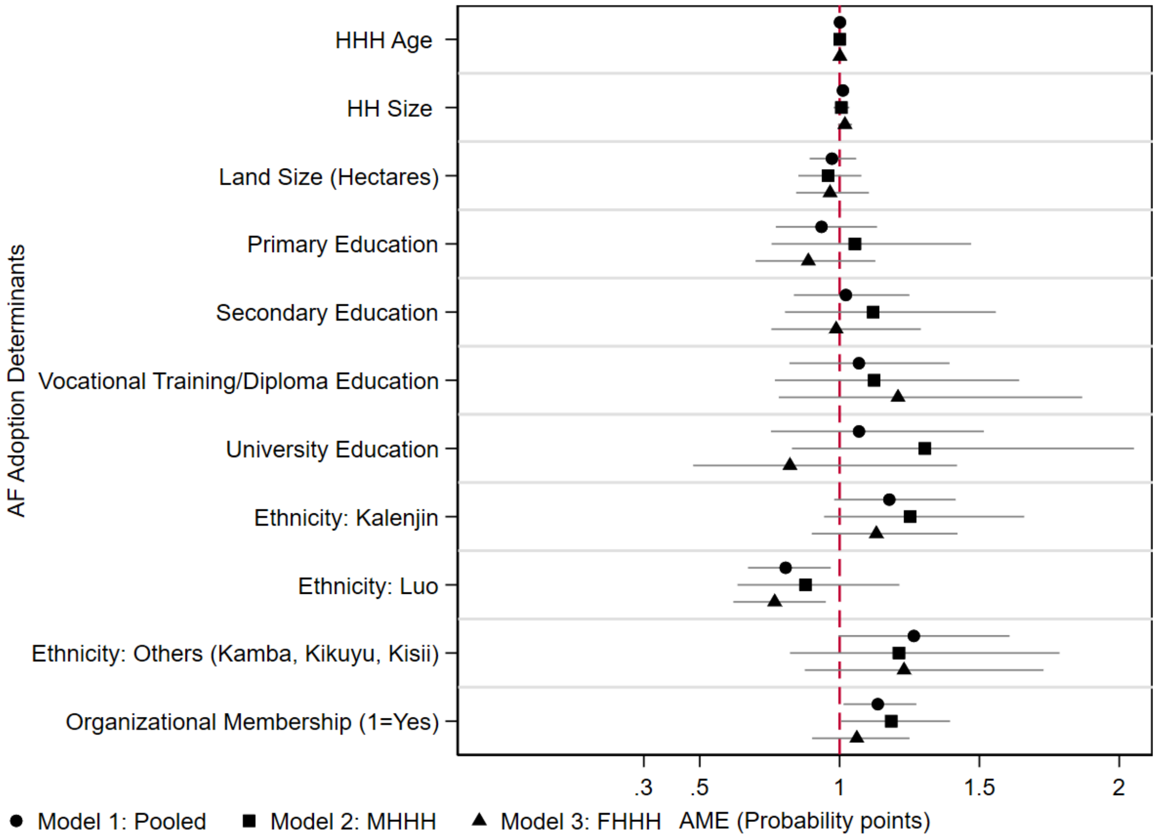

Figure 5.2. Forest plot illustrating the odds ratio of socio-demographic determinants influencing agroforestry adoption

Note: The regression models adjust for project-level effects, which are not shown in the plot.

Table 5.16. 95% confidence intervals of average marginal effects for socio-demographic determinants influencing agroforestry adoption

Variable	Model 1		Model 2		Model 3	
	95% CI (Lower)	95% CI (Upper)	95% CI (Lower)	95% CI (Upper)	95% CI (Lower)	95% CI (Upper)
Age of the household head (in years)	-0.22	0.49	-0.42	0.51	-0.42	0.71
Size of the household	-0.65	3.03	-2.14	3.42	-0.54	4.32
Total cultivated land in hectares in the last 12 months	-11.32	5.78	-15.96	7.51	-16.90	9.97
Education level of the household head						
Primary education	-25.90	12.55	-27.86	38.55	-35.72	12.04
Secondary education	-17.83	22.29	-21.71	44.39	-27.97	25.50
Vocational training/Diploma education	-19.77	33.17	-26.34	49.61	-24.51	62.47
University education	-28.15	41.61	-18.68	71.91	-74.15	35.06
Ethnicity of the household head						
Kalenjin	-1.96	34.72	-5.71	50.70	-10.48	35.19
Luo	-39.66	-3.20	-45.41	19.37	-47.78	-5.04
Others (Kamba, Kikuyu, Kisii)	-0.39	47.49	-19.52	58.02	-13.29	54.77
Project affiliation						
Project 2	-6.44	37.46	-36.08	39.26	-1.19	50.37
Project 3	-30.86	-5.66	-38.42	3.13	-38.37	-3.73
Project 4	-27.54	16.46	-44.27	24.11	-38.58	23.11
Organizational membership (1=Yes)	1.37	24.27	0.61	33.29	-10.36	22.32

Note: The margin for factor levels represents a discrete change from the base level and is expressed in percentage points. CI = Confidence Interval.

Table 5.17. Average marginal effects of age on agroforestry adoption by household head gender

Age	MHH				FHH			
	AME (RSE)	**p-value**	**95% CI (Lower)**	**95% CI (Upper)**	**AME (RSE)**	**p-value**	**95% CI (Lower)**	**95% CI (Upper)**
18	39.69 (8.16)	0.000***	23.71	55.68	32.41 (9.04)	0.000***	14.68	50.13
23	39.93 (7.17)	0.000***	25.87	53.98	33.63 (8.06)	0.000***	17.82	49.43
28	40.17 (6.22)	0.000***	27.98	52.35	34.86 (7.06)	0.000***	21.02	48.71
33	40.40 (5.31)	0.000***	29.99	50.82	36.12 (6.06)	0.000***	24.24	48.00
38	40.64 (4.49)	0.000***	31.84	49.45	37.39 (5.09)	0.000***	27.42	47.37
43	40.88 (3.81)	0.000***	33.41	48.35	38.68 (4.20)	0.000***	30.45	46.92
48	41.12 (3.36)	0.000***	34.53	47.71	39.99 (3.51)	0.000***	33.10	46.88
53	41.36 (3.25)	0.000***	35.00	47.72	41.31 (3.19)	0.000***	35.06	47.56
58	41.60 (3.50)	0.000***	34.75	48.46	42.64 (3.37)	0.000***	36.03	49.25
63	41.84 (4.05)	0.000***	33.90	49.79	43.98 (4.01)	0.000***	36.12	51.84
68	42.08 (4.81)	0.000***	32.65	51.51	45.33 (4.94)	0.000***	35.64	55.01
73	42.33 (5.69)	0.000***	31.17	53.48	46.68 (6.04)	0.000***	34.85	58.51
78	42.57 (6.65)	0.000***	29.53	55.60	48.04 (7.22)	0.000***	33.89	62.19
80	42.66 (7.05)	0.000***	28.85	56.48	48.58 (7.71)	0.000***	33.48	63.69

Table 5.18. Average marginal effects of household size on agroforestry adoption by household head gender

Household Size	MHH				FHH			
	AME (RSE)	p-value	95% CI (Lower)	95% CI (Upper)	AME (RSE)	p-value	95% CI (Lower)	95% CI (Upper)
1	39.11 (7.03)	0.000***	25.34	52.89	32.86 (6.30)	0.000***	20.52	45.20
3	40.09 (4.86)	0.000***	30.57	49.62	36.31 (4.61)	0.000***	27.28	45.34
5	41.08 (3.38)	0.000***	34.45	47.70	39.89 (3.34)	0.000***	33.34	46.45
7	42.07 (3.67)	0.000***	34.88	49.26	43.58 (3.50)	0.000***	36.73	50.43
9	43.07 (5.50)	0.000***	32.29	53.85	47.33 (5.09)	0.000***	37.35	57.30
11	44.07 (7.89)	0.000***	28.61	59.54	51.10 (7.24)	0.000***	36.92	65.29
13	45.08 (10.47)	0.000***	24.55	65.61	54.86 (9.49)	0.000***	36.26	73.47
15	46.09 (13.14)	0.000***	20.33	71.85	58.58 (11.67)	0.000***	35.70	81.46

Table 5.19. Average marginal effects of education level on agroforestry adoption by household head gender

Education Level	MHH				FHH			
	AME (RSE)	p-value	95% CI (Lower)	95% CI (Upper)	AME (RSE)	p-value	95% CI (Lower)	95% CI (Upper)
No formal education	33.33 (16.52)	0.044**	0.96	65.71	47.40 (11.21)	0.000***	25.43	69.36
Primary	37.91 (5.43)	0.000***	27.27	48.55	35.28 (4.22)	0.000***	27.02	43.55
Secondary	44.69 (4.83)	0.000***	35.22	54.15	45.40 (5.46)	0.000***	34.70	56.10
Vocational Training/Diploma	45.05 (10.87)	0.000***	23.75	66.34	65.24 (17.85)	0.000***	30.25	100.23
University	61.30 (14.83)	0.000***	32.23	90.36	24.26 (23.45)	0.301	-21.71	70.23

Table 5.20. Average marginal effects of land size on agroforestry adoption by household head gender

Land Size	MHH				FHH			
	AME (RSE)	p-value	95% CI (Lower)	95% CI (Upper)	AME (RSE)	p-value	95% CI (Lower)	95% CI (Upper)
0	44.32 (5.14)	0.000***	34.25	54.39	41.88 (5.24)	0.000***	31.62	52.15
0.5	42.25 (3.45)	0.000***	35.49	49.01	41.65 (3.31)	0.000***	35.15	48.14
1	40.20 (3.50)	0.000***	33.35	47.06	41.41 (3.81)	0.000***	33.95	48.87
1.5	38.19 (5.12)	0.000***	28.15	48.22	41.17 (6.15)	0.000***	29.13	53.22
2	36.21 (7.23)	0.000***	22.04	50.37	40.94 (8.98)	0.000***	23.34	58.54
2.5	34.27 (9.40)	0.000***	15.84	52.69	40.70 (11.95)	0.001***	17.27	64.13
3	32.37 (11.51)	0.005***	9.82	54.93	40.47 (14.98)	0.007***	11.11	69.82
3.5	30.53 (13.49)	0.024**	4.09	56.98	40.23 (18.02)	0.026**	4.91	75.55
4	28.75 (15.33)	0.061*	-1.30	58.79	40.00 (21.07)	0.058*	-1.30	81.29
4.5	27.02 (17.00)	0.112	-6.30	60.34	39.76 (24.12)	0.099*	-7.50	87.03
5	25.35 (18.49)	0.170	-10.89	61.59	39.53 (27.16)	0.146	-13.70	92.76

Table 5.21. Average marginal effects of organizational membership on agroforestry adoption by household head gender

Organizational Membership	MHH				FHH			
	AME (RSE)	p-value	95% CI (Lower)	95% CI (Upper)	AME (RSE)	p-value	95% CI (Lower)	95% CI (Upper)
No	28.09 (6.80)	0.000***	14.76	41.43	35.03 (7.21)	0.000***	20.89	49.17
Yes	44.94 (3.75)	0.000***	37.59	52.29	43.19 (3.50)	0.000***	36.33	50.05

Appendix 6: Determinants of Carbon Payment Receipt

Table 6.1. Project-wise share of farmers who received carbon credit payments by household head gender

Project	MHH	FHH
1	36%	43%
2	74%	64%
3	0%	2%
4	0%	2%

Table 6.2. Variance Inflation Factors (VIF) for predictors of carbon farming payment

Variable	VIF	1/VIF
Age of the household head (in years)	1.33	0.75
Total cultivated land in hectares in the last 12 months	1.32	0.76
Gender of the household head (1=Female)	1.08	0.93
Education level of the household head		
Primary education	5.73	0.17
Secondary education	6.01	0.17
Vocational training/Diploma education	2.57	0.39
University education	1.54	0.65
Ethnicity of the household head		
Kalenjin	1.19	0.84
Luo	6.08	0.16
Others (Kamba, Kikuyu, Kisii)	1.12	0.89
Project affiliation		
Project 2	4.99	0.20
Project 3	1.79	0.56
Project 4	4.27	0.23
Agroforestry adoption (1=Yes)	1.11	0.90
Organizational membership (1=Yes)	1.14	0.87
Mean VIF	**2.75**	

Note: VIF values indicate the degree of multicollinearity among predictors, with VIF > 10 suggesting potential multicollinearity issues.

Table 6.3. Logit results of socio-demographic factors influencing carbon farming payment

Variable	OR (RSE)	p-value	95% CI (Lower)	95% CI (Upper)
Age of the household head (in years)	1.012 (0.011)	0.271	0.991	1.034
Total cultivated land in hectares in the last 12 months	1.304 (0.300)	0.249	0.831	2.047
Gender of the household head (1=Female)	0.856 (0.245)	0.586	0.488	1.499
Education level of the household head				
Primary education	1.002 (0.669)	0.998	0.270	3.710
Secondary education	0.735 (0.485)	0.641	0.202	2.676
Vocational training/Diploma education	0.173 (0.164)	0.064*	0.027	1.104
University education	0.798 (0.822)	0.827	0.106	6.013
Ethnicity of the household head				
Kalenjin	0.287 (0.156)	0.022**	0.099	0.832
Luo	0.531 (0.547)	0.539	0.070	4.004
Others (Kamba, Kikuyu, Kisii)	0.108 (0.118)	0.042**	0.013	0.925
Project affiliation				
Project 2	5.131 (5.446)	0.123	0.641	41.082
Project 3	0.010 (0.011)	0.000***	0.001	0.078
Project 4	0.027 (0.043)	0.022**	0.001	0.597
Agroforestry adoption (1=Yes)	1.224 (0.350)	0.480	0.699	2.142
Organizational membership (1=Yes)	1.954 (0.771)	0.090*	0.902	4.234
Constant	0.265 (0.269)	0.191	0.036	1.940

Note: "Constant" estimate baseline odds (Baseline categories are Male (0), Project 1, No formal education and Luhya ethnic group). OR = Odds Ratio, RSE = Robust Standard Error
Significance stars indicate p-value thresholds: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6.4. Logit summary of socio-demographic factors influencing carbon farming payment

Statistic	Value
Number of observations	439
Wald chi^2 (15)	75.34
Prob > chi^2	0.0000
Log pseudolikelihood	-153.81168
Pseudo R^2	0.4114

Note: The Wald chi^2 statistic is reported with degrees of freedom (df). Prob > chi^2 values of 0.0000 provide strong evidence against the null hypothesis that all coefficients are zero.

Table 6.5. Hosmer-Lemeshow goodness-of-fit test of the carbon farming payment logit model

Statistic	Value
Variable	CF_Pay_Recv
Number of observations	439
Number of groups	10
Hosmer-Lemeshow chi^2 (8)	6.03
Prob > chi^2	0.6443

Note: A high p-value (> 0.05) indicates no significant evidence of poor model fitness, suggesting that the logistic regression models fit the data adequately.

Table 6.6. Classification table of predicted carbon farming payment at the default cutpoint

Classified	True D	True ~D	Total
+	92	43	135
-	32	272	304
Total	**124**	**315**	**439**

Note: Classified + if predicted Pr(D) ≥ 0.5; classified – if predicted Pr(D) < 0.5. True D is defined as CF_Pay_Recv ≠ 0, indicating that a carbon farming payment has been received.

Table 6.7. Classification performance statistics for predicting carbon farming payment at the default cutpoint

Statistic	Formula	Value (%)
Sensitivity	Pr(+|D)	74.19
Specificity	Pr(-|~D)	86.35
Positive predictive value	Pr(D|+)	68.15
Negative predictive value	Pr(~D|-)	89.47
False positive rate for true ~D	Pr(+|~D)	13.65
False negative rate for true D	Pr(-|D)	25.81
False positive rate for classified +	Pr(~D|+)	31.85
False negative rate for classified -	Pr(D|-)	10.53
Correctly classified		**82.92**

Note: Metrics are based on a classification threshold of Pr(D) ≥ 0.5, where D indicates that a carbon farming payment has been received (CF_Pay_Recv ≠ 0).

Table 6.8. Empirical cutpoint estimation of carbon farming payment using the Liu method

Statistic	Value
Method	Liu
Reference variable	CF_Pay_Recv (0=neg, 1=pos)
Classification variable	phat
Empirical optimal cutpoint	0.37511963
Sensitivity at cutpoint	0.90
Specificity at cutpoint	0.78
Area under ROC curve at cutpoint	0.84

Table 6.9. Classification table of predicted carbon farming payment at empirical cutpoint

Classified	True D	True ~D	Total
+	111	68	179
-	13	247	260
Total	**124**	**315**	**439**

Note: Classified + if predicted Pr(D) ≥ 0.3751196; classified – if predicted Pr(D) < 0.3751196. True D is defined as CF_Pay_Recv ≠ 0, indicating that a carbon farming payment has been received.

Table 6.10. Classification performance statistics for predicting carbon farming payment at empirical cutpoint

Statistic	Formula	Value (%)
Sensitivity	Pr(+|D)	89.52
Specificity	Pr(-|~D)	78.41
Positive predictive value	Pr(D|+)	62.01
Negative predictive value	Pr(~D|-)	95.00
False positive rate for true ~D	Pr(+|~D)	21.59
False negative rate for true D	Pr(-|D)	10.48
False positive rate for classified +	Pr(~D|+)	37.99
False negative rate for classified -	Pr(D|-)	5.00
Correctly classified		**81.55**

Note: Metrics are based on a classification threshold of Pr(D) ≥ 0.3751196, where D indicates carbon farming payment received (CF_Pay_Recv ≠ 0).

Table 6.11. Receiver Operating Characteristic (ROC) analysis of predictive model for carbon farming payment

No. of observations	ROC area	Standard Error	Asymptotic Normal (95% CI)	
			Lower	Upper
439	0.8958	0.0153	0.86584	0.92566

Note: The area under the ROC curve (AUC) is 0.8958, suggesting **excellent** discriminative ability. According to the guideline by Hosmer and Lemeshow (2000), AUC values are interpreted as follows: 0.5 = no discrimination; 0.5-0.7 = poor; 0.7-0.8 = acceptable; 0.8-0.9 = excellent; >0.9 = outstanding.

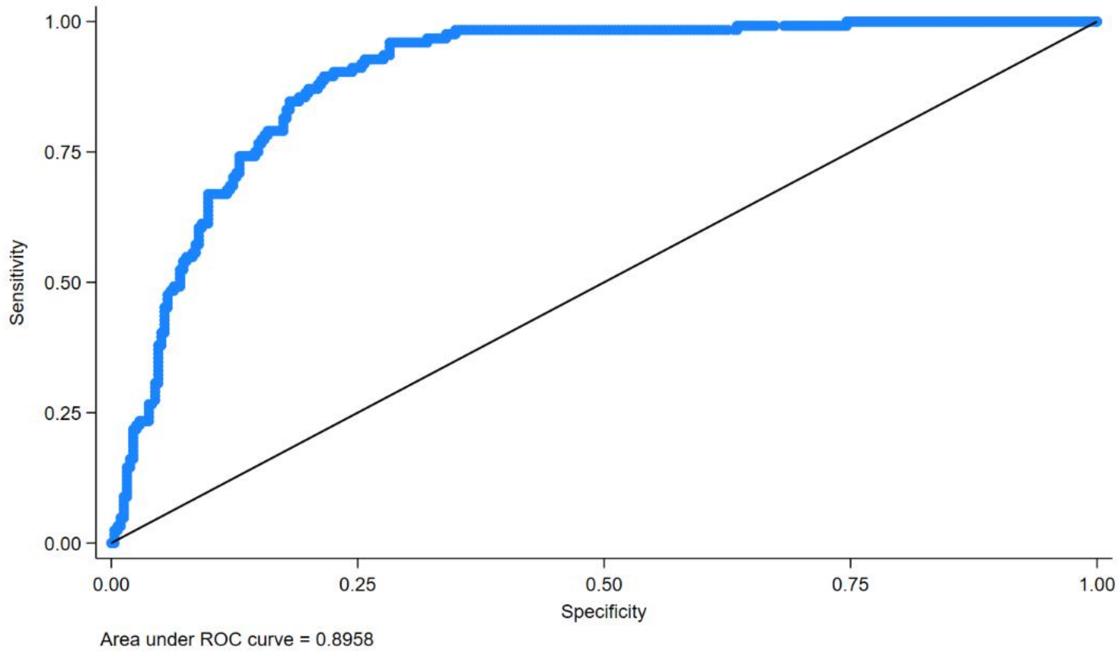

Figure 6.1. ROC curve for predicting the carbon farming payment at the empirical cutpoint

Table 6.12. Average marginal effects of socio-demographic determinants influencing carbon farming payment

Variable	AME (RSE)	p-value	95% CI (Lower)	95% CI (Upper)
Age of the household head (in years)	0.14 (0.13)	0.270	-0.001	0.004
Total cultivated land in hectares in the last 12 months	3.10 (2.65)	0.243	-0.021	0.083
Gender of the household head (1=Female)	-1.81 (3.31)	0.584	-0.083	0.047
Education level of the household head				
Primary education	0.02 (7.93)	0.998	-0.155	0.156
Secondary education	-3.69 (7.83)	0.638	-0.190	0.117
Vocational training/Diploma education	-19.42 (9.61)	0.043**	-0.383	-0.006
University education	-2.70 (12.34)	0.827	-0.269	0.215
Ethnicity of the household head				
Kalenjin	-14.17 (6.18)	0.022**	-0.263	-0.021
Luo	-7.37 (11.03)	0.504	-0.290	0.142
Others (Kamba, Kikuyu, Kisii)	-22.94 (8.32)	0.006***	-0.393	-0.066
Project affiliation				
Project 2	34.11 (18.53)	0.066*	-0.022	0.704
Project 3	-36.17 (8.58)	0.000***	-0.530	-0.194
Project 4	-35.05 (10.44)	0.001***	-0.555	-0.146
Agroforestry adoption (1=Yes)	2.35 (3.31)	0.477	-0.041	0.088
Organizational membership (1=Yes)	7.95 (4.64)	0.087*	-0.011	0.170

Note: The margin for factor levels represents a discrete change from the base level and is expressed in percentage points. AME = Average Marginal Effect, RSE = Robust Standard Error
Significance stars indicate p-value thresholds: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6.13. Average marginal effects of age on carbon farming payment by household head gender

Age	MHH				FHH			
	AME (RSE)	p-value	95% CI (Lower)	95% CI (Upper)	AME (RSE)	p-value	95% CI (Lower)	95% CI (Upper)
18	24.01 (5.82)	0.000***	12.60	35.42	22.10 (8.58)	0.010***	5.27	38.92
23	24.69 (5.16)	0.000***	14.58	34.80	22.79 (7.64)	0.003***	7.81	37.77
28	25.38 (4.50)	0.000***	16.55	34.20	23.48 (6.69)	0.000***	10.36	36.60
33	26.07 (3.87)	0.000***	18.48	33.65	24.18 (5.75)	0.000***	12.91	35.45
38	26.76 (3.28)	0.000***	20.34	33.18	24.88 (4.82)	0.000***	15.43	34.34
43	27.45 (2.75)	0.000***	22.05	32.85	25.59 (3.95)	0.000***	17.84	33.33
48	28.14 (2.36)	0.000***	23.51	32.77	26.29 (3.19)	0.000***	20.04	32.54
53	28.83 (2.17)	0.000***	24.58	33.08	27.00 (2.65)	0.000***	21.81	32.19
58	29.52 (2.23)	0.000***	25.16	33.88	27.71 (2.48)	0.000***	22.85	32.57
63	30.21 (2.52)	0.000***	25.28	35.14	28.42 (2.76)	0.000***	23.00	33.84
68	30.89 (2.97)	0.000***	25.08	36.71	29.13 (3.38)	0.000***	22.49	35.76
73	31.58 (3.51)	0.000***	24.69	38.46	29.83 (4.19)	0.000***	21.62	38.04
78	32.26 (4.11)	0.000***	24.20	40.32	30.54 (5.08)	0.000***	20.57	40.50
80	32.53 (4.36)	0.000***	23.98	41.07	30.82 (5.46)	0.000***	20.12	41.51

Table 6.14. Average marginal effects of agroforestry adoption on carbon farming payment by household head gender

Agroforestry Adoption	MHH				FHH			
	AME (RSE)	p-value	95% CI (Lower)	95% CI (Upper)	AME (RSE)	p-value	95% CI (Lower)	95% CI (Upper)
No	25.63 (3.03)	0.000***	19.69	31.57	28.58 (3.62)	0.000***	21.47	35.68
Yes	32.57 (3.02)	0.000***	26.66	38.48	26.34 (3.31)	0.000***	19.85	32.83

Table 6.15. Average marginal effects of education level on carbon farming payment by household head gender

Education Level	MHH				FHH			
	AME (RSE)	**p-value**	**95% CI (Lower)**	**95% CI (Upper)**	**AME (RSE)**	**p-value**	**95% CI (Lower)**	**95% CI (Upper)**
No formal education	48.76 (4.49)	0.000***	39.96	57.55	23.41 (8.94)	0.009***	5.90	40.93
Primary	34.05 (3.94)	0.000***	26.33	41.77	29.49 (4.02)	0.000***	21.61	37.38
Secondary	27.27 (2.98)	0.000***	21.44	33.11	28.68 (3.53)	0.000***	21.76	35.61
Vocational Training/Diploma	11.61 (6.37)	0.068*	-0.86	24.09	17.86 (15.69)	0.255	-12.89	48.60
University	36.17 (9.12)	0.000***	18.28	54.05	23.30 (15.77)	0.140	-7.62	54.22

Table 6.16. Average marginal effects of land size on carbon farming payment by household head gender

Land Size	MHH				FHH			
	AME (RSE)	**p-value**	**95% CI (Lower)**	**95% CI (Upper)**	**AME (RSE)**	**p-value**	**95% CI (Lower)**	**95% CI (Upper)**
0	26.06 (3.46)	0.000***	19.27	32.85	25.66 (3.75)	0.000***	18.31	33.01
0.5	27.96 (2.39)	0.000***	23.28	32.65	26.70 (2.64)	0.000***	21.52	31.88
1	29.87 (2.17)	0.000***	25.62	34.12	27.74 (2.60)	0.000***	22.63	32.84
1.5	31.76 (2.98)	0.000***	25.91	37.61	28.77 (3.68)	0.000***	21.56	35.98
2	33.63 (4.23)	0.000***	25.33	41.92	29.81 (5.21)	0.000***	19.60	40.02
2.5	35.46 (5.57)	0.000***	24.54	46.38	30.84 (6.88)	0.000***	17.36	44.32
3	37.26 (6.89)	0.000***	23.74	50.77	31.87 (8.58)	0.000***	15.05	48.69
3.5	39.01 (8.17)	0.000***	23.00	55.01	32.89 (10.28)	0.001***	12.73	53.04
4	40.71 (9.37)	0.000***	22.34	59.08	33.90 (11.96)	0.005***	10.45	57.34
4.5	42.37 (10.52)	0.000***	21.74	63.00	34.90 (13.60)	0.010*	8.24	61.55
5	43.99 (11.63)	0.000***	21.19	66.78	35.89 (15.19)	0.018	6.11	65.67

Table 6.17. Average marginal effects of organizational membership on carbon farming payment by household head gender

Organizational Membership	MHH				FHH			
	AME (RSE)	p-value	95% CI (Lower)	95% CI (Upper)	AME (RSE)	p-value	95% CI (Lower)	95% CI (Upper)
No	24.30 (5.18)	0.000***	14.16	34.45	17.81 (6.38)	0.005***	5.30	30.32
Yes	30.04 (2.46)	0.000***	25.22	34.87	29.06 (2.76)	0.000***	23.66	34.47

Appendix 7: Determinants of Carbon Farming Participation

Table 7.1. Variance Inflation Factors (VIF) for predictors of carbon farming participation

Variable	Model 1		Model 2		Model 3	
	VIF	1/VIF	VIF	1/VIF	VIF	1/VIF
County						
Kakamega	2.53	0.40	2.71	0.37	2.5	0.40
Kisumu	9.48	0.11	11.73	0.09	8.32	0.12
Bungoma	1.97	0.51	2	0.50	2.01	0.50
Age of the household head (in years)	1.24	0.81	1.28	0.78	1.28	0.78
Size of the household	1.19	0.84	1.26	0.80	1.2	0.83
Number of income earners in the household	1.16	0.86	1.17	0.86	1.18	0.85
Total cultivated land in hectares in the last 12 months	1.21	0.82	1.3	0.77	1.21	0.83
Education level of the household head						
Primary education	5.61	0.18	6.84	0.15	4.83	0.21
Secondary education	5.72	0.17	7.03	0.14	5.03	0.20
Vocational training/Diploma education	2.62	0.38	3.46	0.29	2.12	0.47
University education	1.51	0.66	1.8	0.56	1.34	0.74
Ethnicity of the household head						
Kalenjin	1.33	0.75	1.33	0.75	1.37	0.73
Luo	9.24	0.11	12.25	0.08	7.55	0.13
Others (Kamba, Kikuyu, Kisii)	1.16	0.86	1.2	0.83	1.18	0.85
Main income from agriculture (1=Yes)	1.10	0.91	1.1	0.91	1.11	0.90
Organizational membership (1=Yes)	1.11	0.90	1.16	0.86	1.11	0.90
Mean VIF	**3.01**		**3.6**		**2.71**	

Note: VIF values indicate the degree of multicollinearity among predictors, with VIF > 10 suggesting potential multicollinearity issues. Model 1 includes a pooled sample, while Models 2 and 3 analyze male-headed households (MHH) and female-headed households (FHH), respectively.

Table 7.2. Logit results of socio-demographic factors influencing carbon farming participation

Variable	Model 1		Model 2		Model 3	
	OR (RSE)	p-value	OR (RSE)	p-value	OR (RSE)	p-value
County						
Kakamega	1.215 (0.361)	0.512	1.162 (0.500)	0.728	1.399 (0.605)	0.438
Kisumu	6.382 (3.712)	0.001***	8.754 (6.302)	0.003**	4.966 (4.882)	0.103
Bungoma	1.285 (0.344)	0.350	1.281 (0.522)	0.543	1.188 (0.469)	0.663
Age of the household head (in years)	1.049 (0.007)	0.000***	1.037 (0.009)	0.000***	1.065 (0.011)	0.000***
Size of the household	1.052 (0.041)	0.189	1.050 (0.061)	0.402	1.069 (0.060)	0.239
Number of income earners in the household	0.865 (0.102)	0.218	0.893 (0.134)	0.45	0.824 (0.155)	0.303
Total cultivated land in hectares in the last 12 months	1.240 (0.206)	0.197	1.403 (0.347)	0.171	1.137 (0.257)	0.571
Education level of the household head						
Primary education	1.726 (0.636)	0.138	2.269 (1.399)	0.184	1.680 (0.757)	0.249
Secondary education	2.455 (0.947)	0.020**	3.578 (2.268)	0.044**	2.311 (1.142)	0.090*
Vocational training/Diploma education	2.171 (1.085)	0.121	3.573 (2.738)	0.096*	1.252 (0.859)	0.743
University education	2.497 (1.838)	0.214	3.161 (2.939)	0.216	3.253 (4.365)	0.379
Ethnicity of the household head						
Kalenjin	0.474 (0.142)	0.013	0.414 (0.190)	0.055*	0.543 (0.234)	0.157
Luo	0.360 (0.197)	0.062*	0.308 (0.214)	0.089*	0.381 (0.343)	0.284
Others (Kamba, Kikuyu, Kisii)	0.802 (0.392)	0.652	0.581 (0.474)	0.506	0.940 (0.633)	0.927
Main income from agriculture (1=Yes)	1.694 (0.542)	0.099*	2.418 (1.096)	0.051*	1.048 (0.502)	0.922
Organizational membership (1=Yes)	6.230 (1.068)	0.000***	5.803 (1.411)	0.000***	6.961 (1.803)	0.000***
Constant	0.007 (0.005)	0.000***	0.006 (0.006)	0.000***	0.005 (0.006)	0.000***

Note: “Constant” estimate baseline odds (Baseline categories are Trans Nzoia county, No formal education and Luhya ethnic group). OR = Odds Ratio, RSE = Robust Standard Error
Significance stars indicate p-value thresholds: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7.3. 95% confidence intervals of logistic regression estimates for socio-demographic factors influencing carbon farming participation

Variable	Model 1		Model 2		Model 3	
	95% CI (Lower)	95% CI (Upper)	95% CI (Lower)	95% CI (Upper)	95% CI (Lower)	95% CI (Upper)
County						
Kakamega	0.679	2.175	0.499	2.701	0.599	3.267
Kisumu	2.041	19.955	2.135	35.888	0.723	34.112
Bungoma	0.760	2.173	0.577	2.847	0.548	2.576
Age of the household head (in years)	1.036	1.063	1.019	1.055	1.044	1.086
Size of the household	0.975	1.135	0.937	1.176	0.957	1.194
Number of income earners in the household	0.687	1.090	0.665	1.198	0.570	1.191
Total cultivated land in hectares in the last 12 months	0.895	1.718	0.864	2.277	0.729	1.771
Education level of the household head						
Primary education	0.839	3.554	0.677	7.600	0.695	4.062
Secondary education	1.152	5.230	1.033	12.395	0.877	6.088
Vocational training/Diploma education	0.815	5.780	0.796	16.042	0.327	4.802
University education	0.590	10.570	0.511	19.556	0.234	45.143
Ethnicity of the household head						
Kalenjin	0.263	0.853	0.169	1.018	0.233	1.264
Luo	0.123	1.055	0.079	1.198	0.065	2.226
Others (Kamba, Kikuyu, Kisii)	0.308	2.092	0.117	2.880	0.251	3.520
Main income from agriculture (1=Yes)	0.905	3.171	0.995	5.881	0.409	2.681
Organizational membership (1=Yes)	4.452	8.719	3.604	9.346	4.191	11.564
Constant	0.002	0.026	0.001	0.041	0.001	0.044

Table 7.4. Logit summary of socio-demographic determinants influencing carbon farming participation

Statistic	Model 1	Model 2	Model 3
Number of observations	859	427	432
Wald chi^2 (16)	187.11	89.51	97.42
Prob > chi^2	0.0000	0.000	0.0000
Log pseudolikelihood	-454.49215	-228.59605	-219.90836
Pseudo R^2	0.2364	0.2275	0.2652

Note: The Wald chi^2 statistic is reported with degrees of freedom (df). Prob > chi^2 values of 0.0000 provide strong evidence against the null hypothesis that all coefficients are zero.

Table 7.5. Hosmer-Lemeshow Goodness-of-Fit test of the carbon farming participation logit model

Statistic	Model 1	Model 2	Model 3
Variable	CF_Pract	CF_Pract	CF_Pract
Number of observations	859	427	432
Number of groups	10	10	10
Hosmer-Lemeshow chi^2 (df = 8)	8.40	5.27	11.49
Prob > chi^2	0.3953	0.7286	0.1754

Note: A high p-value (> 0.05) indicates no significant evidence of poor model fitness, suggesting that the logistic regression models fit the data adequately.

Table 7.6. Classification table of predicted participation in carbon farming at default cutpoint

Model	Classified	True D	True ~D	Total
Model 1	+	337	122	459
	-	102	298	400
	Total	**439**	**420**	**859**
Model 2	+	164	61	225
	-	53	149	202
	Total	**217**	**210**	**427**
Model 3	+	175	61	236
	-	47	149	196
	Total	**222**	**210**	**432**

Note: Classified + if predicted $Pr(D) \geq 0.5$; classified – if predicted $Pr(D) < 0.5$. True D is defined as $CF\_Pract \neq 0$, indicating participation in carbon farming.

Table 7.7. Classification performance statistics for predicting carbon farming participation at default cutpoint

Statistic	Formula	Model 1 (%)	Model 2 (%)	Model 3 (%)
Sensitivity	Pr(+|D)	76.77	75.58	78.83
Specificity	Pr(-|~D)	70.95	70.95	70.95
Positive predictive value	Pr(D|+)	73.42	72.89	74.15
Negative predictive value	Pr(~D|-)	74.50	73.76	76.02
False positive rate for true ~D	Pr(+|~D)	29.05	29.05	29.05
False negative rate for true D	Pr(-|D)	23.23	24.42	21.17
False positive rate for classified +	Pr(~D|+)	26.58	27.11	25.85
False negative rate for classified -	Pr(D|-)	25.50	26.24	23.98
Correctly classified		**73.92**	**73.3**	**75**

Note: Metrics are based on a classification threshold of Pr(D) ≥ 0.5, where D indicates participation in carbon farming (CF_Pract ≠ 0).

Table 7.8. Empirical cutpoint estimation of carbon farming participation using the Liu method

Statistic	Value
Method	Liu
Reference variable	CF_Pract (0=neg, 1=pos)
Classification variable	phat
Empirical optimal cutpoint	0.54012159
Sensitivity at cutpoint	0.74
Specificity at cutpoint	0.75
Area under ROC curve at cutpoint	0.75

Table 7.9. Classification table of predicted participation in carbon farming at empirical cutpoint

Model	Classified	True D	True ~D	Total
Model 1	+	325	104	429
	-	114	316	430
	Total	**439**	**420**	**859**
Model 2	+	161	54	215
	-	56	156	212
	Total	**217**	**210**	**427**
Model 3	+	168	46	214
	-	54	164	218
	Total	**222**	**210**	**432**

Note: Classified + if predicted Pr(D) ≥ 0.5401216; classified – if predicted Pr(D) < 0.5401216. True D is defined as CF_Pract ≠ 0, indicating participation in carbon farming.

Table 7.10. Classification performance statistics for predicting carbon farming participation at empirical cutpoint

Statistic	Formula	Model 1 (%)	Model 2 (%)	Model 3 (%)
Sensitivity	Pr(+|D)	74.03	74.19	75.68
Specificity	Pr(-|~D)	75.24	74.29	78.1
Positive predictive value	Pr(D|+)	75.76	74.88	78.5
Negative predictive value	Pr(~D|-)	73.49	73.58	75.23
False positive rate for true ~D	Pr(+|~D)	24.76	25.71	21.9
False negative rate for true D	Pr(-|D)	25.97	25.81	24.32
False positive rate for classified +	Pr(~D|+)	24.24	25.12	21.5
False negative rate for classified -	Pr(D|-)	26.51	26.42	24.77
Correctly classified		**74.62**	**74.24**	**76.85**

Note: Metrics are based on a classification threshold of Pr(D) ≥ 0.5401216, where D indicates participation in carbon farming (CF_Pract ≠ 0).

Table 7.11. Receiver Operating Characteristic (ROC) analysis of predictive model for carbon farming participation at empirical cutpoint

No. of observations	ROC area	Standard Error	Asymptotic Normal (95% CI)	
			Lower	Upper
859	0.8147	0.0145	0.78630	0.84305

Note: The area under the ROC curve (AUC) is 0.8147 indicating the model's **excellent discriminative ability**. According to the guideline by Hosmer and Lemeshow (2000), AUC values are interpreted as follows: 0.5 = no discrimination; 0.5-0.7 = poor; 0.7-0.8 = acceptable; 0.8-0.9 = excellent; >0.9 = outstanding.

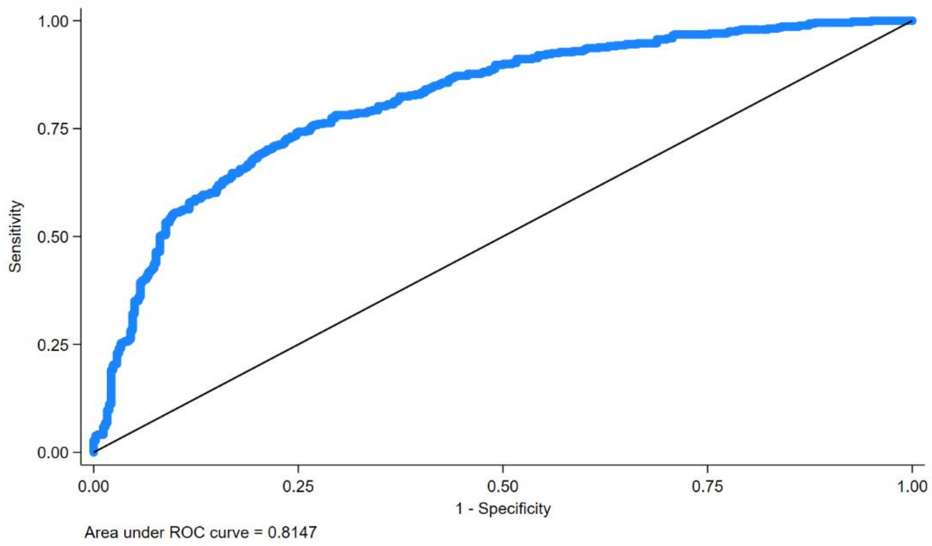

Figure 7.1. ROC curve for predicting carbon farming participation at empirical cutpoint

Table 7.12. Average marginal effects of socio-demographic determinants influencing carbon farming participation

Variable	Model 1		Model 2		Model 3	
	AME (RSE)	p-value	AME (RSE)	p-value	AME (RSE)	p-value
County						
Kakamega	3.42 (5.22)	0.513	2.58 (7.44)	0.729	5.78 (7.45)	0.438
Kisumu	32.15 (8.93)	0.000***	37.12 (10.16)	0.000***	27.00 (15.42)	0.080*
Bungoma	4.40 (4.73)	0.352	4.30 (7.10)	0.545	2.95 (6.79)	0.664
Age of the household head (in years)	0.85 (0.10)	0.000***	0.65 (0.15)	0.000***	1.06 (0.14)	0.000***
Size of the household	0.90 (0.68)	0.187	0.87 (1.04)	0.401	1.12 (0.94)	0.232
Number of income earners in the household	-2.56 (2.07)	0.216	-2.03 (2.68)	0.448	-3.27 (3.14)	0.299
Total cultivated land in hectares in the last 12 months	3.79 (2.93)	0.195	6.07 (4.38)	0.166	2.16 (3.81)	0.571
Education level of the household head						
Primary education	9.59 (6.36)	0.132	14.37 (10.27)	0.162	8.77 (7.53)	0.244
Secondary education	15.78 (6.60)	0.017**	22.57 (10.45)	0.031**	14.12 (8.14)	0.083*
Vocational training/Diploma education	13.63 (8.64)	0.115	22.54 (13.05)	0.084*	3.79 (11.52)	0.742
University education	16.07 (12.72)	0.206	20.35 (16.08)	0.206	19.67 (21.21)	0.354
Ethnicity of the household head						
Kalenjin	-12.59 (5.12)	0.014**	-14.82 (7.75)	0.056*	-9.93 (7.15)	0.165
Luo	-17.22 (8.36)	0.039**	-19.71 (10.11)	0.051*	-15.72 (13.56)	0.246
Others (Kamba, Kikuyu, Kisii)	-3.68 (8.20)	0.654	-9.13 (13.63)	0.503	-0.99 (10.79)	0.927
Main income from agriculture (1=Yes)	9.34 (5.62)	0.096*	15.82 (7.84)	0.044**	0.79 (8.10)	0.922
Organizational membership (1=Yes)	37.00 (3.22)	0.000***	35.89 (4.66)	0.000***	37.51 (4.54)	0.000***

Note: The margin for factor levels represents a discrete change from the base level and is expressed in percentage points. AME = Average Marginal Effect, RSE = Robust Standard Error Significance stars indicate p-value thresholds: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

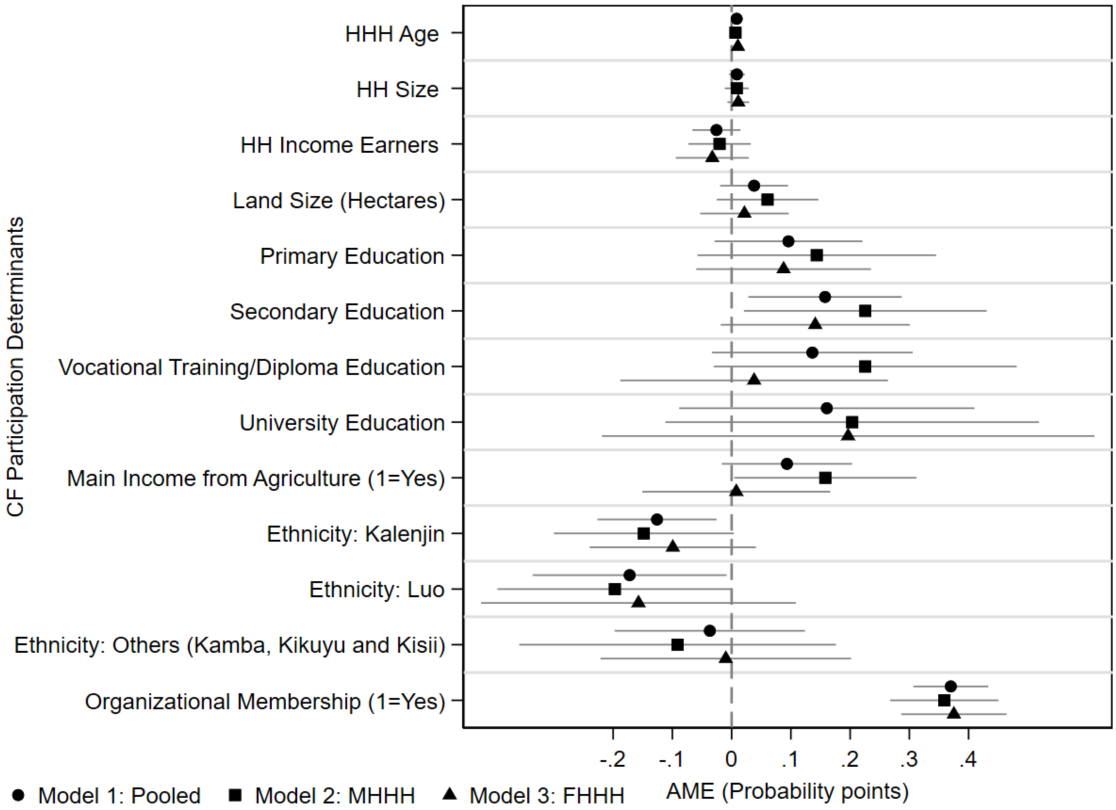

Figure 7.2. Forest plot illustrating the average marginal effects of socio-demographic determinants on carbon farming participation

Note: The regression models adjust for county-level effects, which are not shown in the plot.

Table 7.13. 95% confidence intervals of average marginal effects for socio-demographic determinants influencing carbon farming participation

Variable	**Model 1**		**Model 2**		**Model 3**	
	95% CI (Lower)	**95% CI (Upper)**	**95% CI (Lower)**	**95% CI (Upper)**	**95% CI (Lower)**	**95% CI (Upper)**
County						
Kakamega	-6.81	13.65	-12.01	17.17	-8.82	20.38
Kisumu	14.65	49.64	17.22	57.03	-3.23	57.23
Bungoma	-4.87	13.68	-9.61	18.21	-10.36	16.26
Age of the household head (in years)	0.65	1.05	0.35	0.95	0.79	1.33
Size of the household	-0.43	2.22	-1.16	2.90	-0.72	2.96
Number of income earners in the household	-6.62	1.50	-7.29	3.22	-9.43	2.90
Total cultivated land in hectares in the last 12 months	-1.94	9.53	-2.51	14.65	-5.31	9.64
Education level of the household head						
Primary education	-2.88	22.06	-5.77	34.51	-5.98	23.53
Secondary education	2.83	28.72	2.08	43.05	-1.84	30.07
Vocational training/Diploma education	-3.31	30.56	-3.03	48.11	-18.79	26.38
University education	-8.85	40.99	-11.17	51.88	-21.91	61.24
Ethnicity of the household head						
Kalenjin	-22.63	-2.55	-30.01	0.37	-23.95	4.10
Luo	-33.59	-0.84	-39.53	0.11	-42.29	10.85
Others (Kamba, Kikuyu, Kisii)	-19.74	12.39	-35.85	17.59	-22.14	20.16
Main income from agriculture (1=Yes)	-1.67	20.35	0.44	31.19	-15.08	16.66
Organizational membership (1=Yes)	30.68	43.32	26.75	45.03	28.62	46.40

Note: The margin for factor levels represents a discrete change from the base level and is expressed in percentage points. CI = Confidence Interval

Table 7.14. Average marginal effects of age on carbon farming participation by household head gender

Age	MHH				FHH			
	AME (RSE)	p-value	95% CI (Lower)	95% CI (Upper)	AME (RSE)	p-value	95% CI (Lower)	95% CI (Upper)
18	30.98 (4.81)	0.000***	21.55	40.40	18.49 (3.98)	0.000***	10.69	26.30
23	34.03 (4.32)	0.000***	25.55	42.50	22.93 (3.92)	0.000***	15.24	30.62
28	37.17 (3.79)	0.000***	29.73	44.60	27.91 (3.69)	0.000***	20.68	35.14
33	40.38 (3.26)	0.000***	34.00	46.76	33.35 (3.31)	0.000***	26.87	39.83
38	43.64 (2.75)	0.000***	38.24	49.03	39.10 (2.86)	0.000***	33.50	44.70
43	46.92 (2.36)	0.000***	42.30	51.54	45.05 (2.46)	0.000***	40.22	49.87
48	50.20 (2.15)	0.000***	45.98	54.42	51.03 (2.26)	0.000***	46.61	55.46
53	53.47 (2.20)	0.000***	49.14	57.79	56.94 (2.33)	0.000***	52.38	61.51
58	56.69 (2.48)	0.000***	51.83	61.55	62.66 (2.61)	0.000***	57.54	67.77
63	59.86 (2.90)	0.000***	54.18	65.54	68.08 (2.97)	0.000***	62.27	73.90
68	62.95 (3.37)	0.000***	56.35	69.56	73.14 (3.29)	0.000***	66.69	79.59
73	65.96 (3.85)	0.000***	58.41	73.51	77.74 (3.51)	0.000***	70.86	84.63
78	68.86 (4.30)	0.000***	60.43	77.30	81.85 (3.60)	0.000***	74.81	88.90
80	69.99 (4.47)	0.000***	61.23	78.76	83.35 (3.59)	0.000***	76.32	90.39

Table 7.15. Average marginal effects of household size on carbon farming participation by household head gender

Household Size	MHH				FHH			
	AME (RSE)	p-value	95% CI (Lower)	95% CI (Upper)	AME (RSE)	p-value	95% CI (Lower)	95% CI (Upper)
1	47.47 (4.88)	0.000***	12.16	49.66	46.13 (4.61)	0.000***	31.03	59.08
3	48.83 (3.22)	0.000***	40.25	52.97	48.44 (3.13)	0.000***	44.64	55.99
5	50.19 (2.13)	0.000***	49.76	61.78	50.76 (2.13)	0.000***	47.27	60.44
7	51.55 (2.49)	0.000***	42.05	72.73	53.06 (2.33)	0.000***	26.44	60.85
9	52.90 (3.90)	0.000***	29.29	75.45	55.35 (3.50)	0.000***	21.12	100.02
11	54.25 (5.60)	0.000***	12.16	49.66	57.61 (4.96)	0.000***	31.03	59.08
13	55.59 (7.38)	0.000***	40.25	52.97	59.85 (6.47)	0.000***	44.64	55.99
15	56.93 (9.16)	0.000***	49.76	61.78	62.04 (7.95)	0.000***	47.27	60.44

Table 7.16. Average marginal effects of education level on carbon farming participation by household head gender

Education Level	MHH				FHH			
	AME (RSE)	p-value	95% CI (Lower)	95% CI (Upper)	AME (RSE)	p-value	95% CI (Lower)	95% CI (Upper)
No formal education	30.91 (9.57)	0.001***	37.91	57.02	45.05 (7.16)	0.000***	37.09	55.16
Primary	46.61 (3.25)	0.000***	42.51	55.15	50.32 (2.89)	0.000***	42.31	54.58
Secondary	55.77 (3.07)	0.000***	46.01	54.37	53.86 (3.36)	0.000***	46.59	54.92
Vocational Training/Diploma	57.39 (7.83)	0.000***	46.67	56.43	43.65 (8.78)	0.000***	48.50	57.63
University	52.37 (11.78)	0.000***	45.25	60.56	60.57 (20.13)	0.003***	48.48	62.22

Table 7.17. Average marginal effects of land size on carbon farming participation by household head gender

Land Size	MHH				FHH			
	AME (RSE)	p-value	95% CI (Lower)	95% CI (Upper)	AME (RSE)	p-value	95% CI (Lower)	95% CI (Upper)
0	47.94 (3.35)	0.000***	41.38	54.50	49.85 (2.92)	0.000***	44.12	55.58
0.5	50.24 (2.15)	0.000***	46.03	54.45	51.27 (2.04)	0.000***	47.27	55.27
1	52.52 (2.57)	0.000***	47.48	57.56	52.68 (2.62)	0.000***	47.56	57.81
1.5	54.79 (4.11)	0.000***	46.74	62.85	54.09 (4.04)	0.000***	46.16	62.02
2	57.04 (5.90)	0.000***	45.47	68.60	55.49 (5.70)	0.000***	44.32	66.65
2.5	59.25 (7.72)	0.000***	44.13	74.38	56.88 (7.40)	0.000***	42.37	71.38
3	61.44 (9.49)	0.000***	42.84	80.03	58.26 (9.10)	0.000***	40.42	76.10
3.5	63.58 (11.18)	0.000***	41.66	85.49	59.62 (10.78)	0.000***	38.50	80.75
4	65.67 (12.77)	0.000***	40.64	90.70	60.98 (12.42)	0.000***	36.64	85.31
4.5	67.71 (14.25)	0.000***	39.79	95.63	62.31 (14.01)	0.000***	34.85	89.77
5	69.70 (15.59)	0.000***	39.13	100.26	63.63 (15.55)	0.000***	33.15	94.11

Table 7.18. Average marginal effects of organizational membership on carbon farming participation by gender of household head

Organizational Membership	MHH				FHH			
	AME (RSE)	p-value	95% CI (Lower)	95% CI (Upper)	AME (RSE)	p-value	95% CI (Lower)	95% CI (Upper)
No	29.38 (3.29)	0.000***	22.92	35.83	29.23 (3.50)	0.000***	22.37	36.09
Yes	65.36 (3.02)	0.000***	59.44	71.28	67.07 (2.71)	0.000***	61.76	72.38