RICE VARIETAL SEED TECHNOLOGY ADOPTION ON IMPROVING PRODUCTIVITY AND HOUSEHOLD WELFARE, NORTHERN REGION, GHANA

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THIS THESIS IS SUBMITTED TO THE UNIVERSITY OF GHANA, LEGON IN PARTIAL FULFILMENT OF THE REQUIREMENT FOR THE AWARD OF PHD IN APPLIED AGRICULTURAL ECONOMICS AND POLICY DEGREE

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DECLARATION

I, Essilfie Felix Larry, hereby declare that, with the exception of the references cited, which have been duly acknowledged, this thesis titled "Rice Varietal Seed Technology Adoption on Improving Productivity and Household Welfare, Northern Region, Ghana" is the result of my own research work conducted from August 2020 to June 2022 at the Department of Agricultural Economics and Agribusiness, University of Ghana Legon. This thesis has not been published or submitted in part or in whole to any other university for the award of a degree.

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DEDICATION

I dedicate this thesis to my Uncle Rev. Dr. Francis Acquah and the wife, Mrs. Phyllis Acquah, my Mother, Madam Christina Robertson, and to my dear wife Mrs. Beatrice Akua Gyekye Essilfie and my children Arielle Ewurabena Nyamoawa Essilfe, Arnia Ewurabena Nyamekye Essilfie and Othniel Nhyira Kojo Nyarko Essilfie. This is in recognition and appreciation for the sacrifices you have made towards my education.

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ABSTRACT

The transition from traditional to improved rice varieties signifies a critical technological shift aimed at enhancing farm productivity and household incomes in rural smallholder rice production systems. This technological advancement is expected to address key agricultural challenges and foster rural development. However, empirical findings on the benefits of this transition have been inconsistent, with studies presenting mixed results regarding the extent to which rural farm households realize the expected gains. These outcomes vary across different contexts and highlight the complexities involved in technological adoption in agriculture. This thesis assessed the impact of adopting improved rice varietal seed technologies on farm productivity and household welfare in Northern Region, Ghana. The study employed a robust methodological approach that extends the doubly robust Average Treatment Effect (ATE) and Treatment on the Treated (TT) estimators from the binary treatment framework to a multivalued treatment context under the Conditional Independence Assumption (CIA). Using survey data from 600 rice-farming households across the Kumbungu, Tolon, and Savelugu districts of the northern region, collected after the 2020 rice production season, the analysis models the adoption of rice varietal seed technologies as a nominal multivalued treatment variable. In contrast to conventional studies that primarily model adoption as a binary choice, this study posits that capturing the multivalued nature of varietal seed adoption provides critical insights into its nuanced impacts on key outcome variables, including farm productivity, household income, and food security. To estimate the impact of the adoption decision, a Generalized Propensity Scores (GPS) model was employed, using a multinomial logistic regression to account for the multivalued nature of the treatment, structured into four distinct treatment arms. Marginal probabilities of adoption factors were generated, and potential outcome means for each treatment level were calculated. Pairwise contrasts across the four adoption categories were performed to derive treatment effect estimates, with p-values adjusted using the Bonferroni adjustment technique to account for multiple comparisons. The findings reveal that household-specific characteristics, including gender, household size, farming experience, and formal education, significantly influence the likelihood of adopting improved rice varietal seed technologies. Additionally, farm-specific and institutional factors, such as access to credit, membership in Farmer-Based Organizations (FBOs), extension services, farm size, fertilizer use, and access to farm machinery, play pivotal roles in adoption decisions. Varietal characteristics, particularly early maturation and high-yielding traits, were also found to be critical determinants of adoption. The empirical results underscore the transformative potential of rice varietal seed technology. Specifically, the adoption of Alliance for the Green Revolution in Africa (AGRA), Jasmine-85, and Digang varieties led to significant productivity gains, increasing rice productivity by 580.60 kg/ha, 277.63 kg/ha, and 254.66 kg/ha, respectively, compared to non-adopters. In terms of household welfare, AGRA, Jasmine-85, and Digang adopters experienced an annual household income increase of GHS 699.68, GHS 414.60, and GHS 357.69, respectively, relative to the non-adopters. On food security, AGRA and Jasmine-85 varieties improved household food availability by 3.0% and 4.3%, respectively, while AGRA, Jasmine-85, and Digang varieties enhanced household food accessibility by 14.6%, 10.9%, and 9.2%, respectively. Adoption of the AGRA and Jasmine-85 varieties further improved Household Dietary Diversity (HDD) by 4.0% and 4.3%, respectively, whereas the Digang variety was linked to a 6.5% increase in Women Dietary Diversity (WDD). The Child Dietary Diversity (CDD) of Jasmine-85 and Digang adopters also rose by 5.3% and 5.8%, respectively. The study identifies several key constraints that inhibit the adoption of improved rice varietal seed technologies, notably high input costs, limited access to credit, insufficient government policy incentives, inadequate market infrastructure for local rice, poor access to extension services, and limited availability of farm machinery. The findings of this study demonstrate that the adoption of varietal seed technology plays a pivotal role in enhancing rice productivity and subsequently improving household welfare in the Northern Region of Ghana. The study underscores the critical importance of varietal seed innovation as a transformative factor in agricultural practices, offering substantial benefits to emerging economies by not only increasing productivity but also fostering socioeconomic advancement among farming households. In light of the empirical evidence presented in this study, it is recommended that targeted policy interventions be implemented to mitigate the barriers to varietal seed technology adoption among rice farming households. Specifically, enhancing safety net policies is essential to alleviate the financial burdens associated with accessing critical agricultural inputs. Such measures will not only facilitate increased uptake of improved seed varieties but also create a supportive environment that fosters sustainable agricultural transformation and enhances rural livelihoods. By prioritizing these policy initiatives, stakeholders can significantly contribute to the advancement of rice productivity and the overall welfare of farming communities in the Northern Region of Ghana.

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LIST OF ACRONYMS

AAGDS	Accelerated Agricultural Growth and Development Strategy
AGRA	Alliance for the Green Revolution in Africa
A-IPTW	Augmented Inverse Probability of Treatment Weighting
AoA	Agreement on Agriculture
ANOVA	Analysis Of Variance
APP	Average Physical Product
ATE	Average Treatment Effect
CAADP	Comprehensive Africa Agriculture Development Program
CARD	Coalition for Africa Rice Development
CDD	Child Dietary Diversity
CFS	Committee on World Food Security
CIA	Conditional Independence Assumption
CRI	Crops Research Institute
CSIR	Council for Scientific and Industrial Research
CVM	Contingent Valuation Methods
EIF	Efficient Influence Function
ESM	Explanatory Sequential Method
FAO	Food and Agricultural Organization
FASDEP I	Food and Agricultural Sector Development Policy I
FASDEP II	Food and Agricultural Sector Development Policy II
FBO	Farmer-Based Organization
FGD	Focus Group Discussion
FIES	Food Insecurity Experience Scale
FSN	Food Security and Nutrition
GDP	Gross Domestic Product
GIDA	Ghana Irrigation Development Authority
GMM	Generalized Method of Moments
GNRDS	Ghana National Rice Development Strategy
GPRS I	Ghana Poverty Reduction Strategy I
GPRS II	Ghana Poverty Reduction Strategy II
GPS	Generalized Propensity Scores
GRIB	Ghana Rice Inter-professional Body
GSOP	Ghana Social Opportunities Project
HDD	Household Dietary Diversity
HDDS	Household Dietary Diversity Score

HLPE	High Level Panel of Experts
ICC	Intra-cluster Correlation Coefficient
IDI	In-Depth Conversational Interview
IMF	International Monetary Fund
IRRI	International Rice Research Institute
IV	Instrumental Variable
IPTW	Inverse Probability of Treatment Weighting
IPTW-RA	Inverse Probability of Treatment Weighting with Regression Adjustment
IRVs	Improved Rice Varieties
ITFC	Integrated Tamale Fruit Company
ITT	Intent-To-Treat
KDE	Kernel Density Estimation
LATE	Local Average Treatment effect
MLE	Maximum Likelihood Estimates
MMWS	Marginal Mean Weighting through Stratification
METASIP	Medium Term Agriculture Sector Investment Plan
MDG	Millennium Development Goal
MOFA	Ministry Of Food and Agriculture
MPP	Marginal Physical Product
MT	Metric Tonnes
MFP	Multiple Factor Productivity
NRDS	National Rice Development Strategy
NGO	Non-Governmental Organization
OLS	Ordinary Least Squares
PCA	Principal Component Analysis
PFP	Partial Factor Productivity
POM	Potential Outcome Mean
PPS	probability-proportional-to-size
PSM	Propensity Score Matching
RA	Regression Adjustment
RCT	Randomized Control Trial
RTS	Returns to Scale
RUT	Random Utility Theory
SARI	Savanna Agricultural Research Institute
SAP	Structural Adjustment Programme
SDG	Sustainable Development Goal
SHG	Self-Help Groups

TAM	Technology Acceptance Model
TFP	Total Factor Productivity
TPB	Theory of Planned Behaviour
TT	Treatment on the Treated
UNICEF	United Nations Children's Fund
UNIDO	United Nations Industrial Development Organization
WDD	Women Dietary Diversity
WTO	World Trade Organization
WTP	Willingness To Pay

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

Rice is the second most significant grain food commodity in Ghana after maize, playing a dual role as a vital staple food and a burgeoning source of income for farmers (Amengor et al., 2017; Banful & Attivor, 2017). Recognizing its strategic importance, rice has been prioritized in several national agricultural and development strategies, including the Accelerated Agricultural Growth and Development Strategy (AAGDS) (2000–2009), Food and Agricultural Sector Development Policy I (FASDEP I) (2002–2007) Food and Agricultural Sector Development Policy II (FASDEP II) (2009–2015), Ghana Poverty Reduction Strategy I (GPRS I) (2003–2005), Ghana Poverty Reduction Strategy II (GPRS II) (2006–2009), and the Medium Term Agriculture Sector Investment Plan (METASIP) (2011–2015). These policies underscore the critical role of rice in addressing food security, rural poverty, and agricultural modernization.

Annual per capita rice consumption in Ghana has grown significantly, reflecting the increasing reliance on rice as a staple food. From 17.5 kilograms in 1999–2001, consumption rose to 22.4 kilograms in 2002–2004 and reached 44 kilograms in recent years (Ouédraogo et al., 2021). This growing demand is driven by rapid urbanization, changes in consumer preferences, and population growth, with rice consumption projected to expand at an annualized rate of 11.8%, far outpacing the 2.6% growth in maize consumption (Minten et al., 2016; Ouédraogo et al., 2021). However, Ghana relies heavily on rice imports, which constitute nearly 60% of domestic consumption, costing the nation approximately USD 331 million annually and exerting significant pressure on foreign reserves (Ouédraogo et al., 2021).

Rice occupies a pivotal place in Ghana's agricultural economy, contributing about 20% to the agricultural Gross Domestic Product (GDP) and supplying 50% of the total caloric intake for households (Ouédraogo et al., 2021). Its cultivation spans one-third of the total agricultural area in rice-producing zones and supports two-thirds of farm households in these regions. Despite these economic and nutritional contributions, Ghana's rice production remains suboptimal, with yields averaging 1 metric ton per hectare, far below the potential yield of 4–5 metric tons per hectare achievable under improved management practices (Arouna et al., 2022b).

A key avenue for boosting rice productivity is the adoption of Improved Rice Varieties (IRVs). These varieties have the potential to narrow the yield gap between on-farm and research-station production levels, enhance farm income, and improve food security. However, the adoption of IRVs among Ghanaian smallholder rice farmers remains low. Several challenges impede this process, including limited access to

certified seed and complementary inputs, inadequate extension services, poor market infrastructure, and the inability of many smallholder farmers to bear the risks associated with new agricultural technologies (Adenle et al., 2018; Awotide et al., 2016).

Moreover, socioeconomic constraints such as limited financial resources, low education levels, and gender disparities further hinder adoption. Women, who constitute a significant proportion of the rural farming population, often face greater barriers to accessing productive resources, perpetuating lower adoption rates and reduced farm productivity. Another key challenge is the lack of awareness and understanding of IRVs benefits among smallholders, compounded by weak policy implementation and coordination across the agricultural value chain (Arouna et al., 2021b).

While Ghana has made significant strides in developing IRVs and promoting their dissemination, rice production continues to fall short of meeting domestic demand. Current production often yields as low as 625 kilograms per hectare, significantly below the potential yield of 1,250–1,500 kilograms per hectare achievable with IRVs (Arouna et al., 2021b). Addressing these challenges requires a comprehensive approach that integrates technology dissemination with strengthened agricultural extension systems, farmer education, and improved access to inputs and markets.

The broader impact of IRVs adoption extends beyond increased productivity. It is critical for achieving poverty reduction, enhancing rural livelihoods, and promoting sustainable agricultural development. Empirical evidence suggests that higher adoption rates of IRVs can significantly boost household incomes and food security, thereby reducing the vulnerability of smallholder farming households to economic shocks (Adenle et al., 2018). However, these benefits can only be realized if adoption rates rise to a threshold level where IRVs substantially contribute to increased farm revenue and national food security.

The nexus between IRVs adoption and its impact on productivity and household welfare forms the core of this study, which focuses on smallholder rice farmers in Ghana's Northern Region. Understanding the factors influencing IRVs adoption and quantifying its impact on productivity and household welfare are essential for designing effective interventions to enhance agricultural productivity and reduce rural poverty. This study builds on recent research highlighting the importance of varietal seed technology in achieving sustainable agricultural transformation in sub-Saharan Africa (Arouna et al., 2022b, 2021b; Ouédraogo et al., 2021).

By identifying the key drivers and barriers to IRVs adoption and examining its socioeconomic impacts, this study aims to provide evidence-based recommendations to policymakers and development practitioners. Such insights are vital for addressing the structural constraints in Ghana's rice sector, closing yield gaps, and fostering a transition to high-productivity, market-oriented agriculture.

1.2 Conceptual Framework

The conceptual framework underscores the pivotal role of government and Non-Governmental Organization (NGO) interventions in catalysing the adoption of improved rice seed technologies by rural households in Northern Ghana. These interventions serve as foundational enablers by addressing structural barriers that impede smallholder farmers' access to productive resources and technological innovations. Specifically, government initiatives, including subsidies, credit provision, extension services, infrastructure development, and supportive policies, create a conducive environment for the dissemination and utilization of improved seed varieties. Similarly, NGOs complement these efforts by promoting capacity-building programs, facilitating access to resources, and fostering partnerships with research institutions to introduce context-specific innovations (Mensah et al., 2021).

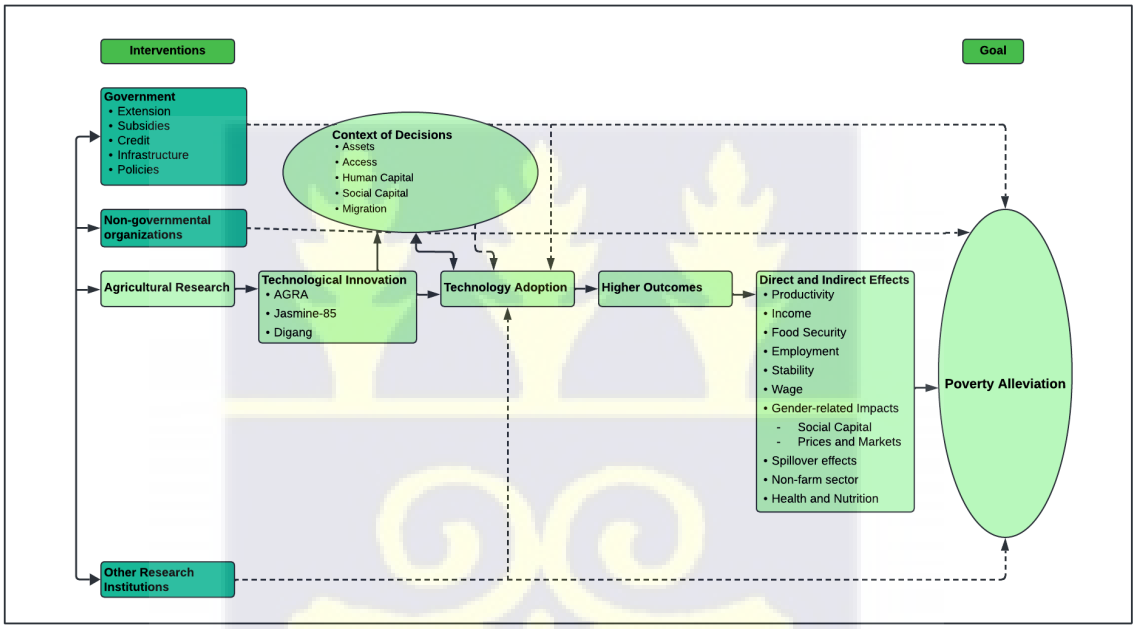


Figure 1.1: The Conceptual Framework Guiding the Study

Agricultural research plays a central role in this ecosystem by generating technological innovations, including the development and dissemination of improved rice varietal seeds such as AGRA, Jasmine-85, and Digang. These varieties are tailored to address key production challenges faced by smallholder farmers, offering traits such as high yield potential and early maturity. As noted by Akoto et al. (2022), these innovations significantly enhance productivity and resilience against climatic and environmental stresses. However, their success hinges on effective dissemination mechanisms supported by government and NGO interventions to ensure that rural households can access, adopt, and benefit from these technologies.

The framework situates technology adoption within the broader context of decision-making, which is shaped by household-specific factors, including access to assets, human capital, social capital, and migration dynamics. These factors influence farmers' willingness and ability to adopt improved

seed technologies. For instance, social capital—manifested through membership in Farmer-Based Organizations (FBOs)—facilitates knowledge sharing and collective action, thereby enhancing adoption rates (Nyarko & Boateng, 2019). Similarly, human capital, represented by education and farming experience, improves farmers' capacity to evaluate and implement new technologies. However, disparities in access to these resources, particularly among women farmers, often limit their participation in and benefits from technological advancements (Asare & Owusu, 2020).

The adoption of improved rice seed technologies directly influences higher outcomes, including increased productivity, income, food security, and employment. These outcomes, in turn, generate significant spillover effects, such as improved stability, wages, and gender-related impacts. For example, studies have shown that the adoption of high-yield rice varieties contributes to enhanced food security by increasing household food availability and reducing dependency on external food sources (Mensah et al., 2021). Additionally, increased productivity leads to higher household incomes, enabling investments in health, education, and other welfare-enhancing activities. However, as Akoto et al. (2022) highlight, the distribution of these benefits often reflects existing inequalities, necessitating targeted interventions to ensure inclusivity.

Ultimately, these outcomes contribute to the overarching goal of poverty alleviation, as illustrated in the framework. By addressing the systemic challenges that constrain productivity and income generation in rural areas, the adoption of improved rice varietal technologies offers a sustainable pathway to reducing poverty and enhancing household welfare. This aligns with the study's focus on leveraging technological innovations to improve the livelihoods of smallholder rice farmers in the Northern Region of Ghana. The interconnectedness of government and NGO interventions, agricultural research, household decision-making, and welfare outcomes emphasizes the need for a holistic approach to policy and program design.

In conclusion, the framework highlights the critical role of multi-stakeholder collaboration in facilitating the adoption of improved rice seed technologies. Government and NGO interventions, supported by robust agricultural research, address structural and institutional barriers, enabling rural households to adopt and benefit from innovations like AGRA, Jasmine-85, and Digang. The resulting productivity and welfare gains underscore the transformative potential of technology adoption in achieving poverty alleviation and improving livelihoods in Northern Ghana.

1.3 Problem Statement

Rural poverty remains a persistent and deep-rooted challenge in Ghana, despite numerous anti-poverty initiatives undertaken by the government of Ghana and international development partners. Recent data from the World Bank (2020) indicates that approximately 30.9% of the Ghanaian population lives in poverty, with rural areas disproportionately affected. Agriculture, the primary source of livelihood for most

rural households, is at the heart of this economic struggle. Efforts such as the Ghana Social Opportunities Project (GSOP) funded by the World Bank, the Comprehensive Africa Agriculture Development Program (CAADP), and UNICEF's Child Protection Programme, as well as Food and Agricultural Organization (FAO) initiatives aimed at food security and resilience, have sought to address poverty. However, these interventions have struggled to achieve significant progress, largely due to inefficiencies in implementation and inadequate emphasis on agricultural growth, which remains the backbone of Ghana's economy.

A critical bottleneck undermining agricultural growth and rural poverty reduction is the underfunding of Ghana's agricultural extension system, which has stymied the dissemination of modern agricultural technologies to farmers (Anang & Asante, 2020b; Asante et al., 2018b). Key challenges such as low agricultural productivity, high post-harvest losses, and inadequate market access exacerbate rural poverty. Research has identified these issues as stemming from reliance on traditional agricultural practices, poor soil fertility, erratic rainfall, high input costs, substandard seed quality, and limited access to financial resources (Anang & Asante, 2020b). The resulting food insecurity, underdevelopment of agribusinesses, and low household incomes have compounded rural vulnerability, with children disproportionately suffering from malnutrition and poor health outcomes.

Rice cultivation, a major agricultural activity in Ghana, illustrates these challenges. For smallholder farmers, the transition from traditional rice varieties to improved varietal seeds represents a critical technological innovation. This shift is economically motivated, as improved rice varieties promise higher yields and income potential. However, resource constraints, including labour and capital, limit smallholder farmers' ability to adopt these technologies widely. When adopted, the impact of improved rice varieties on household productivity and welfare is often contingent upon complementary modern farming practices. This dynamic underscores the importance of evaluating the long-term effects of these technologies on rural livelihoods.

Several recent studies provide insights into the adoption of improved rice varieties and their implications for productivity and welfare. For instance, Assaye et al. (2022) conducted an assessment of rice varietal adoption in Ethiopia, finding that households adopting improved seeds experienced a 22% increase in rice yields compared to non-adopters. However, the study noted that yield gains were not consistently sustained due to limited access to modern farming inputs and inadequate post-adoption support. Similarly, Addis et al. (2021) examined the role of improved rice varieties in Tanzania, reporting that adopters achieved improved food security and income levels. Yet, the study highlighted constraints such as high input costs and poor access to extension services, which limited broader adoption. In Ghana, Anang & Asante (2020b) analyzed the profitability of improved rice seed adoption, revealing significant productivity gains but also identifying persistent challenges, including weak market linkages and poor post-harvest management practices.

While these studies underscore the potential of improved rice varieties to enhance productivity and welfare, they also highlight critical gaps. First, most studies focus primarily on yield and income effects, with limited exploration of broader welfare indicators such as food security, nutrition, and household resilience. Second, there is insufficient understanding of how adoption dynamics vary across different socio-economic and agro-ecological contexts. Lastly, existing research often overlooks the role of complementary practices, such as modern water management techniques and efficient input utilization, in sustaining productivity gains.

This study seeks to assess the impact of rice varietal seed technology adoption on productivity and household welfare in the Northern Region of Ghana. By focusing on this critical region, the study aims to provide a nuanced understanding of how improved rice varieties can transform rural farming systems and contribute to poverty reduction. The study will build on previous research by employing robust econometric methods to isolate the effects of varietal seed technology on key outcomes, including productivity, income, and food security. Additionally, it will examine the role of enabling factors such as access to credit, extension services, and market opportunities in shaping adoption decisions and maximizing benefits for rural households. The findings of this study are expected to provide valuable insights for policymakers, development practitioners, and stakeholders in the agricultural sector. By addressing the limitations of previous studies and filling critical knowledge gaps, the study will contribute to the formulation of evidence-based strategies to enhance the adoption of improved rice varietal seed technologies and foster sustainable improvements in productivity and household welfare. Ultimately, the research aims to advance the broader agenda of agricultural development as a pathway to poverty reduction in Ghana.

1.4 Research Questions

The study sought to address the following research questions:

i. What factors drive the adoption of improved rice varietal seed technologies among rural rice-farming households in the Northern Region?

ii. How does adopting improved rice varietal seed technology affect rice productivity and household income for rural households?

iii. To what extent has improved rice varietal seed technology adoption enhanced food security among rural rice-farming households?

iv. What are the key constraints hindering the adoption of improved rice varietal seed technology among rural rice farmers in the region?

1.5 Objectives of the Study

The main objective of this study was to assess the impact of improved rice varietal seed technology adoption on productivity and household welfare of rural households in Northern Region. Specifically, the study sought:

i. To identify factors influencing rural rice-farming households' decisions to adopt improved rice varietal seed technology in the Northern Region.

ii. To analyse the impact of improved rice varietal seed technology adoption on rice productivity and household income in rural farming households.

iii. To measure the effect of improved rice varietal seed technology on household food security among rural rice-farming households.

iv. To identify and rank the main constraints to adopting improved rice varietal seed technology in the region.

1.6 Hypothesis Underlying the Study

The study sought to test the following underlying hypothesis:

i. Household, institutional, and farm-specific factors, as well as varietal attributes, significantly influence the adoption of improved rice seed technologies.

ii. Adopting rice varietal seed technology significantly enhances productivity and household income of smallholder rice farmers in the region.

iii. Improved rice varietal seed technology adoption enhances household food security.

iv. Adoption of rice varietal seed technology in the region is not hindered by financial, policy, or market constraints.

1.7 Relevance of the Study

The adoption of improved rice varietal seed technology represents a critical pathway for enhancing agricultural productivity and improving household welfare, particularly in rural settings where rice cultivation constitutes a major livelihood activity. Despite its potential, empirical evidence demonstrating causation between the adoption of rice varietal seed technology and improvements in productivity and welfare remains limited. Most existing studies, such as Assaye et al. (2022), Anang & Yeboah (2019) and Ghimire & Huang (2016), have focused on correlations rather than establishing rigorous causal relationships. Additionally, conflicting findings from studies like Bannor et al. (2020) have fueled ongoing debates about the effectiveness of improved rice varieties in boosting agricultural productivity and

household welfare. These gaps underscore the critical need for further investigation to generate robust, evidence-based insights on this subject.

This study aims to address the knowledge deficit by examining the effects of rice varietal seed technology adoption on rural rice-farming households in Northern Ghana. By employing a doubly robust estimation framework under the CIA, this study contributes to the body of knowledge on the nuanced impacts of agricultural technology adoption. The study's focus on both productivity outcomes, such as rice yields, and welfare indicators, including household income, food security, and resilience, makes it uniquely positioned to provide comprehensive insights. Furthermore, the study considers the multivalued structure of adoption, recognizing that the intensity and type of varietal seed technology adoption can yield differential impacts on productivity and welfare outcomes.

Evidence from the literature suggests that the adoption of improved rice varieties can significantly influence agricultural productivity and rural livelihoods. For instance, Assaye et al. (2022) demonstrated that improved rice varieties in Ethiopia led to substantial yield increases but highlighted the lack of sustained benefits due to inadequate complementary services such as access to inputs and extension support. Similarly, Anang & Yeboah (2019) found that adopters of improved rice varieties in Ghana reported increased household income but noted disparities in adoption rates driven by socio-economic and institutional factors. Bannor et al. (2020) explored adoption in Nepal and emphasized the importance of household-specific characteristics, such as access to credit and education, in determining the effectiveness of varietal seed technology. While these studies provide valuable insights, they are limited in their capacity to provide generalizable evidence for different contexts, including Northern Ghana, which faces unique agro-ecological and socio-economic challenges.

This study builds on the existing literature by offering a contextualized understanding of the factors influencing adoption and their subsequent impacts. Specifically, it explores how socio-economic, institutional, and agro-ecological dynamics shape the adoption of rice varietal seed technologies in Northern Ghana. These insights are crucial for designing policies and programs that effectively promote adoption and maximize its benefits. For instance, the study's findings are meant to guide targeted investments in agricultural extension services, financial support mechanisms, and seed distribution networks, addressing the key barriers to adoption identified in prior studies (Assaye et al., 2022; Bannor et al., 2020).

The study's focus on Northern Ghana is particularly pertinent given the region's high poverty rates and reliance on smallholder rice farming. Enhancing rice productivity through improved seed technologies could play a pivotal role in bolstering food security and building rural resilience in the region. The importance of such initiatives cannot be overstated, as recent studies emphasize the need for robust

agricultural policies to counter the adverse effects of climate variability, economic instability, and market uncertainties (Mensah et al., 2021; Nyantakyi-Frimpong & Kerr, 2022). By providing evidence-based recommendations, this study aims to support the development of policies that enhance rice seed adoption and foster sustainable agricultural growth.

In addition to its policy relevance, this study makes a significant contribution to the academic discourse on agricultural technology adoption. Existing literature often overlooks the complex interplay of contextual factors that influence the effectiveness of improved rice varieties. For example, factors such as access to credit, gender dynamics, market conditions, and the availability of complementary inputs are critical determinants of adoption success. This study addresses these gaps by examining these contextual variables and their interactions, thereby enriching the literature on agricultural innovation and its implications for rural development.

Methodologically, the study's use of a doubly robust estimation approach represents an important advancement in evaluating the impacts of technology adoption. This approach combines propensity score weighting with regression adjustment to mitigate biases arising from unobservable confounders, thereby providing more reliable causal estimates. Furthermore, by analyzing the multivalued structure of rice varietal seed technology adoption, the study provides nuanced insights into the differential impacts of varying adoption levels. Such an approach aligns with calls for more sophisticated analytical frameworks to assess agricultural innovations (Kassie et al., 2020).

Finally, the study's emphasis on identifying and addressing barriers to adoption contributes to the broader policy discourse on agricultural transformation in Ghana. By pinpointing constraints such as limited access to finance, inadequate extension services, and weak institutional support, the study provides actionable recommendations for policymakers and development practitioners. These insights are essential for fostering an enabling environment for the widespread adoption of improved rice varietal technologies, which is critical for achieving food security, reducing poverty, and enhancing rural livelihoods.

In conclusion, this study is uniquely positioned to bridge critical knowledge gaps in the understanding of rice varietal seed technology adoption and its impacts on productivity and household welfare in rural Ghana. By integrating robust analytical methods with a context-specific focus, the study not only advance academic knowledge but also inform policy and practice in ways that promote sustainable agricultural development.

1.8 Organization of the Study

This study is organised into five chapters. Following chapter one, which examined the study's background, problem statement, research questions, objectives, and relevance, chapter two discussed relevant literature on the nature of rice production in Ghana, rice variety seed technologies introduced in Ghana, and

measurements of welfare. A review of empirical publications pertinent to this study was also provided. The third chapter addressed the methodology employed to achieve the study objectives. It described the study locations as well as the study design, which comprised the sampling technique, sample size, and data collection method. It also discussed the theoretical framework, empirical modelling approaches, and treatment impact parameter computation for the adoption of rice varietal seed technology. In Chapter four, the descriptive and empirical findings are given and discussed, while in Chapter five, the study's conclusions and policy recommendations are captured and presented.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter reviews the history of rice production, rice farming practices in Ghana, and rice production in Ghana. This chapter also includes a review of Ghana's rice sub-sector policy framework and improved rice variety releases by Ghanaian research institutes. It also includes a review of the theoretical underpinnings for measuring productivity, household welfare, and household food security, as well as treatment effects estimation methods. Finally, the chapter provides an empirical review of treatment effects estimation on improved rice varietal seed technologies in Ghana and elsewhere.

2.2 The History of Rice Production in Ghana

Historically, rice cultivation in Ghana was introduced during the colonial era, primarily to reduce the country's dependency on imported cereals. Over the decades, its production expanded from lowland rain-fed systems to include irrigated schemes aimed at boosting productivity. A study by Martey et al. (2021) highlights the rapid transformation of rice farming systems, driven by increasing demand and government support for irrigation infrastructure. However, Ghana's rice production has struggled to meet domestic consumption needs due to persistent challenges, including low yields and limited adoption of modern farming techniques.

Between 2019 and 2024, research on Ghana's rice sector has emphasized the adoption of innovative practices and technologies to improve yields. Arouna et al. (2023) identified water-saving techniques, such as alternate wetting and drying, as critical innovations for improving water efficiency and maintaining yields. These techniques are particularly relevant in Northern Ghana, where water scarcity is a growing challenge. Similarly, the integration of precision irrigation systems has demonstrated significant potential in enhancing water productivity and reducing environmental impacts. Despite these advancements, several studies, including those by Danquah et al. (2020), underscore the uneven adoption of these technologies across regions. Factors such as limited access to inputs, inadequate extension services, and socio-economic disparities have contributed to variations in productivity. The adoption of improved rice varietal seeds remains a key determinant of yield growth, with evidence suggesting that targeted interventions can significantly enhance household welfare and food security.

Rice farming in Ghana is predominantly undertaken by smallholder farmers, many of whom face resource constraints. The work of Sulemana et al. (2022) highlights the role of gender dynamics in shaping access to resources and decision-making processes in rice production. In the Northern Region, women often face

systemic barriers to adopting improved seed technologies and accessing irrigation facilities. Addressing these gendered inequalities is crucial for ensuring equitable benefits from advancements in rice farming. Additionally, local rice varieties have traditionally dominated production due to their adaptability to local conditions. However, the growing preference for high-yielding and stress-tolerant varieties, as noted by Ansah et al. (2023), reflects a shift towards modern farming practices. This transition has been facilitated by government policies promoting public-private partnerships in seed production and distribution.

Ghana's rice production policies have undergone several iterations, from the introduction of the National Rice Development Strategy (NRDS) to regional programs targeting self-sufficiency. The revised NRDS (2020) outlines ambitious targets for reducing reliance on rice imports, aiming to achieve self-sufficiency by 2024. This strategy aligns with regional efforts supported by international agencies such as the United Nations Industrial Development Organization (UNIDO), which focuses on enhancing post-harvest processes and quality assurance systems (United Nations Industrial Development Organization, 2022). The Northern Region, a hub for rice cultivation, has witnessed significant investments in irrigation, mechanization, and capacity building. However, disparities in access to these resources remain a concern, limiting the impact of national strategies on smallholder farmers (Frimpong-Addo, 2023).

Despite progress, Ghana's rice sector continues to grapple with significant challenges. Sulemana et al. (2022) identified low mechanization levels, poor post-harvest handling, and market inefficiencies as major constraints. Additionally, competition from imported rice, which is often perceived as superior in quality, undermines local production efforts. Policies aimed at enhancing market competitiveness and improving the quality of locally produced rice have been suggested as pathways to addressing these issues. Another critical concern is the impact of climate variability on rice production. Studies by Arouna et al. (2023) and Danquah et al. (2020) highlight the vulnerability of rain-fed systems to erratic rainfall patterns and prolonged droughts. The promotion of climate-smart agricultural practices, such as the adoption of stress-tolerant rice varieties and conservation agriculture, is essential for building resilience in the sector.

The history of rice production in Ghana is marked by both progress and persistent challenges. Recent advancements in water management, precision irrigation, and improved seed technologies hold promise for addressing productivity gaps and enhancing household welfare. However, achieving sustainable growth in the sector requires concerted efforts to address systemic barriers, promote equitable access to resources, and adapt to climate challenges.

2.3 Overview of Rice Production in Ghana

Rice is a staple food in Ghana, with its consumption steadily increasing due to factors such as population growth, urbanization, and changing consumer preferences Adams et al. (2021). The crop is vital for both income generation and food security (Bissah et al., 2022). However, the production of rice in the

country has exhibited significant fluctuations over the years. Between 2008 and 2018, paddy output ranged from 302,000 to 733,000 Metric Tonnes (MT), translating to 181,000 to 469,000 MT of milled rice, with substantial annual variations (Bissah et al., 2022; Ouédraogo et al., 2021; Tanko et al., 2019). During the same period, total rice consumption fluctuated between 500,000 and 900,000 MT, resulting in per capita consumption rates ranging from 26 to 30 kg annually (Adams et al., 2021; Bissah et al., 2022; Kamruzzaman & Takeya, 2008; Ouédraogo et al., 2021). The primary driver of production fluctuations is the variation in the area of land cultivated, coupled with marginal changes in yield per hectare (Bissah et al., 2022; Ouédraogo et al., 2021).

Despite the policy interventions aimed at increasing rice production for food security, poverty alleviation, and import substitution, the sector faces several challenges. These include inadequate agricultural infrastructure, limited access to modern technology, and a lack of mechanization, which hinder the growth and efficiency of the industry (Adams et al., 2021; Bissah et al., 2022). Key infrastructural weaknesses include inefficient irrigation systems, poorly maintained roads, and the lack of modern storage facilities (Adams et al., 2021; Arouna et al., 2021b; Ouédraogo et al., 2021). Additionally, the sector continues to rely on traditional farming techniques, such as the use of rudimentary tools like cutlasses, hoes, and sickles, while also being heavily dependent on unpredictable rainfall (Arouna et al., 2021b; Bissah et al., 2022). These constraints exacerbate the challenges of rice production, leading to low productivity and reduced competitiveness relative to imported rice.

Infrastructure development and the adoption of appropriate agricultural technologies are crucial for transforming Ghana's rice farming from traditional subsistence practices into a more modern and commercialized sector (Adams et al., 2021; Arouna et al., 2021b; Ouédraogo et al., 2021). The introduction of mechanization and improved farming technologies has the potential to reduce labor intensity, improve timeliness in farm operations, and increase yields and the quality of rice production (Adams et al., 2021; Arouna et al., 2021b). However, substantial upfront investments and longer payback periods pose significant barriers to the widespread adoption of mechanization and modern technologies (Arouna et al., 2021b; Bissah et al., 2022). Additionally, weak linkages between rice growers, input suppliers, and financial institutions further impede the uptake of new technologies (Adams et al., 2021; Bissah et al., 2022).

The rice sector in Ghana holds considerable potential for growth, driven by increasing domestic demand and rising prices. The price of domestic rice has more than doubled in recent years, with the average cost of a 100 kg sack rising from GHS 55 in 2006 to GHS 120 in 2011, while foreign rice prices have seen even greater increases (Adams et al., 2021; Béné et al., 2020). Rice consumption, particularly in urban areas such as Accra, represents a substantial portion of household income for middle-income earners, with a monthly wage of approximately GHS 400 (roughly USD$ 57) (Béné et al., 2019; El Bilali et al., 2019; Ouédraogo

et al., 2021). However, foreign rice is often preferred due to its perceived superior quality, with consumers associating imported rice with better flavour, texture, and cooking qualities (Béné et al., 2019; El Bilali et al., 2019; Ouédraogo et al., 2021). Domestic rice, in contrast, is often viewed as being of inferior quality, due in part to poor post-harvest treatment and inconsistent availability (Diako et al., 2010).

The rice sector in Ghana also faces a significant divide in terms of consumer preferences between urban and rural areas. While foreign rice is highly popular in urban centres such as Accra, a shift toward the consumption of aromatic indigenous varieties, such as Aromatic Short and Jasmine 85, has been observed in recent years (Gockowski et al., 2013). In contrast, indigenous rice varieties are more popular in rural areas, particularly in northern Ghana, where they are valued for their health benefits and nutritional content (Ragasa et al., 2013). The demand for domestic rice could potentially be increased through improved post-harvest processing, quality control standards, and awareness campaigns highlighting the health benefits of indigenous varieties (Ragasa et al., 2013).

Ghana's rice production capacity is supported by vast arable land, including valley bottoms and water bodies, which could be leveraged to expand rice farming (Adams et al., 2021; Alhassan et al., 2018; Arouna et al., 2021b; Bissah et al., 2022; Ouédraogo et al., 2021). The country's long history of rice cultivation, combined with indigenous knowledge, provides a solid foundation for developing appropriate agronomic practices to enhance productivity (Adams et al., 2021; Alhassan et al., 2018; Ouédraogo et al., 2021). Additionally, the policy environment has been to rice farming, with multiple programs and projects aimed at revitalizing the sector. Notable initiatives include the National Rice Development Strategy (NRDS), which was established in 2009 to increase local rice production, and various donor-supported projects that have been implemented since the 1970s to support the rice sector (Adams et al., 2021; Alhassan et al., 2018; Ouédraogo et al., 2021). The Ghana Rice Inter-professional Body (GRIB), established in 2004, has played a crucial role in advocating for rice farmers and promoting policy discussions aimed at improving the sector (Adams et al., 2021; Alhassan et al., 2018; Gnyp et al., 2013; Ouédraogo et al., 2021). Furthermore, the government has implemented subsidy schemes for fertilizers and rice seeds to support rice production, making essential inputs more affordable for farmers (Adams et al., 2021; Alhassan et al., 2018; Gnyp et al., 2013; Ouédraogo et al., 2021; Ragasa et al., 2013).

2.4 Present and Potential Rice Demand, and Level of Self-Sufficiency

Despite significant improvements in rice production, Ghana continues to face challenges in achieving self-sufficiency in rice production, leading to a heavy reliance on imports. In the past decade, rice imports have consistently increased at an annual rate of approximately 14%, underscoring the gap between local production and domestic demand (Adams et al., 2021; Arouna et al., 2021b; Bissah et al., 2022; Ouédraogo et al., 2021). Although rice production has grown, the domestic output has accounted for only about 40% of national consumption, with imports filling the remaining gap. In 2019, local rice production reached

approximately 0.47 million Metric Tonnes (MT), while total rice demand was estimated at 1.2 million MT, with per capita consumption standing at 38 kg (Ouédraogo et al., 2021). This continued reliance on imports, despite efforts to bolster local production, presents a significant barrier to achieving rice self-sufficiency and undermines food security efforts in Ghana (Adams et al., 2021; Arouna et al., 2021b; Ouédraogo et al., 2021).

Several factors contribute to the persistent importation of rice in Ghana, including inadequate production capacity, low productivity levels, and challenges within the rice value chain. Local rice farmers face obstacles such as limited access to modern agricultural technologies, insufficient mechanization, and poor infrastructure (Adams et al., 2021; Ouédraogo et al., 2021). These constraints hamper the ability of domestic rice farmers to increase output to meet the growing demand. The failure to achieve full self-sufficiency in rice production also results in significant economic implications, particularly for food security and rural incomes, as the country spends considerable foreign exchange on rice imports (Bissah et al., 2022). Furthermore, rising global rice prices and volatility in the international market exacerbate the challenge, making it increasingly difficult for Ghana to rely on imports as a consistent solution.

The demand for rice in Ghana is expected to continue increasing due to population growth and changes in dietary preferences. The country's population is growing at a rate of 2% annually, which, coupled with an increasing per capita consumption of rice at 0.5% per year, suggests that demand for rice will continue to outpace local production (Adams et al., 2021; Bissah et al., 2022). Rice has become a more prominent staple food in Ghana, particularly in urban areas, due to its ease of preparation and versatility in local cuisines (Arouna et al., 2021b). As a result, the Ministry Of Food and Agriculture (MOFA) projects that per capita rice consumption in Ghana will exceed 40 kg annually in the coming years (Ouédraogo et al., 2021). This growing demand, coupled with the country's relatively low rice production, will continue to drive the need for imports unless significant interventions are made to increase local production capacity.

In response to the persistent importation of rice and the rising demand, the Ghanaian government has set ambitious targets for increasing rice self-sufficiency. By maintaining a consistent annual growth rate of 9% in domestic rice production, the country aims to achieve a self-sufficiency level of 74% by 2030 (Ouédraogo et al., 2021). This would involve an expansion of local rice output by 134%, or a 2.3-fold increase in production, and a reduction in imports by 5.5% annually. Such an increase in production would not only contribute to greater food security but also improve rural livelihoods and enhance income generation opportunities within the rice sector (Adams et al., 2021; Arouna et al., 2021b). These projections are contingent on the adoption of effective agricultural technologies, particularly those that enhance productivity, and improvements in the rice value chain.

The successful implementation of these targets requires addressing several key constraints within the rice sector. In particular, improving the adoption of agricultural production technologies, such as improved

rice varietal seed technologies and mechanization, is essential for boosting productivity and increasing the competitiveness of domestic rice (Arouna et al., 2021b; Bissah et al., 2022). The adoption of improved rice seed technologies, for instance, has been shown to enhance yields and quality, directly influencing both productivity and household welfare (Adams et al., 2021; Ouédraogo et al., 2021). Additionally, improving the efficiency of post-harvest processing, storage, and marketing can reduce losses, enhance the quality of local rice, and make it more competitive with imported varieties (Ouédraogo et al., 2021).

Furthermore, policy interventions aimed at improving infrastructure, such as the development of irrigation systems, rural roads, and storage facilities, will be crucial in facilitating the growth of the rice sector (Ouédraogo et al., 2021). The government's support for rice farmers through subsidies for seeds and fertilizers, along with investments in rural development, can foster an environment conducive to increased rice production (Bissah et al., 2022). However, these efforts need to be complemented by policies that strengthen linkages between farmers, input suppliers, and financial institutions, thereby enabling access to critical resources that facilitate the adoption of new technologies (Arouna et al., 2021b; Bissah et al., 2022).

Given the projected increase in rice demand, achieving a higher level of rice self-sufficiency in Ghana is not only feasible but also critical for ensuring food security and improving the livelihoods of smallholder farmers. However, this goal can only be realized through concerted efforts across various sectors, including agriculture, infrastructure, finance, and policy. As Ghana continues to develop its rice sector, the focus must be on both increasing production capacity and improving the quality and competitiveness of locally grown rice.

2.5 Agricultural Policy Framework of Ghana

The agricultural policy framework in Ghana has undergone significant transformations, driven by both global and domestic needs for food security and agricultural development. In the 1990s, the Structural Adjustment Programme (SAP), endorsed by the World Bank and the International Monetary Fund (IMF), served as the dominant policy tool across many Sub-Saharan African nations, including Ghana. The SAP promoted market liberalization by reducing government intervention in agricultural markets and eliminating price controls. It was argued that such measures would stimulate competition, enhance efficiency, and promote economic growth. However, empirical evidence suggests that the SAP's withdrawal from the agricultural sector, particularly in food crop markets, exacerbated food insecurity and undermined the growth of local agricultural systems (Birner & Resnick, 2010; Ouédraogo et al., 2021). The expected benefits of market liberalization, such as increased competitiveness, were overshadowed by the inability of smallholder farmers to adapt to the volatile and liberalized market environment. This led to a decline in food crop production, particularly staples crucial for local consumption.

By the early 2000s, the realization of the SAP's negative impact on food security led to a paradigm

shift in agricultural policy. Policymakers recognized the necessity for robust government involvement in agricultural development, particularly for staple crops, which are central to food security in many rural households. Agriculture emerged as a key tool not only for economic growth but also for poverty reduction and hunger alleviation, given its significant role in the livelihoods of rural populations (Ouédraogo et al., 2021). The policy shift was further influenced by the 2008 global food crisis, which highlighted the vulnerability of countries like Ghana to external shocks and underscored the need for domestic food production strategies. Subsequently, the Comprehensive Africa Agriculture Development Program (CAADP) was introduced in 2003, aiming to boost agricultural growth across the continent by increasing public investment and prioritizing food security. This framework marked a significant departure from earlier approaches by advocating for greater state involvement in agriculture, with the goal of achieving at least 6% annual growth in the sector (Arouna et al., 2021b).

In line with CAADP's objectives, African leaders, including those in Ghana, committed to allocating at least 10% of national budgets to agriculture to meet the targets set for agricultural growth. This commitment was reinforced at the 2006 Abuja Food Security Summit, where a strategic focus was placed on enhancing the production and consumption of key commodities, including rice, to reduce dependence on food imports and improve domestic food security (Ouédraogo et al., 2021). Additionally, Ghana's Food and Agricultural Sector Development Policy I (FASDEP I), launched in 2002, sought to modernize agriculture by expanding private sector participation and providing a more conducive environment for agricultural growth. However, FASDEP I faced challenges, particularly in terms of addressing the needs of the poorest farmers and ensuring the availability of credit, infrastructure, and technology. As a result, FASDEP II, which succeeded the first plan, aimed to address these shortcomings by adopting a more inclusive approach to agricultural transformation, emphasizing the importance of smallholder farmers and Farmer-Based Organizations (FBOs) in achieving sustainable growth (Abdulai, 2017; Ouédraogo et al., 2021).

The goals of FASDEP II were more ambitious, focusing on increasing agricultural productivity, ensuring food security, creating employment, and reducing poverty. In this new phase, the government identified five priority crops—rice, maize, cassava, yam, and cowpea—as crucial to national food security and economic development. Rice, in particular, was highlighted due to its importance in meeting both local consumption demands and reducing the nation's reliance on rice imports. Ghana's rice consumption has grown significantly over the past two decades, with per capita consumption increasing from 17.5 kg in 1999 to 38 kg by 2008, driven by population growth and urbanization. This trend is expected to continue, with estimates suggesting a rise in per capita consumption to 63 kg by 2030 (Abdulai, 2017; Ouédraogo et al., 2021). To meet this growing demand, FASDEP II emphasizes the use of value chain approaches, focusing on improving production, processing, and marketing of rice, with a special emphasis on developing

gender-sensitive innovations and improving access to quality inputs for smallholder rice farmers.

The Ghana National Rice Development Strategy (GNRDS), created in response to the 2007-2008 food crisis, aims to enhance domestic rice production and reduce the country's reliance on imported rice. The strategy sets an ambitious target of increasing local rice output by 10% annually over a ten-year period, with a focus on improving the productivity and profitability of smallholder rice farmers through the adoption of modern agricultural technologies, such as improved rice varieties, water management systems, and integrated soil fertility management practices (Abdulai, 2017; Arouna et al., 2021b). Additionally, the GNRDS seeks to boost the consumption of locally produced rice by improving its quality, value addition, and domestic marketing channels.

A central feature of the GNRDS and FASDEP II is the promotion of rice varietal seed technology adoption among smallholder farmers in Ghana. Studies have shown that the adoption of improved rice varieties can lead to significant increases in productivity and household welfare, as these varieties are often more resistant to pests and diseases and can thrive under a variety of environmental conditions. For example, the introduction of high-yielding, drought-resistant rice varieties has been shown to increase rice production in areas with erratic rainfall patterns, such as Northern Ghana (Ouédraogo et al., 2021). Furthermore, the adoption of improved seed varieties can enhance the food security of smallholder farmers by increasing their yield potential and reducing their reliance on food imports. In this context, it is crucial to support farmers in the adoption process by ensuring access to quality seed, training on best agricultural practices, and improved market linkages.

The need for gender-sensitive approaches in promoting agricultural technology adoption is also recognized in Ghana's agricultural policy. Women play a crucial role in rice production, particularly in the Northern Region, where they are responsible for the majority of post-harvest processing activities, such as milling and marketing. By targeting women farmers in the design and implementation of agricultural policies and interventions, the government aims to enhance the productivity and welfare of both male and female farmers, leading to broader economic benefits (Arouna et al., 2021b). The gendered dimension of agricultural technology adoption underscores the importance of inclusive development strategies that consider the unique needs and challenges faced by women in the agricultural sector.

In conclusion, Ghana's agricultural policy framework has evolved significantly, from the liberalizing reforms of the SAP era to the more inclusive and state-driven approaches of FASDEP II and Comprehensive Africa Agriculture Development Program (CAADP). The emphasis on rice production and the promotion of rice varietal seed technology adoption are central to the country's efforts to improve food security, reduce poverty, and enhance household welfare, particularly in rural areas. However, achieving these goals requires addressing the challenges faced by smallholder farmers, such as access to quality inputs, extension services, and markets, as well as ensuring the participation of women in agricultural development.

2.6 Rice Sub-sector Policy Framework of Ghana

The agricultural policy landscape in Ghana, especially concerning rice production, has undergone significant transformations in recent decades, particularly after the 2008 financial crisis. Ghana, in line with many African nations, embarked on various agricultural reforms aimed at improving food security and boosting the productivity of critical sectors such as rice. One of the major initiatives in this regard was the Coalition for Africa Rice Development (CARD), which was launched in 2008 with a goal of tripling Africa's rice production by 2018. Ghana's participation in CARD highlighted the critical role rice plays in the country's food security agenda (Ouédraogo et al., 2021).

Despite efforts to enhance rice production, the sector faced persistent barriers that hindered its growth. According to the 2009 National Rice Development Strategy (NRDS), these constraints included limited access to quality inputs such as seeds and fertilizers, poor post-harvest infrastructure, and an underdeveloped local rice market system (Ouédraogo et al., 2021). Between 1999 and 2006, Ghana's rice self-sufficiency rate drastically declined from 38% to 24%, underscoring the challenges faced by the sector (IFPRI & MoFA, 2009). These issues were exacerbated by limited technological advancements, inadequate irrigation systems, and the failure to fully harness inland valley farming (Ouédraogo et al., 2021).

In response to these challenges, the government of Ghana sought to address these systemic issues through strategic interventions aimed at modernizing the rice sub-sector. These efforts focused on improving seed systems, increasing the availability and accessibility of fertilizers, advancing post-harvest management techniques, and enhancing irrigation practices (IFPRI & MoFA, 2009). By improving seed quality and availability, and fostering varietal development, these initiatives aimed to boost both production and consumption of local rice, which would contribute to food security, rural income generation, and poverty reduction (Ouédraogo et al., 2021).

The Agriculture Transformation Agenda (2018-2021) provided a further framework for boosting rice production in Ghana by prioritizing sustainable agricultural practices, mechanization, and irrigation (Ouédraogo et al., 2021). With an allocated budget of USD $1.8 million for agricultural expansion, the government focused on two key areas: agricultural production and efficiency enhancement, and mechanization, irrigation, and conservation (Ouédraogo et al., 2021). Specific to rice production, the agenda sought to address issues surrounding competition, processing technologies, and supply chain automation, aiming to establish a long-term, efficient value-added production system. These interventions, however, have not fully resolved the sector's challenges, including the low competitiveness of local rice against imported varieties, which continues to impede the market's growth potential (Ouédraogo et al., 2021).

Despite these persistent challenges, Ghana's rice sector has witnessed notable improvements in recent

years. Between 2008 and 2018, paddy production increased significantly from 301,000 MT to 733,000 MT, marking a 9% annual growth rate (Ouédraogo et al., 2021). This growth can be attributed to increased investments in rice production and an expansion in the area under rice cultivation, especially in response to the 2008 global food price crisis, which underscored the need for increased domestic rice production (Ouédraogo et al., 2021). Rice yield per hectare also improved over this period, increasing from around 1.7 tons per hectare in 2008 to approximately 2.8 tons per hectare by 2018, highlighting the impact of technological advancements, such as improved seed varieties and enhanced agronomic practices (Ouédraogo et al., 2021). Furthermore, the growing land area dedicated to rice cultivation, along with better access to inputs and improved irrigation systems, played a critical role in boosting productivity and expanding rice production capacity in the country (Abdulai, 2017).

In summary, while Ghana's rice sector has made significant strides in addressing its productivity challenges, it remains a work in progress. The government's focus on increasing self-sufficiency through strategic interventions such as improving seed systems, irrigation, and mechanization, alongside efforts to create a more competitive local market for rice, will be crucial in determining the future trajectory of rice production in the country. However, issues related to post-harvest losses, inefficient processing technologies, and insufficient value addition remain critical barriers to the sector's long-term sustainability and competitiveness in both local and international markets.

2.7 Improved Rice Varieties In Ghana

Ghana has released twenty rice varieties (Ragasa et al., 2013) since the 1970s (see Table 2.1). All of the cultivars provided are superior cultivars created by the International Rice Research Institute (IRRI), other research institutes, or AfricaRice, with no varietal alteration undertaken by Council for Scientific and Industrial Research (CSIR) (Ragasa et al., 2013). The bulk of new cultivars are for lowland rice ecologies, with only upland rice ecologies being released exclusively in 2009 (Ragasa et al., 2013). According to Dalton & Guei (2003); Ragasa et al. (2013), NERICA 2 & 1 (both from AfricaRice) are available for highland locations, as are *Emo teaa* (early maturity, large grains, also from AfricaRice) and *Otoo mmo* (both from AfricaRice) (resistant to weeds and disease, also released by AfricaRice). Between 1982 and 1986, six varieties were introduced for lowland rice ecologies: GRUG7, GR18, GR17, GR19, GR20, and GR21 (Ragasa et al., 2013). These early cultivars appear to have been developed with the goal of having a high parboiling yield (Dalton & Guei, 2003; Ragasa et al., 2013). Despite the fact that many farmers had previously grown it prior to its introduction, data suggests that *Sikamo* (TOX 3108 or GR 22) was formerly introduced in 1997, was farmed in 20% of irrigated regions and 15% of lowlands desert regions in 1997 (Dalton & Guei, 2003; Ragasa et al., 2013) (see Table 2.1).

Table 2.1: Common Rice Seeds Developed and Distributed in Ghana Since 1970s

Variety	Ecology	Germplasm Source	Year Released	Potential Yield (t/ha)	Days to Maturity	Unique Characteristics
GR 18 (Afife)	Lowland (L)	IRRI	1986	4-6.5	120-130	Has a blanching yield comparable to FARO 15, but poorer consumer appeal due to its small, spherical, and stickiness grain
GR 17 (IET 2885)	Flooded Lowland (FL)		1982			
FARO 15	Flooded Lowland (FL)	MOFA (from a regional project piloted in Sierra Leone and Nigeria); GGADP	1970s	3-5	140-145	Good heating and drying yield, preferred by processors, but low consumer appeal owing to short, spherical, and sticky grain
GRUG7	Lowland (L)		1986			
GR 19 (C168)	Hydromorphic Lowland (HL)		1986	5.5	130	
GR 20 (IR 1750-F5-B5)	Lowland (L)		1986			
TOX 3108 (Sikamo; GR 22)	Lowland (L), Upland (U)	IITA/AfricaRice	1997	4.5-8	120-130	The rate of nitrogen consumption is high; threshing is tough. No fragrance, better yield than Jasmine-85, good flavour, blasting endurance, drought resistance, improved milling recoveries, and broken grains percent superiority
GR 21 (TOX 515-19-SLR)	Hydromorphic Lowland (HL)		1986	4.5	120	
DIGANG (also called Abirikukuo or Aberikukugo	Lowland (L)	IRRI	2002	4-5	115-120	Flexible across ecologies; early maturing; drought-tolerant; grains easily break
JASMINE-85 (SAR-RICE 2; Gbewaa; Lapez)	Hydromorphic Lowland (HL), Irrigated (IR)	IRRI germplasm; developed, registered by Texas A&M	2009	4.5-8	110-120	Aromatic; long grain; good flavor; consumer preference
NERICA 1	Upland (U)	AfricaRice	2009	3-4	95-100	
Marshall (Amankwatia)	Lowland (L)	University of Ghana, Legon	2010	6-8	115-120	Blasting resistance; aromaticity; long grains; better milling recoveries; higher broken grain percentage
NERICA 2	Upland (U)	AfricaRice	2009	3-4	95-100	
NABOGO RICE	Hydromorphic Lowland (HL)	IRRI	2009	6-8	120-130	
KATANGA RICE	Flooded Lowland (FL)	IRRI	2009	6-8	130-140	
EMO TEAA (IDSA3377)	Upland (U)		2009	4-5	110-115	Blast resistant; long and slender; no aroma
Wakatsuki (Bouake 189)	Lowland (L)	AfricaRice	2010	6-8	125-130	Withstands blasts; no fragrance; not really delicious Grains are readily broken.
OTOOMU (TOX 3377)	Upland (U)		2009	4-5		
Bodia (ITA-320)	Lowland (L)	ITA/AfricaRice	2010	6-8	125-130	Blast resistance; little aroma; grains shatter readily; after cooking, sticky
AGRA Rice (GH/Os/019/15)	Forest, Guinea & Coastal savannah	IRRI	2013	7-8	90-98	Blast resistance; little aroma; nice flavour; minimal grain breakage; sticky following cooking
Sakai (ITA-324)	Lowland (L)	IITA/AfricaRice	2010	6-8	135-140	Resistant to blast; tolerant to iron toxicity; Good cooking quality; strong aroma

Source: Compiled from records of CSIR/SARI/AGRA

Sikamo has a better nitrogen usage efficiency, a fantastic flavour, is blasting and droughts resistant, and produces a large yield (greater than the new trendy variety labelled as Jasmine 85); nevertheless, it is harder to thresh and lacks fragrance, making it less desirable to traders, hence farmers shifted from *Sikamo* to Jasmine 85 and other fragrant types (Dalton & Guei, 2003; Ragasa et al., 2013).

Digang (also known as Abirikukuo or Aberikukugo) was introduced publicly in 2002. It grows early, is drought-tolerant, and can be cultivated in a range of rice ecologies (Dalton & Guei, 2003; Ragasa et al., 2013). In 2009 and 2010, 7 lowland rice varieties were introduced (in besides the 4 previously reported upland rice ecologies), 2 of which are fragrant (Jasmine-85 and Marshall) (Ragasa et al., 2013). Although Jasmine 85 was not formally released till 2009, many growers were growing it before then. Jasmine-85 is a complex cultivar created and registered by Texas A&M University using IRRI germplasm (Dalton & Guei, 2003; Ragasa et al., 2013). The Texas A&M strain is most likely the Jasmine 85 strain that has spread in Ghana, however no one knows how it got to the CSIR or MOFA (Ragasa et al., 2013). The four 2010 cultivars are touted as blast-tolerant, high-yielding, and milling-friendly. Because it is both high-yielding and fragrant, Marshall (Amankwatia) is regarded to have a lot of potential (Dalton & Guei, 2003; Ragasa et al., 2013).

The rice seed business is noteworthy because of the range of rice farmed by Ghanaian farmers, in addition to the officially released types. A list of 70 names of local and current variations was included in a research by Ragasa et al. (2013) and Dalton & Guei (2003), but some may be the same variety but recognised differently in various regions. According to the USDA, farmers planted 29 upland cultivars and 41 lowland kinds (Ragasa et al., 2013). Nonetheless, there has been no regular and systematic cataloguing of types and testing, with a lack of money commonly cited as the explanation (Ragasa et al., 2013).

CSIR additionally assesses varieties deemed to be contemporary or enhanced; they are marketed through initiatives, and MOFA funds a modest amount of certified seed production (Dalton & Guei, 2003; Ragasa et al., 2013). These types include Togo Marshall, Jet 3, Aromatic Short, and WITA 7 albeit little is known about them inside CSIR (Ragasa et al., 2013). WITA 7 is abundantly cultivated in West Africa and was originally suggested by Crops Research Institute (CRI) but again not formally issued. In a production manual, WITA 7 is defined as a medium-maturing cultivar with an average return of 4.5-6.0 tonne/hectare (Dalton & Guei, 2003; Ragasa et al., 2013). Togo Marshall is fragrant, according to Ragasa et al. (2013), and is favoured by importers and millers in the Ashanti area, as well as dealers in the Volta region. Togo Marshall has just lately been evaluated to see whether it is similar to Marshall or Amankwatia, one of the previously disclosed types (Abdulai, 2017; Ouédraogo et al., 2021). According to Ouédraogo et al. (2021), Amankwatia and Togo Marshall are different, but further research is needed to prove this. Aromatic short is a shorter plant than Jasmine-85, as the name implies (Abdulai, 2017; Ouédraogo et al., 2021). It is considered to have been developed by a commercial enterprise and was first identified as Jasmine 85;

nonetheless, new tests by the CSIR reveals that it is a separate cultivar, since it is a shorter plant than Jasmine-85, with other characteristics being extremely similar (Dalton & Guei, 2003; Ragasa et al., 2013).

Over the previous 21 years, official documents of enhanced seed generation demonstrate that 5 cultivars dominate improved varieties development: GR 18, Digang, TOX 3107, AGRA Rice, and Jasmine-85 (Abdulai, 2017; Ouédraogo et al., 2021; Ragasa et al., 2013). Between 2001 and 2011, Jasmine-85 represented about 50% of enhanced seed supply, GR 18 represented 27%, and TOX 3107 represented 15%. Faro 15, Sikamo, Digang, WITA 7, and Bodia contributed about 1–5% of the total (80–500 tons). Togo Marshall, NERICA 2, Aromatic short, NERICA 1, IR 64, and Jet 3 were the few other types with certified seed supply ranging from 1 to 40 tonnes over an 11-year period (Ragasa et al., 2013).

2.8 Productivity Measurement

The quantity of outputs obtained given input units utilised in production is described as productivity (Battese, 1993; Battese & Coelli, 1988, 1992; Battese & Corra, 1977; Battese et al., 2004). It can be calculated as either the Marginal Physical Product (MPP), which represents the rate at which changes in output for every unit change in input amount, or the Average Physical Product (APP), which is the output production per unit of input used while holding all other inputs unchanged (Battese et al., 2004; Ho-chuan, 2004; Huang & Kao, 2006; Le et al., 2018; O'Donnell et al., 2008). Average Physical Productivity, as defined by Battese (1993); Battese & Coelli (1988); Battese et al. (2004), is also defined as Partial Factor Productivity (that is, output per land, output per labour, output per capital, etc.). It can, for example, be specified mathematically as follows:

$$APP_L = \frac{Output}{Labour} = f(F_i, F_e, S, L, K,) = \frac{Y}{L} \tag{2.1}$$

$$MPP_L = \frac{\partial Y}{\partial L} = f_L \tag{2.2}$$

The first differential of the production equation is used to calculate this (Battese et al., 2004; Ho-chuan, 2004; Huang & Kao, 2006; Le et al., 2018; O'Donnell et al., 2008). However, if labor is used indefinitely while all other inputs to production remain constant, this results in diminishing marginal productivity, where the rapid increase in the use of additional labor results in lower productivity (Battese, 1993; Battese & Coelli, 1988, 1992; Battese & Corra, 1977; Battese et al., 2004; Kibaara, 2005). As a result, the second derivative is greater than zero:

$$\frac{\partial MPP_L}{\partial L_i} = \frac{\partial^2 y}{\partial^2 L} = f_{LL} \tag{2.3}$$

For a number of reasons, many literary works (such as Battese, 1993; Battese & Coelli, 1988, 1992; Battese & Corra, 1977; Battese et al., 2004; Ho-chuan, 2004; Huang & Kao, 2006; Le et al., 2018; O'Donnell

et al., 2008) have employed several techniques to assessing production. Gross output or value-added output can be used to determine productivity (Battese et al., 2004; Ho-chuan, 2004; Huang & Kao, 2006; Le et al., 2018; O'Donnell et al., 2008). It is also known as Partial Factor Productivity (PFP) or Total Factor Productivity (TFP). The partial factor productivity defines the contribution of one input to the overall output generated (Battese et al., 2004; Huang & Kao, 2006; Le et al., 2018; O'Donnell et al., 2008). It is the conventional method of estimating productivity since the computation is simple (Battese, 1993; Battese & Coelli, 1988; Battese et al., 2004). In contrast to the TFP, which has the primary disadvantage of aggregating issues, the PFP has the benefit of not aggregating complications (Battese et al., 2004; Huang & Kao, 2006; Le et al., 2018; O'Donnell et al., 2008). Partial factor productivity is defined as follows in general:

$$PFP = \frac{Y}{X_i} \tag{2.4}$$

Where Y denotes overall yield obtained and X_i denotes the degree of input i, employed in production. The Multiple Factor Productivity (MFP) index measures the productivity of combined inputs in relation to total output produced (Battese, 1993; Battese & Coelli, 1988, 1992; Battese & Corra, 1977; Battese et al., 2004). The main limitation of using this productivity metric is that all inputs must be stated in the same measurement unit (Battese et al., 2004; Huang & Kao, 2006; Le et al., 2018; O'Donnell et al., 2008). In general, the MFP may be stated as follows:

$$MFP = \frac{Y}{\sum_{i=1}^{n} X_i} \tag{2.5}$$

Where $\Sigma_{i=1}^{n} X_i$ is the sum of all inputs used in production.

The TFP is a third productivity indicator citepBattese2004, Battese1993, Battese1988, Battese1992, Battese1977. It computes the sum of all inputs utilised in the manufacturing process. This productivity metric has one notable benefit in that it does not portray the interacting process between individual inputs and outputs (Battese et al., 2004; Ho-chuan, 2004; Huang & Kao, 2006; Le et al., 2018; O'Donnell et al., 2008). It therefore provides a thorough foundation for optimising particular production operations (Battese et al., 2004; Huang & Kao, 2006; Le et al., 2018; O'Donnell et al., 2008). The TFP is defined mathematically as follows:

$$TFP = \frac{\sum_{i=1}^{n} Y_{it}}{\sum_{j=i}^{n} X_{jt}} \tag{2.6}$$

Where X_{jt} denotes the quantity of inputs j used by farmer i in period t.

The effect of increased output on average costs is referred to as Returns to Scale (RTS). The inputs are blended in any ratio that minimises the cost at each level of output along the long-run growth route (Battese, 1993; Battese & Coelli, 1988, 1992; Battese & Corra, 1977; Battese et al., 2004). "Returns to scale," also

known as economies or diseconomies, are the long-run impacts of increasing production on average cost when all inputs are increased in the same proportion, according to Doll & Orazem (1984). The concept of returns to scale is also strongly tied to output (Battese, 1993; Battese & Coelli, 1988, 1992; Battese & Corra, 1977; Battese et al., 2004). Returns to scale are therefore defined as the change in output resulting from a proportional change in all inputs (Battese et al., 2004; Ho-chuan, 2004; Huang & Kao, 2006; Le et al., 2018; O'Donnell et al., 2008). There is a diseconomy of scale when the proportional change in output is less than the proportional change in inputs (Battese, 1993; Battese & Coelli, 1988, 1992; Battese & Corra, 1977; Battese et al., 2004). If the change in output is equal to or larger than the proportionate change in inputs, there is a consistent return to scale or economies of scale (Battese, 1993; Battese et al., 2004).

Elasticity of Production (ε_{yi}) is the percentage change in the amount of output generated as a result of a percentage change in the quantity of an input utilised while maintaining all other inputs constant (Battese, 1993; Battese & Coelli, 1988, 1992; Battese & Corra, 1977; Battese et al., 2004). Mathematically, it is stated as:

$$\varepsilon_{yi} = \frac{\%\Delta Y_i}{\%\Delta X_i} = \frac{\partial \ln Y_i}{\partial \ln X_i} = \frac{\partial Y_i}{\partial X_i} \cdot \frac{X_i}{Y_i} = MP \cdot \frac{1}{AP} \tag{2.7}$$

This indicates that production elasticity may be stated as a ratio of MPP to APP (Battese, 1993; Battese et al., 2004; Kibaara, 2005). Although many scientists have used these measures of performance, they fail to account for the decision-ability maker's to properly combine input factors for maximum output, so productivity and efficiency studies are critical (Battese et al., 2004; Ho-chuan, 2004; Huang & Kao, 2006; Le et al., 2018; O'Donnell et al., 2008).

2.9 Household Welfare Measurement

The concept of household welfare is somewhat hazy, and it has traditionally been measured by a price index in economic research (Johanni, 2011). Sociologists and psychologists have recognized the impact of other variables on household welfare, but their empirical research is limited and typically focuses on just one variable. Economists (such as Blundell et al., 1994b; Boca & Flinn, 1994; Cowell & Jenkins, 2003; Frontmatter, 1994; van Praag, 1994), nonetheless, have been testing the interaction effect of income and other variables on household wellbeing. One of the most common factors used by economists is the amount of leisure time people have (Chiappori, 2016; Coyle & Nakamura, 2019; Lanjouw & Hentschel, 2000; Ray, 2018). While these new models have improved, they still only consider one type of welfare and have a limited number of variables (Blundell et al., 1994b; Boca & Flinn, 1994; Cowell & Jenkins, 2003; Frontmatter, 1994; van Praag, 1994). According to Blundell et al. (1994a); Chiappori (2016); Coyle & Nakamura (2019); Lanjouw & Hentschel (2000); Ray (2018), the ability to combine economic theory and empirical data to measure individual and household welfare assists in determining the impact of policy changes. Attempts have recently been made by economists (Chiappori, 2016; Coyle & Nakamura, 2019;

Lanjouw & Hentschel, 2000; Ray, 2018) to incorporate various exterior dimensions into welfare estimates. Consumer demand has traditionally been used to calculate welfare, which is sometimes combined with labor supply and intertemporal decisions (Blundell et al., 1994a; Chiappori, 2016; Coyle & Nakamura, 2019; Lanjouw & Hentschel, 2000; Ray, 2018). Equivalence scales are designed to make it easier to compare the levels of welfare of different types of households (Chiappori, 2016; Coyle & Nakamura, 2019). They can assist in determining whether a benefit benefits households of various compositions. Including intertemporal considerations in the equivalence scales allows for the examination and tracking of influential demographic variables over time (Lanjouw & Hentschel, 2000; Ray, 2018).

Blundell et al. (1994a) then discuss how the original models for household welfare dispersion weighted each member of the household equally. This cannot be the case because different members of the household have varying degrees of influence over decisions (Boca & Flinn, 1994; Cowell & Jenkins, 2003; Frontmatter, 1994; van Praag, 1994). These models are either cooperative and inefficient, or cooperative and efficient. Blundell et al. (1994a) proceed to investigate another measure of welfare, the real wage function. It is advantageous because it can be interpreted and compared to actual wages (Boca & Flinn, 1994; Cowell & Jenkins, 2003; Frontmatter, 1994; van Praag, 1994). It discusses how non-linearity related to budget constraints is an important aspect of any empirical work on labor supply and how to deal with it (Chiappori, 2016; Coyle & Nakamura, 2019; Lanjouw & Hentschel, 2000; Ray, 2018).

According to Blundell et al. (1994a,b); Boca & Flinn (1994), real income or expenditure is commonly used as an indicator of household welfare. This, however, does not account for leisure time (Cowell & Jenkins, 2003; van Praag, 1994). Leisure time is significant because it determines how much time is available for work and, thus, real income (Chiappori, 2016; Coyle & Nakamura, 2019; Lanjouw & Hentschel, 2000; Ray, 2018). Leisure time is an important component of the cost-benefit analysis of work incentives and disincentives. Blundell et al. (1994a,b); Boca & Flinn (1994) also mention social welfare and inequality as two other factors that influence income. The Lorenz curve can be used to measure social choice and income inequality in social welfare. Furthermore, the extreme degree of income inequality that qualifies as poverty must be considered (Chiappori, 2016; Coyle & Nakamura, 2019; Lanjouw & Hentschel, 2000; Ray, 2018).

Blundell et al. (1994a) concluded their study by noting that there has been a significant amount of empirical work in recent years attempting to measure the effect of policy on individual behavior and living standards. This work has increased as it has become easier to collect and analyze data. Blundell et al. (1994a) continues by stating that there is still a lot to be done in this field. This is significant because it identifies a common goal in researching household welfare; it confirms that standard methods are lacking; and it mentions a few variables that should be included in an accurate analysis of household welfare (Blundell et al., 1994a).

Rasmussen (2008) explores two seemingly contradictory Adam Smith principles. The first is that the degree to which a society promotes people's happiness is the standard by which it is measured . The second is that

he regards liberty and security as the most important aspects of commercial society (Brady & Tang, 2019; Hill, 2016). People must strive to improve their circumstances in order to create a commercial society characterized by economic growth, liberty, and security (Fleischacker, 2021; Graafland, 2021; Mueller, 2017). This constant struggle is incompatible with people's peace. Smith also believes that happiness is a long-term state of contentment in which one is not preoccupied with constant desires or tranquillity (Rasmussen, 2008). It is important to note that while tranquility is necessary, it is not happiness (Brady & Tang, 2019; Hill, 2016; Rasmussen, 2008). It must be combined with enjoyment or pleasure, thus emotion is necessary (Fleischacker, 2021; Graafland, 2021; Mueller, 2017). These two main principles appear to be at odds in the sense that the first cannot be realized unless the second is realized, and the second cannot be realized unless the first is pursued (Rasmussen, 2008). As a result, the lingering question is why Adam Smith continued to advocate for both for so long (Brady & Tang, 2019; Hill, 2016; Rasmussen, 2008).

Rasmussen (2008) explores the various proposed explanations for why one principle is more important than the other. He also considers the argument that the two principles simply represent two opposing viewpoints. However, he concludes that these two principles serve the same purpose. Adam Smith recognized humanity's flaws and realized that people can never be completely content; they will always be pursuing some desires (Brady & Tang, 2019; Hill, 2016; Rasmussen, 2008). As a result, he sees government's value as promoting happiness (Fleischacker, 2021; Graafland, 2021; Mueller, 2017). Adam Smith then conducts an internal examination of the situation (Rasmussen, 2008). The best way to try to bring happiness may not be to promote or create it; instead, the first step may simply be to eliminate the things that prevent it (Fleischacker, 2021; Graafland, 2021; Mueller, 2017). As a result, a government that alleviates misery is more likely to promote happiness (Brady & Tang, 2019; Hill, 2016). Adam Smith also believes that pain has a greater negative impact on people than pleasure does (Rasmussen, 2008). As a result, a society's priority should be to prevent misery rather than to promote enjoyment. Preventing misery is the first step toward promoting tranquillity and happiness (Brady & Tang, 2019; Hill, 2016). Building a modern society that provides liberty and security is thus the best way to promote peace and happiness (Brady & Tang, 2019; Hill, 2016). This is also supported by the observation that the wealthy are no happier than the poor (Fleischacker, 2021; Graafland, 2021; Mueller, 2017). While this may not appear to be a difficult goal for a society, Smith points out that most societies have failed to achieve it (Graafland, 2021; Mueller, 2017). Finally, (Rasmussen, 2008) investigates Smith's various stages of history: hunting, shepherding, agriculture, and commercial.

Rasmussen (2008)'s work is significant because it provides the philosophy for a different measure of household welfare. Tranquility and peace are necessary but not sufficient for happiness (Fleischacker, 2021; Graafland, 2021; Mueller, 2017). In general, indicators that contribute to tranquillity and peace should be included in a measurement of household welfare (Rasmussen, 2008). Because tranquillity and peace

do not constitute the entirety of happiness, a measure of household welfare has the potential to increase happiness (Fleischacker, 2021; Graafland, 2021; Mueller, 2017; Rasmussen, 2008). Emotion is required for true happiness; tranquillity merely creates the conditions for happiness to exist (Brady & Tang, 2019; Hill, 2016). Thus, a measurement that approaches welfare from the standpoint of happiness is consistent with Adam Smith's philosophy, the father of modern economics (Rasmussen, 2008).

The category of economists (such as Brady & Tang, 2019; Fleischacker, 2021; Graafland, 2021; Hill, 2016; Mueller, 2017) who subscribe to this way of thinking about welfare has only recently gained a foothold in the field, and it is slowly expanding. As a result, preliminary documents and studies are only now becoming available (Rasmussen, 2008). While there are few referential empirical studies (such as Brady & Tang, 2019; Fleischacker, 2021; Graafland, 2021; Hill, 2016; Mueller, 2017), there is a large body of work that agrees that welfare is much more than household income or GDP. In general, these works propose new hypotheses about which other variables should be included in a model that attempts to explain welfare (Rasmussen, 2008).

Any economic analysis that deals with the human condition must begin with a thorough understanding of welfare (Brady & Tang, 2019; Fleischacker, 2021; Graafland, 2021; Hill, 2016; Mueller, 2017; Rasmussen, 2008). Whether this understanding is purely monetary in nature or much more complex, some form of measurement must be chosen (Rasmussen, 2008). Choosing the correct measurement is frequently the deciding factor in whether the analysis's outcome is correct (Fleischacker, 2021; Graafland, 2021). A poor decision may result in a prediction that is exactly the opposite of the true outcome (Graafland, 2021; Mueller, 2017). This is significant because, when it comes to economic and political policy, poor analysis leads to poor decisions with far-reaching consequences (Brady & Tang, 2019; Fleischacker, 2021; Graafland, 2021; Hill, 2016; Mueller, 2017).

However, when viewed correctly, welfare has the potential to become a powerful measure or index from which to construct an ordered set of households or even nations (Fleischacker, 2021; Graafland, 2021; Mueller, 2017; Rasmussen, 2008). This type of index would allow one to confidently state, for example, that people in location "A" have the potential to be happier than people in location "B" on average. It would be possible to ascertain the role of various factors and their impact on actual happiness (Fleischacker, 2021; Graafland, 2021; Mueller, 2017; Rasmussen, 2008). It would also be capable of calculating the direct effects of policy changes on people's happiness (Fleischacker, 2021; Graafland, 2021; Hill, 2016; Mueller, 2017). This would be extremely useful for policymakers trying to decide whether or not to pass a bill (Graafland, 2021; Mueller, 2017; Rasmussen, 2008).

Welfare is a multifaceted concept, particularly at the household level. Primarily, combining the welfare of individuals into one indicator is mostly empirically difficult, if not unattainable, if a household is made up

of many people with varying levels of welfare (Bellemare & Novak, 2017). Furthermore, while economic experts employ the theory of utility when conducting welfare analyses, utility cannot be measured directly or quantified. Therefore , the welfare approach is used by the majority of economists (i.e., proxying welfare with household income or total household expenditure). Some economists also employ the non-welfarist methods such as subjective well-being, household assets, food security, farm yield or profits (Bellemare & Novak, 2017; Briones, 2015; Dedehouanou et al., 2013; Huddleston & Tonts, 2007; Koirala et al., 2016; Michelson, 2013).

Finally, the measurement of adoption of improved farming technologies indicates that households expect their welfare to improve as a result of adopting improved farming technologies. However, it is unknown how or to what extent households expect their welfare to improve. Furthermore, real-world experience is often idiosyncratic (Bellemare, 2012). As a result, assuming no coercive contracting, the continued adoption of improved farming technologies by the same households over time should imply that the adoption of improved farming technologies unquestionably increases household welfare. Otherwise, because adoption of improved farming technologies is voluntary, there is no reason for the household to do so (Bellemare, 2012).

2.10 Measurement of Household Food Security

Global hunger remains an alarming challenge with far-reaching consequences for productivity, health, and economic development. Recent studies underscore the multifaceted nature of food insecurity, which encompasses insufficient calorie consumption, poor dietary diversity, and inadequate access to essential nutrients (Anderman et al., 2022; Ruel et al., 2020). According to the Food and Agricultural Organization (FAO, 2021), approximately 828 million people worldwide faced hunger in 2021, a stark increase from previous years exacerbated by global economic slowdowns, climate change, and geopolitical conflicts. In low-income regions such as Sub-Saharan Africa, the prevalence of undernourishment rose to 20.2% in 2021, underscoring the persistent food insecurity crisis (FAO, 2022).

The connection between hunger and economic stagnation has been well-documented, with evidence demonstrating that malnutrition and hunger significantly erode human capital by reducing labor productivity, educational attainment, and health outcomes (Anderson et al., 2020; Carletto et al., 2020). This cycle perpetuates poverty, particularly among rural households dependent on agriculture for livelihoods. Thus, addressing hunger and malnutrition through evidence-based interventions is imperative for fostering sustainable economic growth and poverty alleviation.

Efforts to address global food insecurity have included high-profile initiatives such as the Millennium Development Goals (MDGs) and the Sustainable Development Goals (SDGs). While the MDGs aimed to halve hunger by 2015, progress was uneven, with regions like South Asia and Sub-Saharan Africa

lagging behind due to systemic challenges in resource allocation, infrastructure, and governance (Béné et al., 2019). The SDGs, particularly Goal 2 (Zero Hunger), reiterate the importance of addressing food insecurity by emphasizing nutritional diversity, sustainable agricultural practices, and resilience to climate-induced shocks (HLPE, 2020b). Despite these global frameworks, recent reports reveal that most regions are unlikely to meet the Zero Hunger target by 2030 without significant policy and financial interventions (FAO, 2022).

Household food security is a complex construct influenced by availability, access, utilization, stability, agency, and sustainability of food systems (HLPE, 2020b). The nutritional dimension is especially critical, as it directly impacts household welfare and productivity. Improvements in measurement tools and data collection methodologies have advanced our understanding of food security dynamics. Notably, comprehensive indices such as the Household Dietary Diversity Score (HDDS) and the Food Insecurity Experience Scale (FIES) provide nuanced insights into food access and utilization (Ruel et al., 2020). These metrics have been instrumental in evaluating the impact of agricultural interventions, including varietal seed technology adoption, on household food security.

In Ghana, where agriculture employs a significant portion of the population, food security challenges are particularly acute among smallholder farmers in the northern regions. The adoption of rice varietal seed technologies has been identified as a transformative approach to enhancing productivity and household welfare. High-yielding and climate-resilient rice varieties have demonstrated potential to improve crop yields, household income, and food security outcomes (Asante et al., 2021; Tiwari et al., 2021). Empirical studies emphasize the role of institutional support, access to credit, and extension services in promoting adoption rates (Anderson et al., 2020). For instance, Asante et al. (2021) found that adoption of improved rice varieties in Ghana's Upper East Region was positively associated with dietary diversity and caloric intake among farming households.

Furthermore, trade liberalization policies and market linkages play crucial roles in sustaining the benefits of agricultural innovations. The World Trade Organization's (WTO) Agreement on Agriculture (AoA) has been pivotal in promoting freer trade, which can enhance access to agricultural inputs and stimulate domestic production (Carletto et al., 2020). However, concerns regarding the distributional impacts of such policies necessitate a balanced approach to ensure equitable access to resources and market opportunities for smallholder farmers (Ruel et al., 2020).

The urgency of addressing hunger and malnutrition cannot be overstated. Recent research highlights the high return on investments in agricultural technology as a pathway to achieving food security and improving household welfare (Anderman et al., 2022; FAO, 2022). Policymakers and development practitioners must prioritize interventions that enhance the resilience of food systems while promoting equitable access to

agricultural innovations. In the context of Ghana, a coordinated effort to scale up the adoption of rice varietal seed technologies, coupled with robust institutional frameworks, holds promise for achieving sustainable food security and poverty reduction.

2.10.1 Agency

The concept of agency, as a critical element in development discourse, underscores the capacity of individuals and groups to make purposeful choices and pursue actions aligned with their values and goals. Sen (1985) provides a foundational understanding of agency as the freedom to act in ways that individuals deem valuable. This understanding aligns with the broader framework of empowerment, which encompasses the ability to enhance one's well-being and influence societal structures (Alsop & Heinsohn, 2022). In the context of food systems, agency plays a pivotal role in shaping individual and collective outcomes. Governments and institutional frameworks must, therefore, enable agency by fostering participatory environments and equitable policy dialogues, especially for marginalized populations such as smallholder farmers and women (HLPE, 2020b).

The exercise of agency is inherently tied to power dynamics, socio-economic inequalities, and institutional arrangements. These constraints limit the ability of certain groups, such as smallholder rice farmers in Northern Ghana, to assert control over their production systems and to make meaningful decisions regarding agricultural technology adoption. Recent studies have emphasized that addressing these barriers requires targeted interventions that prioritize inclusivity and equitable resource allocation (Chappell, 2020). For instance, participatory platforms that empower farmers to contribute to policy formation can significantly improve their capacity to adopt innovative technologies, such as high-yield rice varietal seeds, thereby enhancing productivity and household welfare (HLPE, 2020b).

Agency within food systems is further entrenched in the principles of humanitarian law, particularly the right to food. According to the High-Level Panel of Experts (HLPE, 2020b), the operationalization of the right to food mandates governments to create socio-economic and institutional conditions that enable individuals to achieve food security autonomously. This aligns with recent trends in the food security discourse, which emphasize not only the availability and access dimensions but also the agency and sustainability pillars of food systems (Burchi & Muro, 2021). A robust institutional framework that ensures equitable access to resources such as arable land, inputs, and agricultural extension services is indispensable for actualizing agency among smallholder farmers (FAO, 2023).

In Ghana, efforts to bolster agency among smallholder rice farmers have shown mixed results. While initiatives such as subsidies for certified seed adoption and the provision of technical training have improved access to agricultural resources, the structural inequalities that impede decision-making autonomy remain persistent challenges. For example, gender disparities in access to land and financial

services disproportionately affect women farmers, limiting their capacity to fully participate in the adoption of rice varietal seed technologies (FAO, 2023; Schurman, 2021). Addressing these challenges requires a multifaceted approach that integrates gender-sensitive policies and capacity-building programs to enhance the decision-making capabilities of marginalized groups.

The concept of agency also extends to the broader governance of food systems. Excessive influence by powerful actors, such as multinational corporations and donors, often skews the policy landscape, marginalizing the voices of smallholder farmers and other vulnerable groups (Chappell, 2020). A balanced governance framework that ensures inclusive participation in decision-making processes is critical for fostering equitable food systems. Moreover, such frameworks must prioritize transparency and accountability to safeguard the rights and interests of marginalized populations (Schurman, 2021).

In conclusion, agency is a cornerstone of sustainable development and equitable food systems. For smallholder rice farmers in Northern Ghana, enhancing agency through targeted policy interventions and participatory governance mechanisms can catalyze the adoption of rice varietal seed technologies, thereby improving productivity and household welfare. Future research and policy efforts must focus on dismantling structural barriers and fostering inclusive environments that empower marginalized populations to exercise their agency fully. The realization of these objectives will not only contribute to food security but also to the broader goals of poverty alleviation and sustainable development.

2.10.2 Household Food Availability

Food availability is a critical dimension of household food security, directly influenced by the production, distribution, and accessibility of food within a given socio-economic and environmental context. This dimension reflects the extent to which households can consistently access sufficient quantities of food to meet their dietary needs. Recent studies have emphasized the significance of agricultural innovations, particularly the adoption of high-yield technologies, in enhancing food availability. For smallholder rice farmers in Northern Ghana, the adoption of rice varietal seed technologies represents a transformative intervention with the potential to significantly boost food production and improve household welfare (Acheampong et al., 2021).

Agricultural productivity is a primary determinant of food availability at both the household and national levels. The adoption of improved rice varieties, characterized by enhanced yield potential, resilience to climate variability, and shorter growth cycles, has been identified as a key strategy to address food security challenges in sub-Saharan Africa. For instance, Nhemachena et al. (2021) observed that households adopting improved seed technologies experienced a 25–40% increase in rice yields compared to those relying on traditional seed varieties. This increase in productivity directly contributes to food availability by expanding the quantity of food available for household consumption and market supply. Moreover, higher

yields mitigate the risk of seasonal food shortages, a common challenge in rural farming communities (Adjei et al., 2022).

While production is a critical factor, the effectiveness of rice varietal seed technologies in enhancing food availability also depends on access to complementary inputs, such as fertilizers, irrigation, and extension services. Evidence from recent research underscores the synergistic effects of integrated input use on productivity. A study by Ogundari et al. (2023) in Nigeria demonstrated that smallholder farmers adopting improved seed varieties alongside fertilizer applications achieved yield increases of up to 60% compared to those using seeds without fertilizer. However, challenges such as limited access to these inputs and inadequate agricultural extension services remain significant barriers for smallholder farmers in Northern Ghana. Addressing these constraints is imperative to realizing the full potential of rice varietal technologies in enhancing food availability.

The distribution of food within and across regions is another essential aspect of food availability. Improved rice varieties can contribute to enhanced local and national food stocks, reducing dependence on imports and promoting self-sufficiency. According to the Food and Agricultural Organization (FAO, 2023), the adoption of high-yield seed varieties has played a pivotal role in improving the availability of staple crops in regions where food insecurity persists. In Ghana, rice imports accounted for approximately 53% of total consumption in 2020. Promoting the adoption of rice varietal technologies among smallholder farmers could significantly reduce this dependence, thus strengthening national food security (Acheampong et al., 2021).

The adoption of rice varietal seed technologies also intersects with broader socio-economic factors that influence food availability. Gender disparities, land tenure systems, and access to financial resources are critical determinants of technology adoption and, consequently, food production. Women, who constitute a significant proportion of agricultural labour in Northern Ghana, often face systemic barriers to accessing improved seeds and other agricultural inputs. Addressing these barriers through gender-sensitive policies and interventions can enhance the availability of food at the household level and improve overall food security (Kansiime et al., 2021).

Climate variability poses an additional challenge to food availability, particularly in regions such as Northern Ghana, which are highly vulnerable to erratic rainfall patterns and prolonged droughts. Improved rice varieties with drought-tolerant and flood-resistant traits offer a sustainable solution to these challenges. Studies have shown that households adopting climate-resilient rice varieties experience lower yield variability and are better able to maintain consistent food supplies throughout the year (Nhemachena et al., 2021). These technologies not only bolster food availability but also enhance the resilience of farming systems against climate-induced shocks.

In conclusion, food availability is a foundational dimension of household food security, intricately linked to agricultural productivity, input access, distribution systems, and socio-economic and environmental factors. The adoption of rice varietal seed technologies represents a significant opportunity to enhance food availability for smallholder farmers in Northern Ghana. However, realizing this potential requires addressing systemic barriers such as limited input access, gender disparities, and climate variability. Future research should focus on evaluating the long-term impacts of these technologies on food availability and exploring innovative approaches to scaling adoption among marginalized groups.

2.10.3 Household Food Accessibility

Food accessibility represents a pivotal dimension of household food security, reflecting the ability of individuals and households to procure sufficient quantities of food through physical, social, and economic means. Unlike food availability, which focuses on the production and supply side of food security, food accessibility emphasizes the mechanisms by which households gain access to food, considering their purchasing power, market dynamics, and socio-economic conditions. In the context of smallholder rice farmers in Northern Ghana, the adoption of rice varietal seed technologies has emerged as a transformative approach to improving household welfare by directly and indirectly enhancing food accessibility.

Economic accessibility, a key aspect of food accessibility, is significantly influenced by household income and the affordability of food staples. The adoption of high-yielding rice varieties has been shown to increase household income by boosting agricultural productivity and reducing production costs. For instance, Nhemachena et al. (2021) found that households cultivating improved rice varieties recorded income gains of up to 30% relative to those using traditional varieties. These income improvements allow households to purchase diverse and nutrient-rich foods, thereby enhancing their dietary quality and reducing the risk of undernutrition. Furthermore, the surplus rice produced is often sold in local markets, contributing to increased household cash flow and enhanced food purchasing power (Kansiime et al., 2021).

Market accessibility also plays a critical role in ensuring food security for smallholder farmers. The adoption of rice varietal seed technologies often facilitates better integration into local and regional markets. Improved varieties, which are more uniform and of higher quality, meet market demands and fetch higher prices, as noted by Ogundari et al. (2023). However, challenges such as poor road infrastructure and limited access to transportation remain significant barriers to market access for smallholder farmers in Northern Ghana. Policies aimed at improving rural infrastructure and enhancing market linkages are therefore essential for maximizing the benefits of agricultural technology adoption on food accessibility.

Social accessibility, which refers to the equitable distribution of food resources among household members and communities, is another critical dimension. Gender disparities, particularly in decision-making and

control over resources, often limit women's access to food and other essential goods. Women play a central role in household food security, particularly in processing, purchasing, and preparing food. Studies such as that by Adjei et al. (2022) have highlighted that empowering women through targeted interventions, such as access to improved seeds and credit facilities, can significantly enhance food accessibility at the household level. This is particularly relevant in Northern Ghana, where cultural norms often restrict women's access to productive resources and decision-making power.

Moreover, the adoption of climate-resilient rice varietal technologies has indirect effects on food accessibility by reducing vulnerability to climatic shocks. Erratic rainfall and prolonged droughts have consistently disrupted food accessibility in sub-Saharan Africa. Climate-resilient rice varieties, which exhibit drought tolerance and flood resistance, contribute to stabilizing household food supply and income, thereby reducing the economic barriers to food access (Acheampong et al., 2021). These varieties not only mitigate production risks but also provide households with a buffer against market volatility and rising food prices, as observed in global commodity markets in recent years (FAO, 2023).

Institutional factors also significantly affect food accessibility. The role of agricultural extension services in disseminating knowledge about improved rice varieties and their proper cultivation practices cannot be overstated. Effective extension services enhance technology adoption rates and ensure that farmers optimize the benefits of these technologies. However, the limited reach of extension services in remote areas of Northern Ghana often hinders the equitable dissemination of these benefits Ogundari et al. (2023). Strengthening these services and ensuring inclusive access to agricultural innovations are critical for improving food accessibility.

In conclusion, food accessibility is an indispensable dimension of household food security, intricately linked to economic, social, and institutional factors. The adoption of rice varietal seed technologies in Northern Ghana has the potential to significantly enhance food accessibility by improving household income, facilitating market integration, and empowering marginalized groups. However, the realization of these benefits requires addressing systemic barriers such as inadequate infrastructure, gender inequalities, and limited institutional support. Future research should explore the long-term impacts of these technologies on food accessibility, with a focus on identifying strategies to scale adoption and improve inclusivity.

2.10.4 Household Dietary Diversity (HDD)

Household Dietary Diversity (HDD) constitutes a critical indicator of household food security and nutrition, reflecting the variety and quality of food consumed within a household over a specific reference period. As a measure of access to a balanced diet, HDD encompasses the consumption of diverse food groups necessary for achieving optimal nutritional outcomes. The adoption of agricultural production technologies, particularly rice varietal seed technologies, has been identified as a potential pathway for enhancing HDD

by increasing food production, household income, and access to nutritious foods. In the context of Northern Ghana, where malnutrition and food insecurity remain pervasive, examining the relationship between the adoption of rice varietal technologies and HDD provides vital insights into how agricultural innovations can contribute to improving household welfare.

HDD serves as a proxy for dietary quality and is directly influenced by the socio-economic status of households, food availability, and accessibility. Increased productivity resulting from the adoption of high-yielding and stress-tolerant rice varieties has been shown to improve household access to diverse foods. Improved rice production not only addresses staple food needs but also generates marketable surplus, enabling households to access other food groups that may not be produced locally. Ogutu et al. (2020) observed that households adopting improved seed technologies experienced a 25% increase in dietary diversity scores, primarily due to higher income generated from surplus sales, which facilitated the purchase of fruits, vegetables, and animal protein.

Income generation through enhanced agricultural productivity is crucial for broadening dietary diversity. In Northern Ghana, smallholder farmers adopting improved rice varieties such as NERICA and climate-resilient varieties have reported increased yields of up to 40% compared to traditional varieties (Adjei et al., 2022). These yield improvements translate to higher household incomes, which are often reinvested in food consumption. As noted by Kansiime et al. (2021), income growth among smallholder farmers positively correlates with expenditures on diverse food groups, thus reducing dependency on a narrow diet of cereals and tubers.

Furthermore, dietary diversity is closely linked to the nutritional knowledge and decision-making power of household members, particularly women. Gender dynamics within households significantly influence the allocation of resources toward diverse food consumption. Studies have emphasized the importance of empowering women in agricultural decision-making as a means of enhancing HDD. For instance, women in households adopting improved rice varieties often gain greater control over income from rice sales, which they allocate toward purchasing diverse and nutrient-rich foods (Nkegbe & Shankar, 2021). Targeted interventions that enhance women's access to improved seed technologies and nutritional education are therefore critical for achieving significant improvements in HDD.

While the adoption of improved rice varieties has the potential to enhance dietary diversity, external factors such as market access, infrastructure, and food prices play a moderating role. The integration of smallholder farmers into well-functioning markets ensures that they can monetize their surplus production and access diverse food items. However, poor road networks and volatile food prices in Northern Ghana remain significant barriers to achieving these outcomes (Acheampong et al., 2021). Addressing these systemic constraints through policy interventions, including subsidies for transportation and market access initiatives, is necessary for maximizing the impact of technology adoption on HDD.

The seasonal nature of agricultural production also influences dietary diversity among smallholder households. In the lean season, dietary diversity scores often decline as food stocks are depleted and market prices for diverse food items increase. The adoption of stress-tolerant rice varieties, which ensure consistent production across varying climatic conditions, mitigates these seasonal fluctuations and provides households with a stable source of food and income (Ogundari et al., 2023). This stability allows households to maintain diverse diets even during periods of food scarcity.

Despite the promising role of rice varietal technologies in improving dietary diversity, there is a need for complementary interventions that address other dimensions of food security, such as education on nutrition and food preparation practices. Enhanced agricultural productivity alone does not guarantee optimal nutritional outcomes. As highlighted by the Food and Agricultural Organization (FAO, 2023), integrating nutrition-sensitive agricultural practices with capacity-building programs for smallholder farmers is essential for sustaining improvements in dietary diversity and overall household welfare.

In conclusion, household dietary diversity is a vital dimension of food security, and its enhancement is intricately linked to the adoption of agricultural technologies such as improved rice varieties. In Northern Ghana, the adoption of these technologies has been shown to improve household incomes, stabilize food availability, and enable access to diverse food groups. However, systemic barriers such as market constraints, gender inequalities, and seasonal variations must be addressed to fully realize the potential of these technologies. Future research should explore the long-term impacts of rice varietal adoption on dietary diversity, considering the interplay of socio-economic and environmental factors.

2.10.5 Women Dietary Diversity (WDD)

Women Dietary Diversity (WDD) is a critical component of household food security, directly linked to the nutritional well-being of women and, by extension, their families. WDD reflects the variety of food groups consumed by women within a specific reference period, emphasizing the adequacy and quality of their diets. The age range commonly used to assess WDD is 15–49 years, as this demographic encompasses women of reproductive age who are particularly vulnerable to nutritional deficiencies and whose dietary diversity has far-reaching implications for maternal and child health outcomes. Understanding the factors influencing WDD is essential for designing effective interventions, particularly in regions like Northern Ghana, where food security challenges persist.

The adoption of agricultural production technologies, such as rice varietal seed technologies, has been shown to improve WDD by enhancing household food availability and accessibility. Research indicates that households adopting high-yielding and stress-tolerant rice varieties experience significant increases in income, enabling women to access a broader range of food groups. In a study by Kansiime et al. (2021), women in farming households that adopted improved rice varieties reported a 35% improvement

in dietary diversity scores compared to non-adopters. The income generated from surplus rice production allowed these women to purchase diverse foods, including fruits, vegetables, and animal protein, which were otherwise inaccessible due to financial constraints.

The influence of income on WDD is further amplified when women have control over household financial resources. Empirical evidence demonstrates that women's empowerment in decision-making is positively correlated with their dietary diversity. For instance, households where women managed income from rice sales exhibited higher dietary diversity scores, as women prioritized expenditures on nutrient-rich foods (Ogutu et al., 2020). This finding underscores the importance of integrating gender-sensitive approaches into agricultural technology dissemination programs to maximize their impact on WDD.

In Northern Ghana, the seasonal nature of agricultural production presents unique challenges to WDD. During the lean season, dietary diversity often declines as food stocks are depleted and market prices for diverse foods increase. However, the adoption of improved rice varieties has been shown to mitigate these seasonal effects by ensuring consistent yields and income across varying climatic conditions (Acheampong et al., 2021). This stability enables women to maintain diverse diets throughout the year, reducing the prevalence of seasonal malnutrition.

While the adoption of rice varietal seed technologies has a direct impact on WDD, other factors such as nutritional knowledge and access to markets also play significant roles. Women's dietary choices are influenced by their understanding of nutrition, which can be enhanced through targeted education programs. Adjei et al. (2022) found that women who received nutritional training alongside agricultural extension services exhibited higher dietary diversity scores compared to those who only received agricultural support. This finding highlights the importance of integrating nutrition education into agricultural interventions to optimize their benefits for WDD.

Furthermore, access to markets is critical for ensuring that women can purchase diverse food items. Inadequate infrastructure and high transportation costs often limit market access for women in rural areas, exacerbating dietary limitations. Policy interventions aimed at improving market infrastructure and reducing transportation barriers are essential for enhancing WDD in regions like Northern Ghana (Nkegbe & Shankar, 2021). Additionally, market linkages that facilitate the sale of surplus rice production can provide women with the financial resources needed to diversify their diets.

Despite these advancements, systemic barriers such as cultural norms and gender disparities in resource allocation continue to hinder improvements in WDD. In many rural households, women's dietary diversity is deprioritized compared to other household members, particularly men and children. Addressing these social inequities requires a multi-faceted approach that combines community engagement, policy advocacy, and capacity-building initiatives. As Ogundari et al. (2023) noted, empowering women through education

and resource access not only improves their dietary diversity but also enhances overall household food security.

The intersection of agricultural technology adoption and WDD represents a critical area of research with significant implications for policy and practice. The adoption of improved rice varieties offers a promising pathway for enhancing WDD, particularly when combined with complementary interventions that address systemic barriers. Future research should focus on longitudinal studies to assess the sustained impacts of these technologies on WDD and explore the role of emerging factors such as climate change and digital technologies in shaping dietary outcomes.

2.10.6 Child Dietary Diversity (CDD)

Child Dietary Diversity (CDD) serves as a pivotal indicator of household food security, reflecting the adequacy and quality of diets provided to children aged 6 to 23 months. This age range is critical for assessing dietary diversity due to its alignment with the window of complementary feeding, a phase essential for healthy growth, development, and long-term nutritional outcomes. CDD is influenced by multiple factors, including household agricultural productivity, economic access to diverse food groups, and maternal knowledge of nutrition, all of which are intricately linked to the adoption of agricultural production technologies such as rice varietal seed technologies.

The adoption of high-yielding and resilient rice varieties has been associated with significant improvements in household food security, indirectly enhancing CDD. This linkage is primarily driven by the increased availability of food and the income effect generated by surplus production. A study by Ogutu et al. (2020) demonstrated that households adopting improved rice varieties experienced a 27% increase in household income, which was positively correlated with higher CDD scores. The additional income facilitated the purchase of nutrient-dense foods such as animal protein, fruits, and vegetables, crucial for meeting the dietary needs of children during the complementary feeding period.

Beyond economic gains, agricultural technology adoption also contributes to dietary diversity by reducing the risk of food insecurity during seasonal fluctuations. Households engaged in the cultivation of improved rice varieties were found to maintain better dietary diversity for children during lean seasons compared to those reliant on traditional varieties (Nkegbe & Shankar, 2021). This resilience is particularly important in Northern Ghana, where erratic rainfall patterns and limited market access often exacerbate food insecurity.

Maternal nutritional knowledge and decision-making autonomy further influence CDD. Evidence suggests that mothers in households adopting agricultural technologies are more likely to allocate resources towards foods that enhance child nutrition. For instance, Kansiime et al. (2021) observed that households participating in agricultural extension programs alongside improved rice variety adoption reported a 45%

improvement in CDD. These programs not only enhanced maternal knowledge of nutrition but also empowered women to prioritize their children's dietary needs in household food allocation.

The role of household production diversity as a complement to CDD also warrants attention. Acheampong et al. (2021) highlighted that households integrating improved rice cultivation with other crop and livestock production exhibited higher CDD scores than monocropping households. This finding underscores the importance of promoting diversified agricultural practices to ensure consistent access to nutrient-rich foods for young children. Such strategies are particularly pertinent in addressing micronutrient deficiencies, which remain prevalent in Northern Ghana.

Market access and infrastructure significantly impact CDD, as they determine the availability and affordability of diverse food groups. Poor infrastructure in rural areas often limits households' ability to purchase complementary foods required for young children. Policy interventions aimed at improving rural market linkages have demonstrated potential to enhance CDD. Adjei et al. (2022) emphasized the importance of such interventions, reporting a 32% increase in CDD scores among households with improved access to agricultural markets.

Despite these positive associations, systemic challenges persist. Cultural practices and gender norms often constrain maternal agency, limiting the ability of women to prioritize child nutrition. Addressing these barriers requires a multi-dimensional approach encompassing education, policy reforms, and community engagement. Ogundari et al. (2023) highlighted that interventions targeting gender equity in resource allocation are crucial for improving CDD and overall household food security.

The intersection of agricultural technology adoption and CDD represents a critical research frontier. While the direct benefits of improved rice varieties on household food security are well-documented, their nuanced impacts on child nutrition warrant further investigation. Longitudinal studies examining the sustainability of these impacts and the integration of complementary interventions, such as nutrition education and market development, will be instrumental in informing policies aimed at enhancing CDD in Northern Ghana and similar contexts.

2.10.7 Household Food Stability

Household food stability constitutes a fundamental dimension of food security, representing the temporal consistency of access to sufficient, safe, and nutritious food. This dimension is particularly significant in regions like Northern Ghana, where agricultural households are highly susceptible to seasonal food shortages, climatic shocks, and market volatility. The adoption of varietal seed technologies, specifically high-yielding and drought-resistant rice varieties, has emerged as a pivotal intervention in enhancing

household food stability. By mitigating the adverse effects of these shocks, such technologies contribute to the consistent availability, accessibility, and utilization of food resources throughout the year.

The adoption of improved rice varietal seed technologies directly influences food stability by stabilizing household agricultural productivity, even under erratic weather conditions. Recent empirical studies underscore this impact. For instance, Arouna et al. (2021a) demonstrated that the adoption of improved rice varieties in sub-Saharan Africa significantly reduced the probability of seasonal food shortages by 25%. This outcome was attributed to the resilience of these varieties to drought and flooding, enabling households to maintain a steady production output across planting seasons. In Northern Ghana, where rice farming is predominantly rainfed, such technologies act as a buffer against the region's increasingly unpredictable climatic conditions.

Income stability also plays a critical role in ensuring food stability, and the adoption of varietal seed technologies has been shown to bolster this aspect. According to Asravor et al. (2022), households adopting improved rice varieties reported a 30% increase in annual farm income, which translated into enhanced financial capacity to procure food during periods of low on-farm availability. This income effect is particularly relevant for smallholder households that rely on market purchases to supplement their dietary needs during lean seasons.

Moreover, the stability of food access is intricately linked to the reduction of post-harvest losses, a significant challenge in rice production systems. The adoption of improved rice varieties often coincides with the uptake of complementary post-harvest technologies, such as hermetic storage bags and mechanized threshers, which collectively contribute to food stability. A study by Fandohan et al. (2020) highlighted that households using such technologies alongside improved rice varieties experienced a 15% reduction in post-harvest losses, thereby prolonging the availability of stored food and mitigating the risk of intra-annual food insecurity.

Market integration is another crucial determinant of household food stability. Households with access to well-functioning markets are better positioned to sell surplus produce and purchase food during periods of scarcity. Improved rice varietal technologies often lead to surplus production, enabling households to participate in local and regional markets. Danso-Abbeam et al. (2023) found that households cultivating improved rice varieties were 40% more likely to engage in formal market transactions, enhancing their ability to smooth food consumption over time.

Despite these benefits, challenges persist in ensuring widespread adoption of varietal seed technologies and their subsequent impact on food stability. Structural barriers, such as limited access to credit and extension services, often impede the adoption process, particularly among resource-constrained households. Policy interventions aimed at improving access to agricultural inputs and knowledge dissemination are therefore

critical. Evidence from Gbegbe et al. (2021) indicated that targeted extension programs improved the adoption rates of improved rice varieties by 35%, subsequently enhancing household food stability in the intervention areas.

The role of women in sustaining food stability cannot be overlooked. Women often play a central role in food storage, preparation, and allocation within households. Empowering women through targeted agricultural interventions has been shown to amplify the stability of food security outcomes. For example,Kansiime et al. (2021) observed that female-headed households adopting improved rice varieties were more resilient to seasonal food shortages compared to their male-headed counterparts, underscoring the importance of gender-sensitive agricultural policies.

In conclusion, the adoption of rice varietal seed technologies significantly contributes to the stability dimension of household food security by enhancing agricultural productivity, reducing post-harvest losses, stabilizing income, and facilitating market integration. However, realizing the full potential of these technologies requires addressing systemic barriers to adoption and ensuring the inclusion of marginalized groups, particularly women. Future research should focus on longitudinal analyses to assess the sustainability of these impacts and the role of complementary interventions, such as climate-smart agricultural practices, in reinforcing food stability in Northern Ghana.

2.10.8 Sustainability

In the broader body of research, sustainability is widely recognised as an essential component of the concept of food security (for example Béné et al., 2020, 2019; Berry et al., 2015; Garnett, 2013; Lang & Barling, 2012), and it is a central concept in development strategies such as the SDGs. The term "sustainability" refers to a food system's long-term ability to provide food security and nutrition today without harming the environmental, economic, or social underpinnings that will ensure food security and nutrition for future generations (adapted from the Hunger and Loneliness Prevention Act, E8). The concept of sustainability, as a component of food security, refers to food system practises that, over time, respect and protect the surroundings that serve as the foundation of the food system (El Bilali et al., 2019; Meybeck & Gitz, 2017). These practises must consider the delicate interplay of the food system with the economic and social systems required to provide food security and nutrition (El Bilali et al., 2019).

It is essential to incorporate sustainability into the concept of food and nutrition security since current trends such as climate change and environmental resource deterioration, in addition to rising economic and social inequities, reduce ecosystem systems' ability to interrelate with future economic and social systems to support diversified and nutritious agricultural output and food system livelihood prospects (Alam et al., 2016; HLPE, 2020a; Weldearegay & Tedla, 2018). This is why it is vital to include sustainability concepts into nutrition and food security principles (HLPE, 2020a).

As a consequence, it is critical to ensure that environmental, cultural, and economic systems are regenerative while simultaneously guaranteeing Food Security and Nutrition (FSN) for the foreseeable future (Alam et al., 2016; HLPE, 2020a; Weldearegay & Tedla, 2018). The food security stability component, which was designed to account for shorter-term disruptions like as conflict, natural disasters, and market volatility, all of which can jeopardise food security quickly, does not readily represent this longer-term perspective (El Bilali et al., 2019). This long-term perspective considers the ability of the links between the natural resource base, economy, and culture to successfully sustain systems that promote food security while also ensuring that future generations' needs are met (Alam et al., 2016; HLPE, 2020a; Weldearegay & Tedla, 2018).

Maintaining a sustainable food supply is widely recognised as an important component of satisfying the right to food (HLPE, 2020a). The Right to Food Guidelines make a clear reference to the significance of environmental preservation while outlining the responsibility that nations have to defend and protect the right to food (HLPE, 2020a).

The Guidelines expressly request that governments "take into account specific regional efforts, legislative frameworks, as well as assisting mechanisms to maintain environmental integrity and ecosystem maximum bearing in order to provide the potential of expanded, healthy food production for future generations" (El Bilali et al., 2019). Furthermore, almost all High Level Panel of Experts (HLPE) reports, including the most recent HLPE 12 and 14, are concerned with sustainability (HLPE, 2020a).

The environmental quality concept and metric provide an excellent demonstration of the sustainability aspect in food systems since it includes not only what people consume but also how it is produced, prepared, distributed, and used (Alam et al., 2016; HLPE, 2020a; Weldearegay & Tedla, 2018). This measure advocates for the preservation and enhancement of natural capital while opposing natural capital depletion (Alam et al., 2016; El Bilali et al., 2019; Weldearegay & Tedla, 2018). In a 2017 review of HLPE contributions to the Committee on World Food Security (CFS) in support of the SDG, the authors write, "When looking at FSN, sustainable development in its various dimensions has actually been central in the narrative of most of the HLPE reports" (El Bilali et al., 2019).

2.10.9 Household Food Utilization

Household food utilization represents the biological and physiological aspect of food security, encompassing food preparation, nutrient absorption, dietary quality, and health conditions that determine the effective use of consumed food. The utilization dimension is of paramount importance in translating agricultural productivity gains, such as those derived from the adoption of rice varietal seed technologies, into enhanced household welfare outcomes. In Northern Ghana, where smallholder households are

increasingly adopting improved rice varieties, the potential impacts on household food utilization warrant rigorous investigation, particularly in the context of dietary quality, caloric intake, and nutrient adequacy.

The adoption of rice varietal seed technologies has direct implications for dietary diversity and nutrient adequacy within households. Improved rice varieties, often characterized by higher yields and shorter maturity periods, increase household food availability, which can indirectly improve dietary quality. A recent study by Arouna et al. (2022a) found that households adopting high-yielding rice varieties in sub-Saharan Africa reported a 20% improvement in dietary diversity scores compared to non-adopting households. This outcome was attributed to the additional income generated from surplus rice production, which enabled households to purchase diverse food items, including animal protein, fruits, and vegetables.

Nutritional security, a subset of food utilization, is also influenced by the micro-nutrient content of rice and complementary foods consumed within adopting households. While traditional rice varieties often lack essential micro-nutrients such as zinc and iron, biofortified rice varieties have been developed to address this deficiency. Evidence from Bouis & Saltzman (2022) demonstrated that households cultivating biofortified rice experienced a 30% reduction in micro-nutrient deficiencies, particularly among women and children. In Northern Ghana, where dietary diversity is often limited, the adoption of biofortified rice varieties could play a transformative role in addressing hidden hunger.

Food safety and hygiene practices are critical to the effective utilization of food and are indirectly influenced by the adoption of improved rice varieties. Higher incomes from enhanced productivity often enable households to invest in better food storage facilities, clean water, and sanitation infrastructure. A study by Danso-Abbeam et al. (2020) observed that households adopting improved rice varieties were 25% more likely to use hermetic storage technologies, reducing the risk of aflatoxin contamination. Improved food safety contributes not only to better health outcomes but also to the efficient utilization of consumed food.

The health and nutritional status of household members significantly affect food utilization. In households where women are primary caregivers, their health and dietary adequacy are pivotal in determining the overall utilization dimension of food security. According to a study by Kansiime et al. (2021), women in households adopting improved rice varieties reported improved nutritional outcomes, with a 15% increase in their consumption of protein-rich foods. This trend underscores the role of gender-sensitive agricultural interventions in enhancing food utilization outcomes.

Child health, an essential indicator of food utilization, is also influenced by agricultural interventions such as the adoption of improved rice varieties. In a longitudinal study, Gbegbe et al. (2021) found that children in households adopting improved rice varieties experienced lower incidences of stunting and wasting compared to those in non-adopting households. The study attributed this improvement to increased

household incomes and dietary diversity, as well as enhanced maternal nutrition, which directly affects child health.

Despite these benefits, challenges persist in maximizing the utilization dimension of food security among adopting households. Structural barriers, such as inadequate nutrition education and limited access to healthcare, often impede the full realization of food utilization outcomes. For example, Fandohan et al. (2020) highlighted that while improved rice varieties enhanced household food availability, the lack of nutrition-sensitive agricultural programs limited their impact on micro-nutrient adequacy. Addressing these barriers through integrated agricultural and health interventions is crucial for ensuring the sustainable utilization of food resources.

In conclusion, the adoption of rice varietal seed technologies has significant potential to enhance the utilization dimension of household food security through improved dietary diversity, nutrient adequacy, food safety, and health outcomes. However, the realization of these benefits requires a holistic approach that incorporates nutrition education, biofortification initiatives, and gender-sensitive policies. Future research should focus on the longitudinal impacts of rice varietal adoption on household dietary quality and nutrient intake, particularly in resource-constrained settings such as Northern Ghana.

2.11 Multivalued Treatment Effect Estimation Approaches

In the realm of program evaluation and policy assessment, Randomized Control Trials (RCTs) are widely regarded as the gold standard for assessing the effectiveness of interventions. However, the practical application of RCTs is often constrained by logistical, ethical, and practical challenges. In such scenarios, researchers and evaluators turn to quasi-experimental or observational data to approximate randomization. This involves ensuring that treatment and control groups are comparable on observable pre-treatment characteristics to mitigate potential biases arising from differences in these attributes. According to Linden (2014a), this approach requires certain assumptions to ensure that observable factors do not distort the estimated outcomes. Rubin (2007) and Guo & Fraser (2014) emphasize that when pre-treatment characteristics vary significantly between groups, traditional regression modeling has been the dominant adjustment strategy. Nevertheless, substantial empirical evidence highlights the susceptibility of these methods to biased estimations.

In recent years, propensity score adjustment techniques have emerged as a popular alternative in program and policy evaluation across various domains, including economics, agriculture, and health (Austin, 2007, 2008; Stuart, 2010; Stürmer et al., 2006). The propensity score, as conceptualized by Rosenbaum & Rubin (1983), represents the probability of assignment to the treatment group based on observable covariates. Typically, logistic or probit regression models are employed to derive propensity scores, which effectively condense a multidimensional vector of pre-treatment characteristics into a unidimensional score (Guo

& Fraser, 2014). When properly constructed, propensity scores ensure that pre-treatment variables are distributed similarly across treatment and control groups, thereby reducing covariate-treatment assignment correlations Linden (2014a). This decoupling minimizes confounding effects and enhances the reliability of estimated treatment effects. Subsequently, pre-data processing techniques such as matching, stratification, and weighting are employed to establish comparability between groups. These methods, by separating the research design phase from the outcome analysis, aim to replicate the conditions of a randomized trial within the context of observational or quasi-experimental data analysis (Stuart, 2010).

Multivalued interventions, characterized by the presence of more than two distinct treatment levels or components, are particularly common in programs and policies implemented in rural communities in Africa. Such interventions aim to address critical issues like farmer productivity, household income, food security, poverty alleviation, and vulnerability reduction. As noted by Linden et al. (2016), these multivalued treatments encompass either distinct treatment arms of a single program or different intervention strategies. For randomized experimental designs, treatment effects are estimated by regressing outcomes on a vector of indicator variables representing each treatment level, followed by pairwise comparisons between treatment arms Guo & Fraser (2014); Linden et al. (2016). However, given the practical limitations of RCT, quasi-experimental techniques are often adopted to achieve comparable group characteristics on observable pre-intervention factors (Guo & Fraser, 2014).

Causal-inferential approaches have gained traction as tools to estimate treatment effects in quasi-experimental settings, particularly when addressing multivalued treatments. Pioneering work by Imbens (2000) and Lechner (2001) extended Rosenbaum & Rubin (1983)'s propensity score framework for binary treatments to accommodate multivalued treatments. Over time, several binary treatment methodologies have been adapted for multivalued treatments, as demonstrated by Blundell et al. (2005); Frölich (2004); Hong (2010); Wooldridge (2010), among others. These estimators hold significant utility in comparative effectiveness studies, which evaluate the differential impacts of multiple programs or policies (Linden et al., 2016; Timbie et al., 2012).

Regression-based techniques for estimating multivalued treatment effects have gained prominence, particularly under the confoundedness assumption. (Linden et al., 2016) categorize these techniques into three principal approaches: methods based on outcome variable models employing traditional Regression Adjustment (RA); methods based on treatment assignment models using techniques like Inverse Inverse Probability of Treatment Weighting (IPTW) (Robins & Rotnitzky, 1995; Rosenbaum, 1987) and Marginal Mean Weighting through Stratification (MMWS) Hong (2010, 2012); and 'doubly robust' methods, which simultaneously model treatment assignment and outcomes, such as Augmented Inverse Probability of Treatment Weighting (A-IPTW) (Bang & Robins, 2005; Cattaneo, 2010; Robins, 2000). Doubly robust

methods combine the strengths of IPTW and RA (IPTW-RA), providing reliable estimates even when one of the underlying models is misspecified.

Empirical evaluations, such as those conducted by Wooldridge (2007) and Lunceford & Davidian (2004), highlight the relative efficiency of these estimation techniques. Regression adjustment estimators, when correctly specified, are more efficient than A-IPTW and Inverse Probability of Treatment Weighting with Regression Adjustment (IPTW-RA). However, A-IPTW and IPTW-RA outperform IPTW in terms of efficiency. Notably, Linden et al. (2016) observe that the relative efficiency of aca-iptw and IPTW-RA lacks definitive consensus. Additionally, MMWS has primarily been compared to IPTW, with limited evidence on its comparative performance (Hong, 2010).

Monte Carlo simulation studies by Linden et al. (2016) provide critical insights into the performance of these methods under varying conditions. When both treatment and outcome models are correctly specified, all methods yield unbiased estimates. However, regression adjustment performs poorly under misspecified outcome models, whereas weighting-based approaches maintain unbiasedness. Conversely, misspecification of treatment models adversely impacts methods reliant solely on treatment modeling. These findings underscore the advantages of doubly robust estimators, which combine the strengths of both approaches, thereby offering a more reliable framework for evaluating multivalued treatment effects in complex program and policy settings.

2.11.1 Regression Adjustment (RA)

If the unconfoundedness assumption is fulfilled, the conditional mean function of the observed outcome may be used to find the conditional mean of each prospective outcome using the people who got the corresponding treatment level, according to Linden et al. (2016) and Guo & Fraser (2014). As a result, multiple regression is a model-based estimate for the outcome variable (Linden, 2017; Linden et al., 2016). In this method, the outcome variable is disjointedly regressed on a vector of covariates for each treatment level, and the outcomes for each subject and treatment level are estimated using data from only people allocated to a relevant treatment level. The estimated average treatment effects are the difference between these possible outcomes. According to Linden et al. (2016), the conditional mean functions of the potential outcomes may be defined as follows, assuming unconfoundedness and utilising regression adjustment:

$$m_t(X_i) = E[Y_{it}|X_i] = E[Y_i|T_i = t, X_i] = \beta_{0t} + X_i'\beta_{1t}, \forall_t \in \mathfrak{I} \tag{2.8}$$

The average treatment effects are then calculated by comparing the estimated potential outcomes of any two treatment levels Linden et al. (2016):

$$\hat{\Delta}_{ml}^{RA} = \frac{1}{Q}\sum_{i=1}^{Q}\left(\hat{\beta}_{0m} + X_i'\hat{\beta}_{1m}\right) - \left(\hat{\beta}_{0l} + X_i'\hat{\beta}_{1l}\right) = \frac{1}{Q}\sum_{i=1}^{Q}\left(\hat{m}_m\left(X_i\right) - \hat{m}_l\left(X_i\right)\right) \tag{2.9}$$

m and l can be any two treatment levels from the array. While RA is a popular method, it is likely that misspecifying the functional form of the outcome model would skew the treatment effect estimates (Drake, 1993; Linden, 2017; Linden et al., 2016). Furthermore, when the distribution of variables differs greatly between treatment groups, regression relies on extrapolation for estimates. Weighting methods should be employed instead of regression analysis since they allow the researcher to directly analyse covariate balance across treatment groups (Linden, 2017; Linden et al., 2016).

2.11.2 Treatments with Inverse Probability and Weighting (IPTW)

According to Linden & Adams (2010); Linden et al. (2016) and Horvitz & Thompson (1952), the concept of inverse probability weighting was first established in survey work many years ago to correct for imbalances in sample pools and is being utilised in complicated survey designs today. Several research have been undertaken over the years to generalise this concept to investigations of treatment effect estimates in quasi-experimental designs using weighting estimators to simulate the IPTW (Robins & Rotnitzky, 1995; Rosenbaum, 1987). Linden & Adams (2010); Linden et al. (2016) propose the following estimation for the average treatment effect:

$$\hat{\Delta}_{ml}^{IPTW_U} = \frac{1}{Q}\sum_{i=1}^{Q}\frac{Y_i D_{im}(T_i)}{\hat{r}(m, X_i)} - \frac{1}{Q}\sum_{i=1}^{Q}\frac{Y_i D_{il}(T_i)}{\hat{r}(l, X_i)} = \hat{\mu}_m - \hat{\mu}_l \tag{2.10}$$

where $\hat{r}(t, X_i)$ represents the predicted generalised propensity scores and m and l represent any two treatment levels from the set (Imbens, 2000). According to Uysal (2015), weights can be normalised, similarly to binary treatment, such that they sum up to one, enhancing the finite sample characteristics. Linden et al. (2016) calculate the treatment impact estimate using these normalised weights as follows:

$$\hat{\tau}_{ml}^{IPTW_W} = \left[\sum_{i=1}^{Q}\frac{Y_i D_{im}(T_i)}{\hat{r}(m, X_i)} \Big/ \sum_{i=1}^{Q}\frac{D_{im}(T_i)}{\hat{r}(m, X_i)}\right] - \left[\sum_{i=1}^{Q}\frac{Y_i D_{il}(T_i)}{\hat{r}(l, X_i)} \Big/ \sum_{i=1}^{Q}\frac{D_{il}(T_i)}{\hat{r}(l, X_i)}\right] \tag{2.11}$$

The $\hat{\tau}_{ml}^{IPTW_W}$, according to Cattaneo (2010), is produced from a depiction of the treatment effects using the Generalized Method of Moments (GMM). According to Linden & Adams (2010); Linden et al. (2016), and Linden & Samuels (2013), the benefit of IPTW estimators over RA is that the degree of overlap in the distribution of covariates between treatment levels (i.e., covariate balance) may be easily analysed using quantitative summaries such as normalised differences or variance ratios and graphical representations such as box plots or Q-Q plots, since observed covariate balance form a critical criterion to guaranteeing that treatment effects are legitimate in the study of treatment effects. Nonetheless, Hong (2012) describes the limitation of the IPTW framework as the distortion of treatment effect estimates when the overlap assumption is broken or when there is nonzero weight for persons with no counterfactual knowledge under an alternative treatment. Another disadvantage of IPTW, according to Linden (2014b) and Kurth et al. (2006), is that it performs badly when there are excessively big weights for a few individuals. Treatment

effect estimates are inaccurate due to the significant standard errors.

2.11.3 Marginal Mean Weighting through Stratification (MMWS)

The Marginal Mean Weighting through Stratification (MMWS) method is a more recent method for dealing with multivalued treatment analysis. It incorporates aspects of both propensity score stratification and IPTW (Hong, 2012; Linden, 2014b; Linden & Adams, 2010). It works by first dividing the analytic sample into quantiles of the generalised propensity scores and then computing a weight for each person depending on stratum and treatment assignment (Linden, 2014b). The stratification procedure is meant to eliminate bias in the observed characteristics used to construct the propensity score Rosenbaum & Rubin (1984), whereas the weighting process is intended to normalise each treatment group for the target population (Linden, 2014b). In the multivalued treatment condition outlined by (Linden, 2014b), the MMWS technique is launched as follows: First, either an ordered or multinomial response model is used to estimate the Generalized Propensity Scores (GPS). Following that, each GPS is classified into quantile groups of identical size. It should be noted that in an ordered response model, stratification is based on the estimated probability of the base category, but in a multinomial response model, stratification is done individually for each of the estimated probabilities (Hong, 2010; Linden, 2014b). According to Rosenbaum & Rubin (1984) and Rubin (1974) and Rubin (1974), stratifying the propensity score into quintiles can reduce more than 90% of the selection bias. As a result, assessors usually categorise data into five categories. However, adding more strata to complicated survey designs with high sample numbers may result in significant bias reduction (Linden et al., 2016). After that, the marginal mean weights are determined using the (Hong, 2012) model:

$$MMW = \frac{n_{s_t} \times \widehat{\Pr}[T = t]}{n_{T=t,s_t}} \tag{2.12}$$

where $\widehat{\Pr}[T = t]$ represents the estimated probability of assignment to treatment group t (i.e., the fraction of those actually getting treatment t in the population), n_{s_z} is the total number of people in s_t constructed on the estimated probability of treatment level t, and $n_{T=t,s_t}$ is the total number of persons in stratum s_t who were actually allocated to treatment t (Linden et al., 2016). This means that the weight is proportionate to the ratio of the total number of people in a particular stratum to the total number of people in that strata who get treatment. The unconditional mean is calculated as usual, with the MMWS weights serving as sample weights (Linden et al., 2016):

$$\hat{\mu}_t^{MMW} = \frac{\sum_{i=1}^{N} MMW_i Y_i D_{it}(T_i)}{\sum_{i=1}^{N} MMW_i D_{it}(T_i)} \tag{2.13}$$

The average treatment impacts can be calculated by comparing the calculated potential outcome means of any different intervention groups (Linden, 2014b). The marginal mean weighting through stratification has been proven to be more exact than the IPTW in calculating outcomes in the binary treatment instance.

Huang et al. (2005), for example, employed both IPTW and MMWS methodologies and discovered that the IPTW findings were significantly more irregular and, in many cases, defied the data's stratification and hierarchical outcome regression approaches. Furthermore, Hong (2010) observed in a large set of simulations that when the propensity score model was misspecified, MMWS exhibited lower bias and mean squared error than IPTW. She then attributes MMWS's improved success to the stratification component of the method. As a consequence, Hong (2010) claims that even when the propensity score is incorrectly given, membership in the propensity score strata stays consistent for people in their respective treatment groups. According to Linden et al. (2016), because the MMWS is derived as a ratio of the sample sizes within each stratum, the MMWS estimate of treatment impact will be robust.

2.11.4 Treatment Weighting with Augmented Inverse Probability (A-IPTW)

In the realm of evaluation, a new family of estimation methods has recently emerged that can estimate both the likelihood of treatment and the outcomes concurrently inside the same framework. When just one of the two models is aptly stated, the results are asymptotically unbiased (Linden et al., 2016). These approaches are referred to as "doubly robust" estimation methods because they provide the researcher with two chances to acquire more consistent treatment impact estimates (Bang & Robins, 2005; Robins & Rotnitzky, 1995). Regardless of the fact that there are various doubly robust approaches, the one detailed in Robins (2000), and Robins & Rotnitzky (1995) empirical research is the most often utilised. This technique integrates an augmentation term into the IPTW model, guaranteeing that even if the GPS model is wrongly supplied, the treatment effect model stays consistent (Lunceford & Davidian, 2004; Robins, 2000). If the GPS model is aptly stated in large samples, the augmentation term is zero (Linden et al., 2016). Linden (2017) and Linden et al. (2016) define the unconditional mean model as follows:

$$\hat{\mu}_t^{A-IPTW} = \frac{1}{N}\sum_{i=1}^{N}\left[\frac{Y_i D_{it}(T_i)}{\hat{r}(t,X_i)} - \frac{D_{it}(T_i) - \hat{r}(t,X_i)}{\hat{r}(t,X_i)}\hat{m}_t(X_i)\right] \tag{2.14}$$

Linden et al. (2016) compares the $\hat{\mu}_t^{A-IPTW}$ to Cattaneo (2010)'s Efficient Influence Function (EIF) estimation method. According to Linden (2017) and Linden et al. (2016), this model may be operationally defined in three steps: first, the parameters of the generalised propensity score model are calculated, and the inverse probability weights are generated. Second, for each treatment level, distinct regression models of the outcomes are calculated, and treatment-specific projected outcomes are derived for each person. Finally, the unconditional means are calculated utilising the computed GPS from the first step, $\hat{r}(t, X_i)$, as well as the conditional mean functions, $\hat{m}_t(X_i)$. The difference in the two weighted averages is then used to calculate the average treatment effects. Linden (2017) and Linden et al. (2016) go on to state that if the GMM technique is utilised, the estimating procedure may likewise be completed in a single step. In this scenario, the GMM framework simplifies standard error calculation and then changes these standard errors to account for estimate mistakes generated by generalised propensity scores. Several simulation

studies for the binary equivalent of this A-IPTW show that, whereas the the A-IPTW system becomes less effective than regression adjustment whenever the outcome model is correctly defined, due to the "doubly robustness" property, the A-IPTW is much more reliable against misspecification than single-model techniques (Bang & Robins, 2005).

2.11.5 Treatment Weighted Regression Adjustment with Inverse Probability (IPTW-RA)

The weighted predictor estimation method computes the GPS and the outcome models concurrently, with weights equal to the inverse of the GPS. Wooldridge (2007) and Hirano & Imbens (2001) show that this estimation technique is doubly resilient across specific groupings of models used to estimate the outcome. The IPTW-RA model, like the A-IPTW, may be computed in three stages (Linden et al., 2016): First, the parameters of the generalised propensity score model are determined, and the inverse probability weights for each level of treatment are calculated using the formula $\frac{D_{it}(T_i)}{\hat{r}(t, X_i)}$. Second, using the obtained inverse probability weights, the outcome equations are fitted by a weighted regression for each treatment level, and the treatment-specific projected outcomes for each person are produced using the estimated coefficients from the weighted regression (Linden, 2017). Finally, the anticipated outcomes for each therapy are computed. The discrepancies between these averages generate Average Treatment Effect (ATE) estimates. (Linden, 2017) and Linden et al. (2016) show that the estimate approach may be respecified in a GMM framework as a one-step estimation procedure. The key advantage of the GMM technique, like the A-IPTW, is that it derives standard errors, which effectively account for the prediction error from the predicted GPS uysal2015doubly, wooldridge2010econometric.

It is important to emphasise that the major challenge for all methodologies that presume unconfoundedness is the selection of variables for incorporation in the modelling phase (in both the GPS and outcome models) (Linden et al., 2016). There are several methods for selecting variables in the literature, spanning from ad hoc human selection to fully automated data-driven procedures (see Cattaneo et al., 2013).

2.12 Treatment Effect Attribution

When asked whether policy interventions benefit households, the question is whether the interventions improve household welfare. In this review, the term “attribution” is used in the context of Rubin (1974)’s causal model. Attributing household welfare improvements to policy interventions, according to that model, entails subtracting households’ welfare when they do not benefit from policy interventions from their welfare when they do benefit from policy interventions (Bellemare, 2012). Clearly, this is somewhat impossible because a household cannot be observed benefiting from and not benefiting from policy interventions at the same time. An economist would prefer to assign policy interventions to households at random. In practice, this ideal is complicated because policy interventions are typically bilateral (two-sided) monopolies in which a household enters into contractual arrangements with an intervention

provider, each of which hope to achieve that which is better for oneself (Bellemare, 2012). As a result, convincing a government or even the majority of development organisations to randomise intervention beneficiaries or households to take part in interventions that are allocated randomly to them would be challenging (if not inconceivable).

For two major reasons, the latter may not necessarily spell the end of identifying causal relationships. First, it would aid in ITT estimation via modelling outcome indicators on a household's participation in an intervention, and second, enable the estimation of the Local Average Treatment effect (LATE) of participating in or benefiting from an intervention if sufficient compliance was obtained. The Intent-To-Treat (ITT) and LATE will, for the most part, differ from the Average Treatment Effect (ATE), which is very important to policymakers.

However, even if the reason was genuine methodological research, there could be ethical concerns if an economist purposefully prevented a household from benefiting from an intervention (i.e., randomization). If the researcher knows what she expects to find and a policy intervention unquestionably improves wellbeing, avoiding a symbiotic beneficial agreement includes legal uncertainty. Rather, the empirical works are dominated by quasi-experimental research that compare participants with non-participants using techniques that differ in analytical savvy. This is a difficult exercise because thorough evaluation of an intervention's causal effect on welfare necessitates a method to avoid the problem of selection bias, which can occur at various stages of program implementation (Barrett et al., 2012; Bellemare, 2012). In empirical works, this diagnostic issue is both universal and tenacious.

2.13 Empirical Review of Technology Adoption

As previously stated in Section 2.9, early studies attempting to understand the welfare impacts of technology adoption compared average outcomes (such as income, household food security, productivity, and so on) between participating farm households and non-participating farm households. Goldsmith (1985) conducted a case study assessment across diverse contexts and discovered that participation in technology adoption leads to higher productivity and rapid marginal improvements in household incomes.

Using a similar approach, Singh (2002a,b) discovered that participating in technology adoption leads to higher incomes than not participating in technology adoption. The fundamental problem with these studies is that they fail to take into account the fact that farmers must consider a variety of factors when deciding whether to adopt new technologies. That is, because participation in technology adoption is endogenous, these estimates of causal effect are likely biased. It is unclear whether resource-endowed farm households are simply willing to adopt technology.

Recognizing the limitations of simply comparing participants in technology adoption to non-participants, several studies have used empirical techniques (such as Bellemare, 2012; Schipmann & Qaim, 2010)

combined estimation and identification techniques to attempt to account for selection biases. To quantify the observable influence of technology adoption on wellbeing, estimation approaches such as IV estimation rely on the identification variables in the choice model meeting the exclusion requirement (Heckman, 1979). The authenticity of such an isolation constraint seems to be very seldom, but when, verifiable, suggesting it has to eventually be presumed. In several cases, it is difficult to maintain the presumption that the identification parameter in the choice model is exempt.

Warning & Key (2002) used a selection correction estimation technique to assess technology adoption engagements in Senegal and discovered that technology adoption increases household income. The identifying variable in their estimation model is an indicator of the honesty of the primary decision-maker in the household. The distinguishing assumption in this regard is that honesty is both associated with technology adoption and not predictive of household income unless participation in technology adoption is included. As a result,Warning & Key (2002) indicate their lack of anticipation for integrity to be connected to welfare, however they do not justify with reason. It is unclear the reason a household that has a very trustworthy decision-maker will not obtain a greater overall income. This can actually indicate that trustworthy individuals like to work with other genuine individiuals, and thus contracts involving genuine individuas produce a higher profit than contracts involving lesser upright individuals. If this were completely accurate, integrity can be linked with welfare regardless of technology adoption, skewing the estimated causal effect.

A similar study by Miyata et al. (2009) also examined the effect of technology adoption on welfare using a choice modelling estimation technique. Miyata et al. (2009) discovered that technology adoption raises welfare using this identification approach. Their differentiating hypothesis was that proximity from the community chief's residence is related to technology adoption but not to welfare in different means except via technology adoption. Miyata et al. (2009) also claimed that the community leadership has a crucial role in considering individuals for farm technology intervention, which provides a suitable theoretical explanation for the reason this is an useful instrument. Nevertheless, it is less obvious that this proximity has no independent effect on income. For example, soil fertility (or other agro-environmental factors) may be greater near the community ruler's residence. Whether this is true, the evidence suggesting technology adoption improves welfare may be biassed.

PSM are another approach for refining estimations of the impact of technology adoption. (Miyata et al., 2009). In that the evaluation of treatment effects is based on covariates, Propensity Score Matching (PSM) and other matching techniques are strongly associated to Ordinary Least Squares (OLS) model. The difference here is that the well-known OLS regression measures impacts in relation to other covariates while it does not correct these effect estimations for a matching counterpart (Cahyadi & Waibel, 2013).Matching approaches attempt to build realistic counterfactuals based on observable covariates in

order to calculate impacts. One significant advantage of PSM approaches is that identification does not depend on an identifiable factor meeting an exclusionary criterion. PSM analyses the individual probability to adopt a technology conditional on observed attributes rather than a predicted probability of technology adoption (as in Heckman's selection technique) (Bolwig et al., 2009; Warning & Key, 2002).

Mishra et al. (2016) calculated the causal influence of technology adoption on the costs, yield, and profitability of smallholder farmers in Nepal using Propensity Score Matching (PSM) analysis. According to their findings, technological adoption increased revenues, profitability, and yield while decreasing production costs. Concerning yield per hectare, they discovered that smallholder farmers benefit much more. PSM has the benefit of removing the selection bias associated with differences noticed between participants and non-participants. Nonetheless, unobservable differences in technology adoption, such as experience or education, tend to skew the results. Bannor et al. (2017); Cahyadi & Waibel (2013) are examples of such empirical works in this area.

The instrumental variable approach has been used by Bellemare (2012); Briones (2015); Simmons et al. (2005) to address the endogeneity problem. In order to enhance the influence of technology adoption on family income, Bellemare (2012) employed Contingent Valuation Methods (CVM) to account for unobserved variation among Madagascar households. Willingness To Pay (WTP) indicators, in particular, for technology adoption, are employed as an array of Instrumental Variable (IV)s for involvement in technology adoption. Using these acwtp measurements as an instrumental variable, Bellemare (2012) discovered results of an improved household welfare from agricultural technology adoption. This approach has the benefit of accounting for several characteristics that other empirical works may ignore (such as uncertainty and risks, personal judgement of technology adoption, entrepreneurship aptitude, specialized knowledge, time choices, and so on). However, this method of identification is not without limitations. Despite the fact that the WTP instrument adequately accounts for selectivity bias and other difficulties associated with confounding, the presence of spurious regression may nevertheless distort estimations of the impact of technology adoption. Well-off individuals, for example, could have a greater WTP for technology adoption and are hence more inclined to adopt agricultural technology. If such a trend continues, findings of a favourable impact of technology adoption on welfare may become distorted. Monte Carlo simulation tests, according to Bellemare & Bloem (2018), have indicated that employing Willingness To Pay (WTP) as a covariate performs well than using it as an intervening variable.

Several more research have used the choice-on-observables approach, with the assertion that the explanatory variables included in the estimation allow for farmer self-selection towards technology adoption. Employing Bellemare (2012)'s WTP trial as a covariate rather than IV, Bellemare & Novak (2017), and Bellemare & Bloem (2018) assert that since farmer WTP to partake in a tentative technology adoption is a suitable substitute for a farmer's utility for engaging in technology adoption, factors that

are typically unobserved (such as uncertainty abhorrence, interest rate, entrepreneurship, regret aversion, overweighting of small-probability events, risk aversion, technical ability, or any other factor that moves around the utility for participating in technology adoption) are accounted for, which obviates the need for more statistical sophistication. Dedehouanou et al. (2013); Lemeilleur (2013); Maertens & Swinnen (2009); Wendimu et al. (2017) all employed selection-on-observables designs.

Given the constraints and problems of determining a realistic estimate of the causal influence of technology adoption, a Randomized Control Trial (RCT) appears to be the best alternative. Ashraf et al. (2009) carried out an RCT study with a Kenyan NGO that assists farmers in exporting crops, randomly assigning Self-Help Groups (SHG) to 3 study groups: (i) offering assistance from an NGO with loans (i.e., the first group assignment); (ii) offering from an assistanceNGO without loans (i.e., the second group assignment); and (iii) no assistance from an NGO and no loan (that is, the non-beneficiary). Instead of working with a commercial firm that buys farm products, Ashraf et al. (2009) collaborated with a NGO mediator with limited service capability. While this design has internal consistency and could avoid moral considerations associated with randomisation, its external validity is constrained as it is highly improbable to adequately mimic the institutional framework of technology adoption in all other situations; in reality, often these technology adoption interventions occur among a farmer and a private entity, for-profit processor instead of between a farmer and a Nonprofit processor. With these limits in mind, Ashraf et al. (2009) discover that the causal effects of the intervention on wellbeing are reliant on the sample's definition. When the entire sample is examined, participation has a positive but economically inconsequential influence on income. This includes both first-time farmers and growers who may have previously farmed export crops. The welfare effect was favorable, economically important, and statistically significant when the sample was restricted to farmers cultivating export crops for the first time. Despite this, an issue developed a year after the trial was completed. The exporter declined to keep purchasing stuff cultivated by Nonprofit members because of the challenges faced in acquiring legal certification for the farmers. As a result, declaring this intervention a success may be rather arbitrary, and the exchange between inner and outward validity appears to be a limiting restriction (Ashraf et al., 2009).

Despite methodological concerns and the presence of potentially invalid identifying assumptions, it is worth noting that the impact of technology adoption on income is positive in each of the aforementioned empirical works. According to Wang et al. (2014), 75% of research demonstrate a favourable welfare impact. However, publication bias clouds this finding (Bellemare, 2015). Implying that, if null or opposing results are not mentioned throughout the publishing process, published research may be a biassed source of information. Furthermore, technology adoption initiatives that may result in a decrease in welfare are more inclined to fail and, as a result, are much less prone to be experimentally examined; such effect is referred to as "survival biases" (Bellemare, 2012). Ton et al. (2018) studied such processes by conducting

a thorough review of studies on the impact of income on technological adoption. The authors discovered publishing and survival biases. Ton et al. (2018) assessed the possibility of biasness by regressing the effect size received from several empirical studies on the standard error of the regression. The correlation between effect size and standard error should be close to zero if there is no publication bias. Ton et al. (2018), on the other hand, discovered statistically significant positive associations between reported standard errors and observed effect sizes. Survivorship prejudice is logically researched. Because farmers are unable to participate in prior unsuccessful technology adoption programs, the findings from these past partnerships are excluded from Ton et al. (2018)'s investigation. Any thorough estimate of the influence of technology adoption on welfare is upwards skewed since empirical works that did not survive the test of time are routinely excluded.

This review cautions against reading too much into the survivorship bias results. While it is true that some technology adoption projects fail and are seldom documented in research publications, in examining technology adoption, it is important to take care to accurately define what is being examined. Several studies in this review describe technology adoption as an institutional structure in which farmers are provided with enhanced varietal seed for cultivation with the goal of improving or enhancing their welfare. As a result, in impact assessment terminology, the "treatment" is the desire to adopt an enhanced varietal seed in an efficient input-output relationship setting for improved farm production results.

Income is only a proxy for welfare, regardless of how information on the economic repercussions of technology adoption is viewed. Moreover, gains in household income do not necessarily translate into other positive outcomes. According to Bellemare & Novak (2017), any additional money earned by technology adoption is most likely collected during harvest season, with necessary expenditures occurring at other times of the year (Duflo et al., 2011). Concerns about self-control Banerjee & Mullainathan (2010) and other issues with the institution of saving Dupas & Robinson (2013) may also prevent families from reaping long-term benefits from technology adoption. As a result, some academics have shifted their focus away from household income and toward other indicators of household well-being, such as food security.

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

This chapter outlines the methodological approach used to achieve the study's objectives. It presents the theoretical foundations and empirical model specifications for the study. Additionally, it details the data collection methods, including data sources, study area, and sampling procedures for respondent selection.

3.2 Choice of Agricultural Technology Adoption Theory

Agricultural technology adoption is a complex and multidimensional process influenced by a combination of economic, social, psychological, and institutional factors. These dimensions shape the decision-making behaviours of farmers as they evaluate, adopt, or reject innovations. Theoretical frameworks serve as vital tools for understanding the underlying mechanisms of adoption, addressing key motivations, constraints, and pathways to the diffusion of innovations in agricultural contexts.

Recent studies highlight the role of individual farmer characteristics, such as education level and resource endowments, alongside external factors like government policies, market access, and extension services in influencing adoption. For instance, the adoption of precision agriculture has been closely linked to its perceived relative advantages, compatibility, and simplicity of use (Lee et al., 2021). Similarly, institutional support mechanisms such as credit accessibility and extension services play significant roles in fostering adoption, particularly in resource-constrained settings (Geng et al., 2024).

Social networks and community-based approaches are also pivotal in diffusing agricultural innovations. These networks facilitate trust-building and knowledge sharing, which are critical for addressing uncertainties about new technologies. Despite these advantages, low adoption rates remain a challenge, especially in developing regions, due to limited awareness, high costs, and lack of infrastructure. The mismatch between technology design and local farming needs further exacerbates these barriers (Geng et al., 2024).

These insights underscore the importance of integrating farmer-centric and context-sensitive strategies in promoting agricultural innovations. Theories such as the Diffusion of Innovations, Human Capital Theory, and others provide a robust foundation for understanding adoption behaviours while pointing to the necessity of tailoring interventions to local realities.

3.2.1 Diffusion of Innovations Theory

The Diffusion of Innovations Theory (Rogers, 2003) has been a foundational framework in understanding the adoption of agricultural technologies, emphasizing the role of social networks in the spread of innovations. It posits that the adoption process is influenced by individual and group interactions within social systems, with key elements such as innovation characteristics, communication channels, time, and the social system driving the dissemination of technologies. In the context of agriculture, this theory has been instrumental in explaining how farmers adopt new technologies such as improved seed varieties, fertilizers, and irrigation techniques.

Despite its utility, the theory has notable limitations when applied to heterogeneous and context-specific environments, such as Northern Ghana. Rural areas like this are characterized by diverse socioeconomic, cultural, and agroecological conditions, which significantly influence farmers' decisions to adopt technologies. The Diffusion of Innovations Theory assumes a relatively homogeneous social and cultural landscape, where innovation diffusion proceeds in a linear fashion from early adopters to laggards. This assumption often fails to capture the complex and dynamic realities of smallholder farmers operating under varying constraints, such as limited access to credit, land tenure insecurity, gender disparities, and inadequate extension services (Doss, 2020; Martey et al., 2022). Consequently, its explanatory power is diminished in studies focused on rural agricultural systems that exhibit significant heterogeneity in farmers' resource endowments, risk preferences, and access to institutional support.

In the specific context of rice varietal seed technology adoption in the Northern Region of Ghana, this limitation becomes pronounced. Northern Ghana is characterized by significant diversity in farming systems, gender roles, and access to information. Studies have highlighted that women, who often constitute a significant proportion of smallholder farmers, face structural barriers to accessing agricultural innovations, including seeds, due to cultural norms and inequities in resource allocation (Kassie et al., 2021). The Diffusion of Innovations Theory's emphasis on social networks and communication channels does not sufficiently address these localized barriers, particularly gender-related constraints, which are critical to understanding adoption dynamics in such settings.

Furthermore, the theory underestimates the role of institutional and contextual factors, such as government policies, extension services, and market conditions, which are pivotal in shaping technology adoption. For instance, Martey et al. (2022) found that institutional interventions, such as targeted subsidies and farmer training programs, significantly enhance the adoption of improved rice varieties in Ghana. These factors, which are external to the social system but highly influential, are inadequately integrated into the Diffusion of Innovations framework.

Additionally, recent empirical studies have criticized the theory's implicit assumption that all innovations

are universally beneficial and readily adoptable, failing to consider farmers' subjective evaluations of the risks and benefits associated with new technologies. Mabe et al. (2021) observed that farmers in Northern Ghana are often reluctant to adopt high-yielding rice varieties due to concerns about input costs, perceived production risks, and uncertain market conditions. These findings underscore the need for a more nuanced approach that incorporates local contexts and farmer-specific constraints.

In conclusion, while the Diffusion of Innovations Theory provides a foundational lens for analyzing technology adoption, its application to studies like rice varietal seed technology adoption in Northern Ghana requires augmentation. Addressing its limitations necessitates integrating local contextual factors, particularly gender dynamics, institutional influences, and economic constraints, to provide a more comprehensive understanding of adoption processes. Future research in this area should combine the theory with complementary frameworks, such as the Sustainable Livelihoods Approach or institutional economics, to better account for the complex realities faced by smallholder farmers.

3.2.2 Human Capital Theory

The Human Capital Theory, as introduced by Becker (1993), emphasizes the role of human skills, knowledge, and education in driving adoption behaviours. Within the context of agricultural technology adoption, the theory posits that farmers with greater education or technical training are better equipped to access, understand, and implement advanced agricultural technologies, such as rice varietal seed technologies. In the Northern Region of Ghana, where education levels and agricultural extension services are often limited, the Human Capital Theory provides a useful lens for understanding disparities in adoption rates among farming households.

Empirical studies support the assertion that human capital significantly influences adoption. For instance, Adebayo et al. (2022) found that farmers with higher education levels were more likely to adopt climate-resilient rice varieties due to better comprehension of their benefits. Similarly, Zewdie et al. (2021) highlight that formal education improves the ability to evaluate the economic and agronomic advantages of adopting modern seed technologies, particularly in resource-constrained environments.

However, the application of Human Capital Theory to rural Ghana reveals notable limitations. It often underestimates the importance of cultural norms, gendered access to resources, and socio-economic constraints, which are critical in shaping adoption decisions. For instance, Chirwa et al. (2021b) underscore that entrenched patriarchal systems and land tenure arrangements in rural African settings often prevent women, who constitute a significant portion of agricultural labour, from adopting improved technologies despite possessing the requisite knowledge. Additionally, socio-economic challenges, including lack of access to credit, infrastructure, and market linkages, further hinder adoption efforts, even for farmers with adequate knowledge and training (Ndiaye et al., 2023).

Moreover, the theory assumes a uniform ability to leverage knowledge for decision-making, which neglects the heterogeneity of farming systems and the non-linear, multi-dimensional factors influencing adoption. For instance, decision-making in subsistence farming contexts is often mediated by risk aversion, traditional beliefs, and immediate household needs, which may not align with the longer-term productivity focus emphasized by the theory. In this regard, Ndungu et al. (2020) argue that knowledge alone is insufficient without parallel investments in supportive institutional frameworks, such as agricultural extension services and farmer cooperatives.

In conclusion, while Human Capital Theory provides a foundational understanding of the role of knowledge and education in agricultural technology adoption, its limitations underscore the need for a more integrated approach. Future frameworks should incorporate socio-cultural and institutional factors to offer a more holistic explanation of adoption behaviours in rural Ghana. Addressing these gaps is vital for designing policies and interventions that not only enhance human capital but also mitigate the structural and socio-economic barriers that impede technology adoption.

3.2.3 Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM), developed by Davis (1989), is a foundational framework for understanding technology adoption behaviour, particularly within agricultural contexts. The model identifies two primary factors influencing adoption decisions: perceived ease of use and perceived usefulness. In agricultural technology adoption, such as rice varietal seed technologies, TAM posits that farmers are more likely to adopt innovations they perceive as simple to use and effective in addressing productivity or livelihood challenges. The model assumes that individuals make rational decisions based on these perceptions, aligning with the broader behavioural theories of technology acceptance.

In the context of rice varietal seed technology adoption in the Northern Region of Ghana, TAM provides valuable insights into the cognitive processes influencing farmer decision-making. For instance, studies have demonstrated that perceived benefits, such as increased yield and resilience to climate variability, significantly drive the adoption of improved seed varieties (Ojo et al., 2020). Additionally, farmers' confidence in their ability to integrate these technologies into their existing farming systems plays a crucial role in shaping their adoption behavior (Adu et al., 2022).

However, TAM's application to agricultural settings in rural Ghana exposes its critical limitations. The model's narrow focus on individual perceptions neglects the broader environmental, cultural, and policy-related factors that significantly influence technology adoption. For example, access to extension services, market linkages, and supportive agricultural policies are often decisive in determining whether farmers adopt improved seed varieties. Adu et al. (2022) emphasize that in rural Africa, institutional and policy environments can either enable or constrain adoption regardless of perceived usefulness or ease of

use. Furthermore, cultural factors, such as gendered decision-making dynamics and traditional farming practices, frequently override individual perceptions in influencing technology adoption decisions (Yeboah et al., 2023).

Moreover, TAM assumes a level of autonomy in decision-making that may not align with the realities of subsistence farming communities, where collective household decisions often take precedence (Nsiah et al., 2021). This limitation underscores the need for more comprehensive frameworks that integrate environmental, institutional, and socio-cultural dimensions alongside the cognitive elements emphasized by TAM.

In conclusion, while the Technology Acceptance Model provides a robust theoretical basis for examining the psychological factors influencing technology adoption, its limitations highlight the need for a more holistic approach. Future studies and interventions aimed at promoting rice varietal seed technology adoption in the Northern Region of Ghana should incorporate multi-dimensional frameworks that address not only perceived ease of use and usefulness but also the socio-economic and institutional barriers affecting adoption behaviour.

3.2.4 Theory of Planned Behaviour (TPB)

The Theory of Planned Behaviour (TPB), introduced by Ajzen (1991), is a widely recognized framework for understanding behavioural intentions and actions. It posits that individual behaviour is shaped by three key components: attitudes toward the behaviour, subjective norms, and perceived behavioural control. In the context of agricultural technology adoption, such as the uptake of rice varietal seed technologies, TPB provides valuable insights into the psychosocial factors influencing farmer decision-making. For instance, farmers' attitudes toward improved seeds—whether they perceive them as beneficial or risky—can significantly shape their adoption behaviour. Similarly, subjective norms, or the influence of social networks and community leaders, play a critical role in shaping adoption decisions. Finally, perceived behavioural control, which reflects the farmers' sense of agency or confidence in their ability to use the technology effectively, is another essential determinant of adoption.

Despite its relevance, the application of TPB in rural Ghana, particularly in examining rice varietal seed technology adoption, reveals key limitations. One of the model's primary weaknesses is its limited attention to external factors such as economic shocks, market access, and agricultural policies. Adongo & Nketiah-Amponsah (2023) argue that while TPB effectively captures individual-level psychological determinants, it does not account for the structural constraints that smallholder farmers in Northern Ghana often face. These constraints, such as unpredictable weather patterns, fluctuating input prices, and lack of access to extension services, significantly affect the ability of farmers to adopt and sustain new agricultural technologies.

Moreover, TPB assumes that farmers act rationally based on their intentions, which may not fully capture the complexities of decision-making in resource-constrained environments. For instance, unexpected economic shocks, such as inflation or crop failure, can force farmers to prioritize short-term survival over long-term productivity gains (Badu et al., 2020). Similarly, external agricultural policies, such as subsidies for specific inputs or restrictions on others, often shape the feasibility of adopting improved seed varieties (Owusu et al., 2022). These external factors are critical in the context of Ghana, where smallholder farmers operate within a fragile agricultural ecosystem influenced by both national policies and global market dynamics.

Furthermore, TPB does not adequately address gendered dimensions of decision-making, a critical factor in Northern Ghana, where socio-cultural norms often influence resource allocation and access to technology (Amponsah et al., 2021). For instance, female farmers may face additional barriers to adoption due to limited access to land or credit, which are not explicitly considered in the TPB framework.

In conclusion, while the Theory of Planned Behaviour offers valuable insights into the psychological underpinnings of agricultural technology adoption, its application to the adoption of rice varietal seed technologies in Northern Ghana requires augmentation. Future studies should integrate Theory of Planned Behaviour (TPB) with complementary frameworks that account for external factors, such as economic shocks, policy interventions, and socio-cultural dynamics, to provide a more comprehensive understanding of adoption behaviour in rural contexts.

3.2.5 Random Utility Theory (RUT)

The Random Utility Theory (RUT) provides a robust framework for understanding farmer technology adoption, particularly in complex and heterogeneous settings such as Northern Ghana, where rice varietal seed technologies are promoted to improve productivity and household welfare. RUT, grounded in microeconomic principles, posits that farmers make decisions by comparing the utilities associated with available alternatives, including adoption and non-adoption. This framework has notable strengths over other prominent theories in agricultural technology adoption literature, making it the most suitable theoretical foundation for this study.

RUT surpasses the Diffusion of Innovation Theory, which emphasizes social influence and information spread but fails to account for individual-level heterogeneity in preferences and constraints (Rogers, 2003). In contrast, RUT enables a nuanced examination of how farmers weigh factors such as costs, expected benefits, and risk tolerance. This feature is particularly relevant in Northern Ghana, where farmers face diverse socioeconomic and resource conditions that influence their decision-making processes (Adu et al., 2021). By incorporating both observed and unobserved determinants, RUT captures the complexity of adoption behaviour more effectively than the Diffusion of Innovation Theory.

Similarly, RUT addresses the limitations of Human Capital Theory, which attributes adoption to education and knowledge acquisition (Becker, 1993). While education is undoubtedly crucial, Human Capital Theory inadequately accounts for external structural barriers, such as limited access to credit or markets, which significantly influence adoption outcomes in rural Ghana (Chirwa et al., 2020). RUT incorporates these constraints by considering the relative utility derived from competing options, offering a broader explanatory scope.

The Technology Acceptance Model (TAM) and the Theory of Planned Behaviour (TPB) are also outperformed by RUT in explaining adoption behaviour. While TAM highlights perceived ease of use and usefulness (Davis, 1989) and TPB emphasizes attitudes, norms, and perceived behavioural control (Ajzen, 1991), both frameworks neglect external economic shocks and policy influences that are critical in dynamic agricultural environments. For instance, Adu et al. (2022) note that factors such as market access and weather variability play a substantial role in shaping farmers' decisions. RUT's capacity to incorporate such externalities through utility functions makes it more applicable to the realities of rice farming in Northern Ghana.

Moreover, RUT's empirical rigor sets it apart. Through econometric models such as multinomial logit, mixed logit, and probit, RUT allows for precise estimation of adoption probabilities and marginal effects of influencing factors (Train, 2009). This contrasts with the often descriptive nature of alternative frameworks. For a study aiming to derive actionable insights for policy and intervention design, the predictive accuracy and explanatory power of RUT are invaluable (Greene, 2020).

The choice of RUT as the theoretical framework for this study is further justified by its alignment with the study's objectives. This research seeks to understand how various factors, including socioeconomic, institutional, and environmental determinants, influence the adoption of rice varietal seed technologies and their subsequent impact on productivity and household welfare. RUT's comprehensive approach to modelling farmer decision-making under uncertainty makes it uniquely suited to address these objectives. While other theories offer valuable insights, they lack the integrative capability of RUT to holistically evaluate adoption behaviour in the presence of diverse and interacting influences.

In summary, the Random Utility Theory offers a superior framework for examining rice varietal seed technology adoption in Northern Ghana. Its ability to incorporate heterogeneous preferences, external constraints, and dynamic shocks, coupled with its empirical rigour, makes it the most appropriate theoretical underpinning for this study. By adopting RUT, this research can generate nuanced, evidence-based findings that inform policies aimed at enhancing agricultural productivity and rural livelihoods.

3.3 Theoretical Framework

Following the work of Ragasa et al. (2018), the study uses a random utility framework to model rural farm households' decision to adopt rice varietal seed technology. The utility, U, is calculated by taking into account a vector of farm-specific (including varietal attributes), household, institutional, and community-related factors, X, that influence a rural farm household's decision to use improved rice variety seed technology. Therefore, the utility-maximizing function for rural farm households is specified as follows:

$$MAX\ U = f(X) \tag{3.1}$$

At time t, it is anticipated that a rural farm household i would adopt a rice varietal seed technology j if the expected utility of adopting the rice varietal seed technology, U_{ijt}, is larger than the expected utility, U_{imt} of not adopting, m. It is also worth noting that the second utility might evolve over time t. Furthermore, j can be any rice varietal seed technology, giving the rural farm family i a choice of rice varietal seed technologies. As a result, the rural farm household's net utility function is as follows:

$$U^* = U_{ijt} > U_{imt} \tag{3.2}$$

where U^* signifies the benefits made by the rural farm household i from adopting an improved rice varietal seed technology j as opposed to not using any rice varietal seed technology, m. It is worth noting that, while U^* is unobserved, the rice varietal seed technology used by the rural farm household i might be seen as that household's disclosed choice. According to Ragasa et al. (2018), the likelihood that a rural farm household i will adopt a rice varietal seed technology j for plot k is given as $Pr(I = 1)$. If the rural farm household does not employ rice varietal seed technology, U^* is equal to 0. Under the assumption of a linear relationship, U^* may be stated as follows:

$$U_{ijkt} = \beta_{jt} X_{ikt} + \varepsilon_{ijkt} \tag{3.3}$$

where β_{jt} represents a vector of coefficients to be estimated and ε is the error term representing a set of random disturbances of the unobserved factors affecting the rural farm household's varietal seed technology adoption decision. Ragasa et al. (2018) points out that in a smallholder rice production environment where market imperfections are a common phenomenon, utility maximization may differ from income maximization. Therefore, the set of variables representing X needs to include a broad vector of socio-economic and political economy factors that capture individual market access conditions, connectivity, incentives, ability, and risk preferences (Ragasa et al., 2018).

3.4 Empirical Model Specification

The doubly robust estimation process, which combines regression and weighting techniques for a multivalued treatment study, is used in the analytical framework considered for this study. While there is a large body of literature on binary treatment trials, studies on multivalued treatments is significantly more contemporary (for binary treatment, see for instance Heckman & Vytlacil, 2007; Hirano et al., 2003; Imbens, 2004; Rosenbaum & Rubin, 1983; Wooldridge, 2007). Rosenbaum & Rubin (1983)'s potential outcome model for a binary treatment study is generalised to the multivalued treatment study situation by Lechner (2001) and Imbens (2000). Following on from these studies, Lechner (2002) and Frölich (2004) make substantial contributions to the debate by generalising matching estimation approaches for different treatment parameters when a large number of treatments are available. To estimate the treatment parameters of interest in the case of multivalued treatments, regression and weighting algorithms can be used instead of matching estimation methods (Uysal, 2015). Blundell et al. (2005) examined the impact of schooling on incomes using a multivalued regression estimation technique. Weighting estimation methods were used in the studies of Frölich (2004); Imbens (2000); Linden et al. (2016); Uysal (2015).

The proposed doubly robust approach is based on Imbens (2000) and Lechner (2001). The purpose of this study is to assess the effects of the treatment (adoption of improved rice varietal seed technology) on certain indicators (production and household welfare), where T_i is an integer ranging from 0 to K. Consider a random sample of N households drawn from a large population of rural rice-farming households. In the selected sample, the tripple (Y_i, T_i, X_i) is observed for each household i, $i = 1, ..., N$. $D_t(T_i)$ is the indicator of rice-farming household i adopting a specific improved rice varietal seed technology t:

$$D_t(T_i) = \begin{cases} 1, & \text{if } T_i = t, \\ 0, & \text{otherwise} \end{cases}$$

X_i represents the vector of pre-adoption characteristics for the i^{th} rural rice-farming household. Each rural rice-farming household has a set of potential outcomes $(Y_{i0}, \ldots, Y_{iK})$. Y_{it} represents the outcome for each rural rice-farming household i where $T_i = t$ and $t \in \mathfrak{T} = \{0, \ldots, K\}$. It should be noted that only one of the potential outcomes is observed based on the adoption status. Using Rubin (1974)'s potential outcomes framework, the observed outcome, Y_i, can be defined in terms of the treatment indicator, $D_t(T_i)$, and the potential outcomes, Y_{it} as:

$$Y_i = \sum_{t=0}^{K} D_t(T_i) Y_{it} \tag{3.4}$$

Using the potential outcome framework, Lechner (2001) presents many pairwise treatment effects. The first is the average impact of treatment level m compared to treatment level l. It computes the average effect

over the entire rural rice-farming household population:

$$\tau^{ml} = \mathbb{E}[Y_{im} - Y_{il}] \tag{3.5}$$

The expected effect for a rural rice-farming household selected at random from the population of rice varietal seed technology adopters in treatment only m:

$$\gamma^{ml} = \mathbb{E}[Y_{im} - Y_{il} \mid T_i = m] \tag{3.6}$$

Uysal (2015) asserts that the average treatment effects τ^{ml} and τ^{lm} have a symmetric relationship, that is, $\tau^{ml} = -\tau^{lm}$, but $\gamma^{ml} \neq -\gamma^{lm}$. It should be emphasised that γ^{ml} assesses the impact of adoption status m on adoption status l for households using improved rice varietal seed technology m. $-\gamma^{ml}$, on the other hand, compares the treatment impact of adoption status m to l for households who adopt the improved rice varietal seed technology l.

Since only one of the potential outcomes is observed, the treatment effects defined in Equations (3.5) and (3.6) cannot be determined without making additional assumptions. It is assumed that Imbens (2000)'s Conditional Independence Assumption (CIA) holds throughout this work:

Definition 1: *Conditional Independence Assumption (CIA)* $Y_{it} \perp D_t(T_i) \mid X_i, \forall\ t \in \mathfrak{T}$, *where* $\perp$ *denotes independence or orthogonality*

Given the vector of pre-technology adoption covariates X, it implies that treatment assignment is weakly unconfounded. Imbens (2000) compares this assumption to the missing at random assumption of Rubin (1976) and Little & Rubin (1989) in the missing data literature. By correcting for X, the $\mathbb{E}[Y_{it}]$ can be defined under this assumption:

$$\begin{aligned}\mathbb{E}[Y_{it} \mid X_i] &= \mathbb{E}[Y_{it} \mid D_t(T_i) = 1, X_i] = \mathbb{E}[Y_i \mid D_t(T_i) = 1, X_i] \\ &= \mathbb{E}[Y_i \mid T_i = t, X_i] \qquad \forall t \in \mathfrak{T}\end{aligned}$$

As a result, the unconditional means can be computed by averaging these conditional means, as proposed by Uysal (2015):

$$\mu_t \equiv \mathbb{E}[Y_{it}] = \mathbb{E}[\mathbb{E}[Y_{it} \mid X_i]] \tag{3.7}$$

Following the identification result in Equation (3.7), the regression adjustment can be employed to calculate $K + 1$ conditional mean functions for the binary treatment case using a parametric regression, as Hirano &

Imbens (2001); Rubin (1977) have done. Imbens (2000) presents the following conditional mean functions for the various outcomes:

$$\mathbb{E}[Y_{it} \mid X_i] = \mathbb{E}[Y_i \mid T_i = t, X_i] = \beta_{0t} + X_i'\beta_{1t} \tag{3.8}$$

$\beta_t = [\beta_{0t} \quad \beta_{1t}']'$ represents an unknown set of parameters, and β_{1t} and X_i have the same dimensions. Applying $\hat{\beta}_t$, the treatment effect parameters, τ^{ml} and γ^{ml}, based on the work by Uysal (2015), can be defined as:

$$\hat{\tau}^{ml} = \left(\hat{\beta}_{0m} - \hat{\beta}_{0l}\right) + \frac{1}{N}\sum_{i=1}^{N} X_i'\left(\hat{\beta}_{1m} - \hat{\beta}_{1l}\right) \tag{3.9}$$

$$\hat{\gamma}^{ml} = \left(\hat{\beta}_{0m} - \hat{\beta}_{0l}\right) + \frac{1}{N_m}\sum_{i:D_t(T_i=m)=1} X_i'\left(\hat{\beta}_{1m} - \hat{\beta}_{1l}\right) \tag{3.10}$$

$T_i = t$, where N_t signifies the number of adopters of the improved rice varietal seed technology. Rather than specifying $(K+1)$ regression models, a single model based on the treatment parameter of interest can be specified (derivation can be seen from Uysal, 2015). Using the observed outcome specifications in Equation (3.4), the regression model may be re-defined according to Uysal (2015) as in Equation (3.11) to compute the unconditional means as regression model parameters and therefore compute τ^{mk} as:

$$Y_i = \sum_{t=0}^{K} \alpha_{0t} D_t(T_i) + \sum_{t=0}^{K} D_t(T_i)\left(X_i - \overline{X}\right)'\alpha_{1t} + \varepsilon_i \tag{3.11}$$

$\overline{X} = \frac{1}{N}\Sigma_{i=1}^{N} X_i$. The parameter vector $\alpha_t = [\alpha_{0t} \quad \alpha_{1t}]'$ is calculated by minimising the objective function, which is equal to the sum of squared residuals (Uysal, 2015):

$$\min_{\alpha_{0t},\alpha_{1t}} \frac{1}{N}\sum_{i=1}^{N}\left(Y_i - \sum_{t=0}^{K}\alpha_{0t}D_t(T_i) - \sum_{t=0}^{K} D_t(T_i)\left(X_i - \overline{X}\right)'\alpha_{1t}\right)^2 \equiv \min_{\alpha_{0t},\alpha_{1t}} \frac{1}{N}\sum_{i=1}^{N}\varepsilon_i^2 \tag{3.12}$$

Uysal (2015) asserts that if the conditional mean function in Equation (3.8) is appropriately stated, $\hat{\alpha}_{0t} \xrightarrow{p} \mu_t = \mathbb{E}[Y_{it}]$. As a result, using the estimation methods for α_{0m} and α_{0l}, τ^{ml} may be calculated as follows:

$$\hat{\tau}^{ml} = \hat{\alpha}_{0m} - \hat{\alpha}_{0l} \tag{3.13}$$

Since the treatment effect parameter, γ^{ml} (that is, the average treatment effect for the treated) is also of great importance to this study, the empirical model in Equation (3.11) can be reformulated as follows (see Uysal, 2015):

$$Y_i = \sum_{t=0}^{K} \alpha_{0t}^{m} D_t(T_i) + \sum_{t=0}^{K} D_t(T_i)\left(X_i - \overline{X}_m\right)'\alpha_{1t}^{m} + \varepsilon_i \tag{3.14}$$

where $\overline{X}_m = \frac{1}{N_m}\Sigma_{i:D_t(T_i=m)=1}X_i$. The minimization problem for this equation is defined as:

$$\min_{\alpha_{0t}^m,\alpha_{1t}^m}\frac{1}{N}\sum_{i=1}^{N}\left(Y_i-\sum_{t=0}^{K}\alpha_{0t}^m D_t(T_i)-\sum_{t=0}^{K}D_t(T_i)\left(X_i-\overline{X}_m\right)'\alpha_{1t}^m\right)^2 \equiv \min_{\alpha_{0t}^m,\alpha_{1t}^m}\frac{1}{N}\sum_{i=1}^{N}\varepsilon_i^2 \tag{3.15}$$

Uysal (2015) explains further that the coefficients of the treatment indicator variables α_{0t}^m, estimate $\mathbb{E}[Y_{it} \mid T_i = m] \equiv \mu_t^m$ consistently if the conditional mean of Y_{it} is correctly specified. Hence, Uysal (2015) specifies the following equation:

$$\hat{\gamma}^{ml} = \hat{\alpha}_{0m}^m - \hat{\alpha}_{0l}^m \tag{3.16}$$

Another method is to use propensity score weighting to develop estimate techniques for the relevant treatment impact parameters. The idea of propensity score must be generalised for the situation of a multivalued treatment effect study using weighting estimation methods. According to Imbens (2000), the generalised propensity score is defined as follows:

Definition 2: *The Generalized Propensity Scores (GPS) is the conditional probability of receiving a particular level of the treatment given the pre-treatment covariates:*

$$r(t,x) \equiv Pr[T_i = t \mid X_i = x] = \mathbb{E}[D_t(T_i) \mid X_i = x] \tag{3.17}$$

Using the GPS, Imbens (2000) explains that, just like the binary treatment case, the unconditional means of the potential outcomes can be identified by weighting:

$$\mathbb{E}\left[\frac{Y_i D_t(T_i)}{r(t,X_i)}\right] = \mathbb{E}[Y_{it}] \tag{3.18}$$

Following this identification result in Equation (3.18), the treatment effect equations are defined according to Uysal (2015) as:

$$\hat{\tau}^{ml} = \frac{1}{N}\sum_{i=1}^{N}\frac{Y_i D_t(T_i=m)}{\hat{r}(m,X_i)} - \frac{1}{N}\sum_{i=1}^{N}\frac{Y_i D_t(T_i=l)}{\hat{r}(l,X_i)} \tag{3.19}$$

$$\hat{\gamma}^{ml} = \frac{1}{N_m}\sum_{i=1}^{N}Y_i D_t(T_i=m) - \frac{1}{N_m}\sum_{i=1}^{N}D_t(T_i=l)Y_t\frac{\hat{r}(m,X_i)}{\hat{r}(l,X_i)} \tag{3.20}$$

$\hat{r}(t,X_i)$ is the predicted GPS. According to Imbens (2000), the $\hat{r}(t,X_i)$ may be analysed using choice modelling if the multivalued treatment has illogical ordering, or ordered response framework if it follows an ordered pattern.

To gain some robustness against misspecification, the weighted formulation of the regression adjustment can be employed. According to Robins & Rotnitzky (1995), if the weights are calculated based on an

accurate GPS specifications or if the potential outcomes are accurately defined, the resultant model will be consistent. To obtain a doubly robust $\hat{\tau}^{ml}$, the model in Equation (3.11) is estimated using a weighted least squares model with weights obtained (Uysal, 2015) as follows:

$$\sum_{t=0}^{K} \frac{D_t(T_i)}{\hat{r}(t, X_i)} \tag{3.21}$$

The minimisation problem for the doubly robust analysis is stated by Uysal (2015) as follows:

$$\min_{\alpha_{0t}, \alpha 1t} \frac{1}{N} \sum_{i=1}^{N} \left(\sum_{t=0}^{K} \frac{D_t(T_i)}{\hat{r}(t, X_i)} \right) \left(Y_i - \sum_{t=0}^{K} \alpha_{0t} D_t(T_i) - \sum_{t=0}^{K} D_t(T_i) \left(X_i - \overline{X} \right)' \alpha_{1t} \right)^2 \tag{3.22}$$

The resulting estimators, α_{0t}^{w}, are consistent for μ_t if:

i. the conditional mean of is correctly specified,

ii. the conditional mean of $D_t(T_i)$ is consistently defined or

iii. both (Uysal, 2015).

The treatment effect τ^{ml} is computed using a doubly robust estimation approach using the weighted model of α_{0m} and α_{0l} in Equation (3.13). (see Uysal, 2015 for the specification of the double robustness). The model presented in Equation (3.14) with the weights below may be used to create doubly robust modelling of γ^{ml}:

$$\sum_{t=0}^{K} D_t(T_i) \frac{\hat{r}(m, X_i)}{\hat{r}(t, X_i)} \tag{3.23}$$

Consequently, the weighted regression estimators of α_{0t}^{m} and α_{1t}^{m} solve the following minimization problem:

$$\min_{\alpha_{0t}^{m}, \alpha_{1t}^{m}} \frac{1}{N} \sum_{i=1}^{N} \left(\sum_{t=0}^{K} D_t(T_i) \frac{\hat{r}(m, X_i)}{\hat{r}(t, X_i)} \right) \left(Y_i - \sum_{t=0}^{K} \alpha_{0t}^{m} D_t(T_i) - \sum_{t=0}^{K} D_t(T_i) \left(X_i - \overline{X}_m \right)' \alpha_{m}^{1t} \right)^2 \tag{3.24}$$

$(\hat{\alpha}_{0t}^{m})^{w}$, which is obtained as the result from the above minimization problem, is doubly robust model of μ_t^m (Uysal, 2015). Following Uysal (2015) we substitute the unweighted regression estimators of α_{0m}^{m} and α_{0l}^{m} in Equation (3.16) as a regression adjustment to calculate γ^{ml} doubly robustly.

The techniques for getting the asymptotic distribution for treatment parameter estimation approaches are worth detailing after the explanation of the doubly robust modelling method for multivalued treatment effect. This includes determining the asymptotic distribution of the estimating techniques, which are the solutions to the minimisation issues shown in Equations (3.22) and (3.24). (Uysal, 2015). In this work, Uysal (2015)'s modification of Wooldridge (2007)'s asymptotic distribution for the computation of a weighted regression with binary treatment variable is applied.

Let $r(t, X_i; \psi_t)$ be the parametric model for $r(t, x)$, i.e. $Pr[T_i = t \mid X_i] = r(t, X_i; \psi_t)$, where $\psi \in \mathbf{\Psi} \subset \mathbb{R}^{M\times(K+1)}$ with $\psi = [\psi_0' \quad \psi_1' \ldots, \psi_K']'$. The estimator $\hat{\psi}$ solves a conditional likelihood problem of the form:

$$\max_{\psi\in\mathbf{\Psi}} \sum_{i=1}^{N} \ln L\left(\psi; D_t(T_i), X_i\right) = \sum_{i=1}^{N}\sum_{t=0}^{K} D_t(T_i) \ln r(t, X_i; \psi_t) \tag{3.25}$$

Since the probabilities sum up to one, parameter identification requires a normalization such as $\psi_{\mathbf{0}} = \mathbf{0}$ (Uysal, 2015). Thus the individual score functions of dimension $(M \times 1)$ are given as:

$$c_{ti}(\psi; D_t(T_i), X_i) \equiv \frac{\partial \ln L(\psi; D_t(T_i), X_i)}{\partial \psi_t}, \quad t = 1, \ldots, K$$

Let θ be $(P \times 1)$ parameter vector contained in a parameter space $\mathbf{\Theta} \subset \mathbb{R}^P$. θ denotes either $(\alpha_{0t}, \alpha_{1t})$ or $(\alpha_{0t}^m, \alpha_{1t}^m)$. Thus, according to Uysal (2015), $\hat{\theta}$ solves the following minimization problem:

$$\min_{\theta\in\mathbf{\Theta}} \frac{1}{N}\sum_{i=1}^{N} \hat{\omega}_i \varepsilon_i^2$$

where ε_i is the sum of squared residuals for the corresponding regression model and $\hat{\omega}_i = \Sigma_{t=0}^{K} \dfrac{D_t(T_i)}{r(t, X_i; \hat{\psi}_t)}$ or $\hat{\omega}_i = \Sigma_{t=0}^{K} D_t(T_i) \dfrac{r(m, X_i; \hat{\psi}_m)}{r(t, X_i; \hat{\psi}_t)}$ depending on the treatment parameter of interest (Uysal, 2015). Since the estimation problem in the multivalued treatment case is same as the binary treatment case, Theorem 3.1 in Wooldridge (2007) applies here immediately. Define $s_i = s(Y_i, X_i, T_i; \theta, \psi) \equiv \omega_i \dfrac{\partial \varepsilon_i^2}{\partial \theta}$ as the $P \times 1$ weighted score of the (unweighted) objective function $q(\cdot)$, $H(Y_i, X_i; \theta) = \dfrac{\partial^2 \varepsilon_i^2}{\partial\theta\partial\theta'}$ as the $P \times 1$ Hessian of the objective function $q(\cdot)$. Uysal (2015) indicates that under standard regularity conditions,

$$\sqrt{N}(\hat{\theta} - \theta) \xrightarrow{d} N(0, A^{-1} D A^{-1}) \tag{3.26}$$

where $A \equiv \mathbb{E}[H(Y_i, X_i; \theta)]$, $D \equiv \mathbb{E}\left[e_i e_i'\right]$, $e_i \equiv s_i - \mathbb{E}\left[s_i c_i'\right]\left[\mathbb{E}\left[c_i c_i'\right]\right]^{-1} c_i$, $c_i \equiv c_i(\psi) = [c_{1i}', \ldots, c_{Ki}']'$ is the $MK \times 1$ score for the Maximum Likelihood Estimates (MLE) of ψ. The term D in the asymptotic distribution includes the score of the first step estimation. Therefore, the resulting asymptotic distribution for second step takes into account that the weights are estimated (Uysal, 2015). Wooldridge (2007) proposes consistent estimators of A and D in the binary treatment framework, which can be generalized in multivalued treatment case. Hence,

$$\hat{A} \equiv \frac{1}{N}\sum_{i=1}^{N} \hat{\omega}_i H(Y_i, X_i; \hat{\theta}) \tag{3.27}$$

and

$$\hat{D} \equiv \frac{1}{N}\sum_{i=1}^{N}\hat{e}_i\hat{e}_i' \tag{3.28}$$

are consistent estimators of A and D where the $\hat{e}_i \equiv \hat{s}_i - (N^{-1}\,\Sigma_{i=1}^{N}\hat{s}_i\hat{c}_i')(N^{-1}\,\Sigma_{i=1}^{N}\hat{c}_i\hat{c}_i')^{-1}\hat{c}_i$ are the $P \times 1$ random errors from the multivariate modelling of $\hat{s}_i$ on $\hat{c}_i$ and hatted quantities are estimated at $\hat{\theta}$ or $\hat{\psi}$. Because the treatment effects τ^{ml} and γ^{ml} are computed as differences of regression parameters in Equations (3.10) and (3.13), estimation of the variances of τ^{ml} and γ^{ml} is simple after obtaining a variance-covariance results of $\hat{\theta}$ (Uysal, 2015).

3.5 Description of Variables for the Estimation of GPS and Treatment Effects Parameters

The details of the variables used in the rice-farming households' adoption decision (and the GPS) and treatment effects estimation models are presented in Table 3.1.

Table 3.1: Description of Variables

Variable	Measurement Description
Treatment Indicator	
Adoption	0 = No Adoption; 1 = AGRA; 2 = Jasmine-85; 3 = Digang
Outcome Indicators	
Productivity	Quantity of Rice Harvested (Kg/ha)
Income	Annual Household Income (GHS)
Availability	Household Food Availability Index (%)
Accessibility	Household Food Accessibility Index (%)
HDD	Household Dietary Diversity Index (%)
WDD	Women Dietary Diversity Index (%)
CDD	Child Dietary Diversity Index (%)
Pre-Adoption Covariates	
Gender	Gender of Household Head (1 = Male; 0 = Female)
Age	Age of Household Head (in Years)
Household Size	Number of People in the Household (Number)
Education	Education of Household Head (1 = Formal; 0 = No Formal Education)
Credit	Household has Access to Farm Credit (1 = Access; 0 = No Access)
FBO	FBO Membership (1 = Member; 0 = Non-member)
Extension	Access to Extension (1 = Access; 0 = No Access)
Land Size	Size of Plot Allocated to Rice Farming (Ha)
Fertilizer	Fertilizer Use (1 = Use; 0 = No Use)
Machinery	Access to Tractor Services (1 = Access; 0 = No Access)
Land Tenure	Land Ownership (1 = Owner; 0 = Otherwise)
Early Maturity	Perception of Early Maturity Attribute (1 = Yes; 0 = No)
High Yielding	Perception of Higher Yielding Attribute (1 = Yes; 0 = No)

The dependent variable used in the study was a nominal multivalued rice varietal seed technology adoption variable that takes the value of 1, if the rice-farming household adopts AGRA rice varietal seed technology; 2, if the rice-farming household adopts Jasmine-85 rice varietal seed technology; 3, if the rice-farming household adopts Digang rice varietal seed technology; and 0, if no adoption of rice varietal seed technology was recorded. The outcome variables used in this study are annual household income

measured in Ghana Cedis (GHS), productivity measured in kilograms per hectare (kg/ha), household food availability, household food accessibility, household dietary diversity, women dietary diversity and child dietary diversity indices all measured in percentage (%)

3.6 Construction of the Household Food Security Indicators

Food availability and accessibility indices were rigorously constructed by aggregating household-level data on food quantity, quality, and the coping mechanisms employed during periods of food shortages within a 30-day recall period, consistent with established methodologies (Akalu et al., 2019; Owusu et al., 2020). Responses reflecting experiences such as shortages, reliance on borrowing, or dietary adjustments were systematically coded to generate composite scores that encapsulate the household's status regarding food availability and accessibility. These composite scores were subsequently aggregated using Principal Component Analysis (PCA), yielding standardized indices for food accessibility and availability. The application of PCA ensured the reduction of dimensionality and addressed potential multicollinearity issues, thereby enhancing the robustness of the constructed indices (Adams & Smith, 2019).

Household Dietary Diversity (HDD) was constructed to capture the variety of foods consumed by households during the 30-day recall period. This index quantified consumption across major food groups, including staples, proteins, and vegetables, offering a multidimensional perspective on food security (Ali et al., 2020b). Women Dietary Diversity (WDD) was similarly derived, focusing on foods consumed by women aged 15–49 years. The emphasis was placed on nutrient-dense food sources such as proteins, dairy products, and micronutrient-rich items to evaluate nutritional adequacy (Nyantakyi-Frimpong et al., 2019). For children, Child Dietary Diversity (CDD) was calculated by assessing the range of foods consumed by those aged 6–23 months, prioritizing the inclusion of critical food groups such as fruits, vegetables, dairy, and protein sources. These indices were designed to reflect individual and household-level dietary patterns while addressing the unique nutritional requirements of women and children (Asare et al., 2020).

Similar to the construction of food availability and accessibility indices, PCA was applied to dietary diversity scores for HDD, WDD, and CDD. This aggregation technique ensured that the resulting dietary diversity indices accurately captured underlying patterns and variations in food group consumption. By utilizing PCA, the indices were standardized, enabling their inclusion as dependent variables in subsequent regression analyses. This methodological rigour facilitated the robust estimation of the impacts of agricultural technology adoption on food security outcomes, aligning with best practices in food security research (Adams & Smith, 2019; Nyantakyi-Frimpong et al., 2019).

The constructed indices collectively provided a comprehensive framework for evaluating household food security. The food availability and accessibility indices quantified the extent to which households could secure sufficient and quality food during the recall period, while the dietary diversity indices for households,

women, and children offered granular insights into nutritional adequacy. By integrating these indices into the analytical framework, the study robustly captured the multifaceted dimensions of food security, emphasizing the critical linkages between technology adoption and improved dietary outcomes.

3.7 Construction of the Garrett Ranking Scores

The Garrett ranking procedure is a robust and systematic method utilized to identify and rank constraints to the adoption of varietal seed technologies, particularly in contexts like rice farming in Northern Ghana. This procedure is widely recognized for its ability to translate ordinal ranking data into interpretable numerical scores, making it highly suitable for analyzing subjective responses related to constraints.

In applying the Garrett ranking procedure to the study, farmers in the Northern Region of Ghana were asked to identify and rank constraints hindering the adoption of improved varietal seed technologies. Constraints such as the high cost of certified seeds, limited access to improved seeds, insufficient extension services, credit unavailability, and farmers' perceptions about varietal benefits were considered. These rankings were transformed into numerical scores using the Garrett formula:

$$\text{Percent Position} = \frac{100 \times (R_i - 0.5)}{N} \tag{3.29}$$

where R_i denotes the rank assigned by a respondent to a specific constraint, and N is the total number of constraints being ranked. The resulting percent position values were then matched to corresponding Garrett scores, typically derived from a pre-established table. These scores ensured that the rankings reflected the relative importance of constraints objectively and consistently.

The aggregated Garrett scores for each constraint were calculated by averaging individual scores across all respondents. This aggregation provided a comprehensive understanding of the community's collective perception of the barriers to adoption. Constraints were ranked based on their average Garrett scores, with higher scores indicating more significant barriers.

The use of Garrett ranking in this study aligns with its broader applications in agricultural research. Recent studies underscore its efficacy in prioritizing constraints across diverse farming systems. For instance, Akinnagbe & Nwaiwu (2021) utilized this method to rank constraints in cassava farming systems in Nigeria, demonstrating its capacity to generate actionable insights for policymakers. Similarly, Chhetri et al. (2020) employed Garrett ranking to identify challenges in the adoption of climate-resilient farming practices in South Asia, emphasizing its versatility in different agroecological and socio-economic settings.

The method's primary advantage lies in its capacity to simplify and quantify qualitative data, facilitating statistical analysis and enabling evidence-based decision-making. By converting subjective ranks into standardized scores, Garrett ranking minimizes biases inherent in raw ranking systems. Furthermore, its

compatibility with other analytical tools enhances its utility in multi-dimensional studies. For example, combining Garrett ranking results with regression analysis enables researchers to evaluate the impact of ranked constraints on adoption rates quantitatively, as demonstrated by Ali et al. (2022) in their analysis of seed technology adoption in Pakistan.

In this study, the Garrett ranking results were integrated into a broader analytical framework to assess the relationship between identified constraints and adoption outcomes. This approach allowed for a nuanced understanding of how barriers such as high seed costs or inadequate extension services influenced productivity and household welfare. The findings not only highlighted priority areas for intervention but also provided empirical evidence to support targeted policy recommendations.

The methodological rigour of the Garrett ranking procedure, including its adaptability to diverse research contexts, makes it an indispensable tool in agricultural and development studies. Its application in this study underscores the critical importance of systematically identifying and prioritizing constraints to enhance the adoption of rice varietal seed technologies. By addressing these barriers, policymakers and stakeholders can design interventions that maximize the productivity and welfare benefits of improved agricultural technologies.

3.8 Description of the Study Area

The Northern Region of Ghana, previously the largest of the country's sixteen administrative regions, encompassed approximately 70,384 square kilometers, accounting for 31% of Ghana's total land area. This expansive territory was redefined in December 2018 when portions were annexed to form the Savannah and North East Regions. Geographically, the region shares boundaries with the North East Region to the north, Togo to the east, the Oti Region to the south, and the Savannah Region to the west. Tamale serves as its administrative capital, anchoring governance and regional activities. Divided into 16 districts, the region exhibits diverse administrative and cultural dynamics (see Figure 3.1).

The Northern Region's proximity to the Sahel and Sahara shapes its climatic and ecological profile, making it markedly drier compared to Ghana's southern regions. The landscape is dominated by grasslands and savanna vegetation, punctuated by desert tree species such as the baobab. The dry season, characterized by scorching temperatures and the Harmattan winds, extends from January to March, while the rainy season spans July to December, with annual precipitation ranging between 750 to 1050 mm. Temperatures during the dry season can reach extreme highs of 40°C during the day and drop to 14°C at night, particularly from December to February.

Economically, agriculture is the dominant livelihood activity, engaging over 75% of the population. However, the region's low population density, shaped by emigration and its challenging topography and

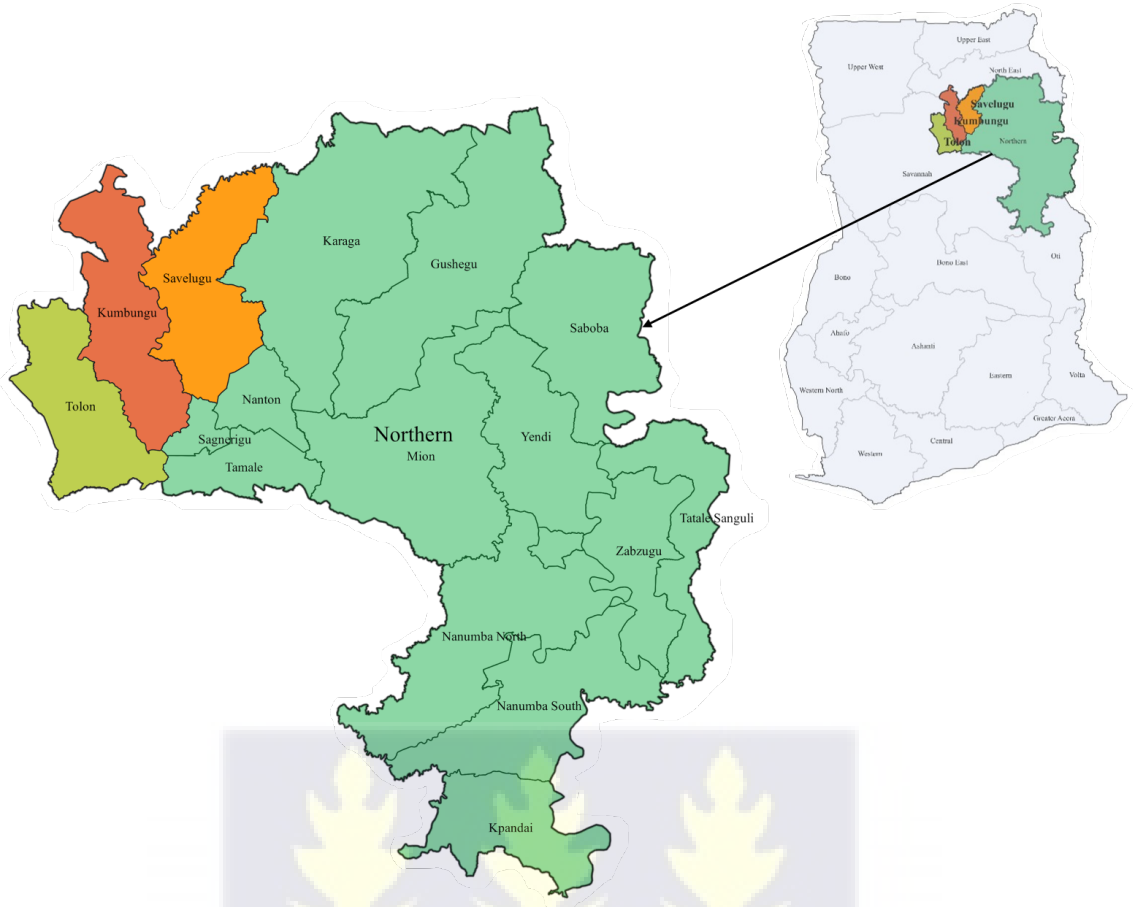


Figure 3.1: The Geographical Map for the Study Area

climate, influences settlement patterns. Culturally, it is home to the Dagbon Kingdom, with the Dagomba tribe and other ethnic groups such as the Mamprusi and Konkomba speaking Niger-Congo dialects alongside English as the official language.

This study focuses on the Savelugu, Kumbungu, and Tolon districts, which are recognized as pivotal hubs for rice cultivation, reflecting the region's agricultural potential and significance. These districts exemplify the intersection of ecological, economic, and cultural attributes that define the broader Northern Region.

3.8.1 Tolon District

The Tolon District, located within Ghana's Northern Region, is geographically bordered by Kumbungu to the north, North Gonja to the west, Central Gonja to the south, and Sagnarigu to the east. The district has a population of 80,193, consisting of 40,245 females and 39,948 males, with an average household size of 6.4 individuals. This demographic distribution underpins the predominantly rural character of the district, where subsistence and peasant farming dominate livelihood activities.

Agriculture serves as the mainstay of the district's economy, with 94.4% of households engaged in activities such as crop cultivation and livestock rearing. However, limited commercial opportunities compel most farmers to operate at a subsistence level, which constrains their ability to market surplus produce effectively.

Rice farming, a key agricultural activity, relies heavily on rainfall as the primary water source. Mechanized practices, including tractor plowing, form the core of primary tillage, while secondary tillage, such as rotovating and harrowing, is primarily associated with the Golinga Irrigation Gravity Scheme. Despite its potential, this scheme utilizes only 40 hectares of its 100-hectare irrigable area, with oversight provided by the Ghana Irrigation Development Authority (GIDA). Additional smaller dugouts in the district support vegetable farming, reflecting the diversity of agricultural practices.

Infrastructure challenges remain a critical impediment to agricultural productivity and marketing. Inadequate road networks between farms and the poor condition of major routes linking farming communities to commercial hubs hinder farmers' ability to access markets. Consequently, significant quantities of agricultural produce are wasted post-harvest due to limited transportation and storage facilities. These barriers underscore the pressing need for infrastructure development and strategic interventions to enhance agricultural value chains and reduce post-harvest losses within the district.

3.8.2 Kumbungu District

The Kumbungu District, one of the Northern Region's most notable areas, is bordered by Mamprugu/Moagduri to the north, Tolon and North Gonja to the west, Sagnerigu to the south, and Savelugu/Nanton Municipal to the east. It is geographically one of the smallest districts in the region, encompassing a total land area of 1,599 square kilometers, with Kumbungu serving as its capital. The district has a population of 39,341, comprising 50.03% males and 49.97% females, reflecting a nearly equal gender distribution.

The economy of Kumbungu is entirely rural and fundamentally driven by agriculture, which serves as the primary livelihood for the majority of its inhabitants. Agricultural activities are largely subsistence-based and seasonal, with limited irrigation practices concentrated near the Bontanga Dam. Crop cultivation dominates, with maize, rice, groundnut, and yams being the principal crops. Rice cultivation, in particular, thrives in lowland areas, utilizing both irrigated and rain-fed systems. In 2018, approximately 5,225 hectares were allocated to agriculture, yielding an average of 2.00 metric tons per hectare.

Mechanization in farming is evident, with tractor ploughing forming the backbone of tillage practices. Secondary tillage methods, including rotovating, harrowing, and the use of boom sprayers and levellers, are primarily observed in areas surrounding the Bontanga Irrigation Scheme. Despite the presence of a gravity irrigation system with a potential area of 800 hectares, only 490 hectares have been developed and are currently usable. The shortage of essential farming equipment, such as crawler and wheeled combine harvesters, poses a significant challenge. Further investments are necessary to develop the undeveloped irrigable lands and enhance agricultural productivity within the district. This reflects the district's untapped potential, highlighting opportunities for targeted agricultural interventions and infrastructural development.

3.8.3 Savelugu-Nanton District

The Savelugu-Nanton District, located in the Northern Region of Ghana, shares its borders with West Mamprusi to the north, Karaga to the east, Kumbungu to the west, and the Tamale Metropolitan Assembly to the south. Covering approximately 2,022.6 square kilometers, the district has a population density of 68.9 persons per square kilometer, with a total population of 139,283, comprising 48.5% males and 51.5% females. The district's savanna forest ecological zone provides an ideal environment for diverse agricultural activities, including crop cultivation and large-scale cattle husbandry.

Agriculture is the dominant economic activity in the district, with most residents engaged in subsistence farming to meet household needs. The primary food crops cultivated include rice, groundnut, maize, millet, sorghum, cassava, yams, cowpeas, and guinea corn. Additionally, cotton, shea nuts, and soybeans serve as significant cash crops. Small-scale agricultural processing, utilizing traditional methods, is common, though there are notable commercial farming operations, such as the Integrated Tamale Fruit Company (ITFC)-managed grafted mango plantation in Gushie, which provides employment to many residents.

Rice farming is predominantly practised in lowland areas with consistent rainfall. In 2018, approximately 6,553.5 hectares of land were cultivated, achieving an average yield of 2.50 metric tonnes per hectare. Mechanized farming is well established, with commercial farmers employing advanced equipment, including rotovators, seed drills, boom sprayers, levellers, threshers, and combine harvesters (both crawler and wheeled).

The district is endowed with several irrigation facilities, including dams at Libga, Nasia, Dipale, Sogo, and Dinga. Libga features a potential irrigation capacity of 22 hectares, of which 16 hectares are developed for cultivating rice, maize, and vegetables. Dipale has 148 hectares of potential irrigation land, with 114 hectares developed, while the Dinga pump-and-gravity irrigation system supports 125 hectares, of which 85 hectares are utilized for similar crops. These irrigation schemes underline the district's significant potential for enhancing agricultural productivity and food security.

3.9 Study Design/Approach

The study employed a mixed-method approach, integrating qualitative and quantitative methodologies to comprehensively assess the performance of varietal rice seed technologies among farm households. This methodological integration aimed to leverage the strengths of both approaches while mitigating their individual limitations. The use of mixed methods facilitated the addressing of diverse research questions and provided a robust framework for drawing more nuanced conclusions regarding the adoption and impacts of the varietal technologies.

Specifically, the Explanatory Sequential Method (ESM) was adopted, as outlined by Creswell (2014),

offering a structured process for data collection and analysis. The ESM approach involves an initial phase of quantitative data collection and analysis, followed by a qualitative phase aimed at contextualizing and explaining the quantitative findings. This sequential design enabled the study to delve deeper into the causal mechanisms and contextual factors underpinning the observed outcomes of varietal rice seed technology adoption. The qualitative phase served as a critical component in elucidating the nuances of the quantitative results, particularly by providing insights into outlier cases of both success and failure.

The integration of qualitative data allowed for a richer interpretation of the findings, particularly through the exploration of key factors driving behavioural changes, decision-making processes, and adoption dynamics. This dual-phase approach enabled the study to effectively enter the "black box" of household decision-making and technology use, offering a comprehensive understanding of the mechanisms at play. Moreover, the methodological rigour provided by the ESM enhanced the ability to develop systematic explanations for observed trends and variances, fostering a deeper understanding of the relationships between farm households and the varietal technologies.

By employing this design, the research also ensured the generation of evidence-based insights to inform policy recommendations. The qualitative insights derived from this approach provided the necessary depth to address critical policy concerns and offered practical solutions to challenges identified through quantitative analysis. Overall, the adoption of the mixed-method explanatory sequential approach provided a holistic lens for understanding the multi-dimensional impacts of varietal rice seed technologies, ensuring the study's outcomes were both robust and actionable.

3.10 Sampling Design for the Study

This section outlines the procedures used to determine the appropriate sample size for the study. It also provides a detailed discussion of the method used to select the study's sample.

3.10.1 Sample Size Determination

The determination of the sample size for the study was grounded in a robust and systematic statistical approach, leveraging key outcome indicators such as productivity and household welfare. The complete sample design and the power calculation methodology are elaborated in Appendix IV. The sample size calculations incorporated regional agricultural data obtained from the Ministry Of Food and Agriculture (MOFA), specifically focusing on Intra-cluster Correlation Coefficients (ICCs) to account for the clustering effects of communities. The estimated intra-class correlation, representing the proportion of variation between clusters relative to total variability, was determined to be 0.016.

A statistical power of at least 80% was set as the baseline to ensure reliable detection of meaningful differences in the key outcomes. Comparisons were also made with a more conservative power threshold

of 90% to validate the robustness of the estimates across a range of statistical powers. Based on these parameters, the calculations yielded a minimum required sample size of 600 rural rice-farming households distributed across the three selected districts in the Northern Region. This sample size was deemed sufficient to achieve 80% statistical power to detect an average effect size of 0.1352 (13.52%) on the primary study outcomes. This effect size was considered significant and indicative of the anticipated changes in productivity and household welfare attributable to the adoption of improved rice varietal technologies.

The sample size determination was further refined using an F-test for group effects, with estimates of between-group variance informed by a one-way Analysis Of Variance (ANOVA) framework. The households were divided into two groups: 450 households in the improved rice varietal technology adoption group and 150 households in the non-adoption group. Given an error variance of 457,527.44, the calculations yielded estimates of between-group variance ranging from 8,368 to 10,878. These estimates provided confidence that the design could detect statistically significant effects under the defined parameters.

The adopted methodology underscores the rigorous attention to statistical precision, ensuring that the sample size is adequate to capture the anticipated impacts of rice varietal technology adoption while accounting for the variability inherent in clustered rural settings. By basing the calculations on empirical data and validated statistical models, the study design demonstrates its capacity to provide robust and generalizable insights into the dynamics of productivity and welfare improvements among rural households in the region. For detailed calculations and underlying assumptions, Appendix IV provides comprehensive evidence from the power calculations.

3.10.2 Sample Selection Procedure

The selection of rural rice-farming households for the study employed a rigorous multi-stage cluster sampling methodology to ensure representativeness and statistical robustness. The initial stage involved the purposive selection of three districts, namely Kumbungu, Tolon, and Savelugu, within the Northern Region of Ghana. These districts were chosen based on their prominence in rice production and the high density of rice-farming households, making them ideal for capturing the variability and dynamics within the study population.

In the subsequent stage, ten (10) communities, serving as primary sampling units (clusters), were randomly selected from each of the three districts. This clustering approach was employed to balance logistical considerations with the need for comprehensive data coverage across diverse locales. The final stage entailed the selection of a minimum of twenty (20) rural rice-farming households from each community.

This number was informed by pre-survey statistical power analyses, ensuring sufficient sample sizes to detect meaningful differences across study variables.

The random selection of households within communities utilized a probability-proportional-to-size (PPS) sampling technique. This method ensured that larger communities, with higher numbers of rice-farming households, contributed proportionally more to the sample, while still maintaining the equal likelihood of selection for any household within a stratum (district). By employing PPS, the sampling design minimized bias and maximized the efficiency of the selected sample.

Overall, a total of 600 rice-farming households were systematically selected and surveyed across the three districts. The sampling procedure adhered to principles of statistical rigour, ensuring that the selected sample accurately represented the target population, thereby enhancing the validity and generalizability of the study findings. This methodological approach underscores the study's commitment to robust research design, facilitating a nuanced understanding of rice production dynamics in the Northern Region.

3.11 Method of Data Collection

Both quantitative and qualitative data were collected in order to appropriately address the objectives of the study outlined in Section 1.5. As a result, the relevant data were collected using quantitative and qualitative surveys:

3.11.1 Quantitative Survey

The quantitative survey employed a structured questionnaire administered through Android tablets to ensure high-quality data collection. The choice of mobile devices and electronic questionnaires was instrumental in enhancing data accuracy and reliability, primarily through the incorporation of built-in data validation protocols and consistency checks within the application. This approach minimized errors during data entry by enabling real-time verification at the enumerator level. Using SurveyCTO server technology, data collected through the Android devices were uploaded in real-time via internet connectivity. This system streamlined the data management process, reducing the manual burden of data entry and allowing for immediate consistency reviews and quality assessments.

The electronic questionnaire was initially developed in English but was dynamically translated into local languages during interviews to accommodate respondents' linguistic diversity. This approach ensured inclusivity and accuracy in capturing the participants' responses. A pilot test was conducted prior to the main survey to evaluate the reliability, clarity, and appropriateness of the questionnaire items and expected responses. This pre-testing phase allowed for the identification and rectification of any errors or ambiguities, thereby optimizing the instrument for the field survey.

The adoption of a mobile-based data collection methodology also facilitated the seamless transition from data collection to analysis. Real-time uploads and validation minimized delays, ensuring that the dataset was ready for analysis upon completion of fieldwork. The systematic use of this technology underscores the commitment to rigorous data collection practices, improving the efficiency and quality of the overall research process.

3.11.2 Qualitative Survey

The qualitative survey employed two principal methods for data collection: In-Depth Conversational Interviews (IDIs) and Focus Group Discussions (FGDs). The FGDs were specifically designed to elicit group-level insights by engaging FBOs and key stakeholders within the communities. This approach was particularly effective in gathering collective perspectives from individuals residing in the same neighborhoods or sharing critical decision-making responsibilities concerning varietal technology adoption. To ensure manageability and depth of discussion, focus groups comprised 5 to 7 participants per session. Given the anticipated lack of substantial heterogeneity in FGD outcomes across the selected districts, only two sessions were conducted in each district, targeting representative groups from key communities.

The In-Depth Conversational Interviews (IDIs) constituted the cornerstone of the qualitative data collection effort. This approach facilitated the capture of nuanced, individual-level insights by enabling participants to freely express their thoughts, feelings, and beliefs in a naturalistic and guided interview environment. Conducted on a one-on-one basis, these interviews allowed respondents to discuss sensitive or complex issues without the influence or suppression often associated with group settings. This method was particularly valuable for uncovering deeper, subjective experiences and attitudes that might otherwise be overlooked in a group dynamic. To ensure comprehensive coverage, five (5) IDIs were conducted within each of the selected districts.

Both methods were systematically applied to maximize the reliability and richness of the data collected. The FGDs provided a platform for understanding community-level dynamics and shared experiences, while the IDIs offered an in-depth exploration of individual perspectives. Together, these methods ensured a holistic and robust qualitative data collection process, yielding valuable insights into the adoption and impact of varietal technologies within the study area.

3.12 Method of Data Analysis

The data analysis was conducted using methods outlined in Section 3.4, with specific approaches tailored to address the study's objectives. To address the first objective, which focused on identifying factors influencing rice-farming households' decisions to adopt rice varietal seed technology, a multinomial logistic regression model was employed, as defined in Equation (3.17). This model enabled the estimation of

probabilities associated with different adoption choices and facilitated an understanding of the determinants shaping these decisions. Covariate selection for this model adhered to the procedure outlined by Linden et al. (2016), incorporating recommendations by Cattaneo et al. (2013) to ensure robust and relevant variable inclusion.

The second and third objectives aimed to estimate the average treatment effects of rice varietal seed technology adoption on key outcomes, including productivity, annual household income, and household food security. These were analyzed using models specified in Equations (3.13) and (3.16), with regressions weighted as per the specifications in Equations (3.21) and (3.23). The Generalized Propensity Scores (GPS) derived from the multinomial logistic regression model facilitated the calculation of treatment effects, ensuring that the overlap assumption and the Conditional Independence Assumption (CIA) were rigorously tested and met. The overlap assumption was validated to confirm sufficient common support across adoption statuses, while the CIA ensured that observed covariates adequately accounted for the assignment mechanism, thus enhancing the validity and robustness of the estimated effects.

Potential outcome means for each adoption status were estimated based on the model defined in Equation (3.4). This enabled the derivation of unbiased treatment effects through pairwise comparisons across all adoption statuses. To account for multiple comparisons and mitigate the risk of inflated Type I error, p-values were adjusted using the Bonferroni correction procedure, ensuring the reliability of statistical inferences drawn from the results.

The fourth objective focused on identifying and ranking the primary constraints hindering the adoption of rice varietal seed technology among rice-farming households in the northern region. This was analyzed using the Garrett ranking technique, a robust method that enabled systematic prioritization of constraints based on their perceived importance. This approach provided valuable insights into the barriers to adoption and informed policy recommendations aimed at addressing these challenges.

Throughout the analysis, stringent statistical checks and validations were performed to ensure the integrity and robustness of findings. The careful adherence to methodological rigor and the implementation of corrective procedures, such as overlap and CIA testing, underscore the reliability and relevance of the study's conclusions.

3.13 Ethical Consideration

The study adhered strictly to ethical protocols established by the University of Ghana's Ethics Council, ensuring full compliance with relevant laws, policies, and regulations governing the conduct of research. Ethical considerations were integrated into all stages of the study, including the design, implementation, and fieldwork processes. These measures were essential in upholding the principles of respect, integrity, and accountability while safeguarding the rights and welfare of all participants involved in the research.

Voluntary participation was a cornerstone of the study's ethical framework. All potential respondents were provided with detailed information regarding the study's purpose, procedures, and potential implications. This enabled participants to provide informed consent voluntarily, without coercion or undue influence. Respondents were also assured of their autonomy, with the freedom to withdraw from the study at any point or to decline to answer specific questions without facing any repercussions. These provisions underscored the commitment to respecting individual agency and choice.

Confidentiality and data protection were rigorously maintained throughout the research process. Personal information and survey responses were anonymized and securely stored to prevent unauthorized access. Data were reported exclusively in aggregate form to ensure that no individual respondent could be identified. Such measures aligned with international best practices for ethical research and demonstrated a strong commitment to preserving participants' privacy.

Comprehensive training sessions were conducted for enumerators to equip them with the skills required to interact ethically and effectively with respondents. Enumerators were sensitized to the importance of confidentiality, the need for cultural sensitivity, and strategies for eliciting accurate and truthful information, particularly when addressing potentially sensitive issues. This training was instrumental in fostering trust between enumerators and respondents, thereby enhancing the quality and reliability of the data collected.

The study also adhered to international ethical standards, reinforcing its commitment to global best practices in research. These included adherence to principles such as beneficence, by minimizing potential risks to participants; justice, by ensuring equitable selection of respondents; and respect for persons, by upholding the dignity and rights of all participants. Collectively, these ethical measures contributed to the credibility, integrity, and social responsibility of the research.

CHAPTER FOUR

RESULTS AND DISCUSSION

4.1 Introduction

This chapter discusses the results of the study. The first part of the chapter presents the marginal effect estimates of the pre-adoption factors and the estimation of the Generalized Propensity Scores (GPS). In this case the results for the factors influencing varietal rice seed technology adoption are discussed. This is followed by the results from the test of the overlap assumption. Finally, it presents the results of the doubly robust potential outcome means, and the impacts of the improved varietal rice seed technologies on the main outcomes (i.e, productivity, Household Income, and Household Food Security indicators).

4.2 Factors Influencing the Adoption of Rice Varietal Seed Technology

The estimated marginal effects of the factors that affect improved rice varietal seed technology adoption are presented in Table 4.1. For purposes of results discussions, the factors that were incorporated in the model are put into three main categories: (i) Household-specific factors; (ii) Institutional and Farm-specific factors; and (iii) Varietal attribute factors.

4.2.1 Household-Specific Factors Influencing Rice Varietal Seed Technology Adoption

Following Adekambi et al. (2020); Kshirsagar et al. (2002), the key household-specific factors considered in the estimation of the marginal effects and Generalized Propensity Scores (GPS) were the gender of the household head, age of the household head, household size, number of years spent in rice production, and formal education status of the household head. The marginal effects estimates reveal a significant gender-based differential in varietal seed technology adoption, with the marginal effects for the gender of the household head being negative for Jasmine-85 and positive for Digang, both statistically significant at 1% level. These findings suggest that female-headed households are more inclined to adopt the Jasmine-85 variety, while male-headed households exhibit a stronger preference for the Digang variety. The observed gender-based differential in adoption patterns underscores the nuanced dynamics influencing varietal seed technology adoption among rice-farming households in Northern Ghana. Female-headed households may prioritize Jasmine-85 due to its shorter maturity period and market-preferred attributes such as aroma and grain quality, aligning with their emphasis on household consumption and income security. In contrast, male-headed households may opt for Digang, which potentially offers higher yields and aligns with productivity-driven objectives for commercial farming. These findings are consistent with studies highlighting the influence of gender roles in shaping agricultural technology adoption. For instance, Quisumbing & Pandolfelli (2020) emphasize that women's adoption decisions often prioritize household

food security and market preferences, while men are more likely to focus on productivity and profitability. Similarly, Tambo & Wünscher (2019) report that male-headed households in sub-Saharan Africa exhibit a higher propensity for adopting productivity-enhancing technologies, reflecting their control over critical production resources and larger farm sizes. FGD participants corroborated these findings, with women expressing a clear preference for Jasmine-85 owing to its beneficial attributes and accessibility. As one participant stated,

> *"We the women prefer the Jasmine-85 variety to all the varieties because of the benefits we obtain from its attributes such as aroma and grain quality when we cultivate it. Again, when we want to get the seeds, we don't suffer."* ***(FGD Participant B in Kumbungu district).***

However, the discussion also emphasized structural barriers faced by women, including financial constraints and cultural norms that grant men greater purchasing power and priority access to preferred seeds. Another participant noted,

> *"Even though some of us also like the Digang, the males use their dominance over us to get the Digang because they have money and power over us, and also in our culture, we respect the men a lot and so we have to allow them to buy their own before if some is left, we the women can also buy if we have money."* ***(FGD Participant E in Tolon district).***

These results reaffirm the interplay of socio-economic and cultural factors in shaping gender-specific preferences for rice varietal seed technologies. They also emphasize the importance of understanding gendered roles and decision-making dynamics in agricultural production, highlighting the need to integrate these considerations into the design and promotion of agricultural innovations.

Household size, another significant determinant, exhibited a negative marginal effect on AGRA varietal seed technology adoption, significant at 5% level, while showing a positive and highly significant effect at 1% level for Digang varietal seed technology. The contrasting effect of household size between AGRA and Digang varietal seeds may be indicative of the labour and resource allocation dynamics associated with the household's capacity to cultivate diverse seed varieties (Adu-Baffour et al., 2021). Larger households, which typically have greater labour resources, may find Digang technology more feasible as it potentially allows for productivity gains that are scalable with additional labour inputs (Kassie et al., 2022). This pattern underscores the role of household labour in determining technology adoption, consistent with studies by Mishra et al. (2022), who observed that larger households tend to adopt resource-intensive technologies more readily when the expected productivity benefits justify the additional labour demands.

The results also reveal that years of rice farming experience exerted a minimal impact on the adoption of rice varietal seed technologies, with negative and statistically insignificant marginal effects for AGRA and Jasmine-85, and a negative but significant effect at 5% level for Digang. The absence of a strong positive influence from farming experience may suggest that experience alone does not drive adoption in

Table 4.1: Marginal Effect Estimates of Pre-Adoption Characteristics for the Varietal Seed Technology

	(1) AGRA	(2) Jasmine-85	(3) Digang
Household-Specific Factors			
Gender of Household Head	−0.0151	−0.1635***	0.1634***
	(0.0232)	(0.0240)	(0.0310)
Age of Household Head	0.0008	0.0006	0.0008
	(0.0006)	(0.0007)	(0.0007)
Household Size	−0.0050**	0.0004	0.0079***
	(0.0022)	(0.0021)	(0.0022)
Years of Rice Production	−0.0004	−0.0006	−0.0018**
	(0.0007)	(0.0008)	(0.0008)
Housedhold Head Has Formal Eduction	−0.0068	0.0400***	−0.0191
	(0.0144)	(0.0147)	(0.0151)
Institutional and Farm-Specific Factors			
Access to Credit	−0.0496**	−0.0235	−0.0515*
	(0.0238)	(0.0245)	(0.0275)
FBO Membership	−0.0580***	0.0465***	−0.0040
	(0.0153)	(0.0151)	(0.0157)
Access to Extension Services	−0.0450***	0.0540***	0.0570***
	(0.0135)	(0.0140)	(0.0140)
Land Size (Ha)	−0.0001	0.0140***	−0.0169***
	(0.0018)	(0.0015)	(0.0018)
Fertilizer Use	0.2352***	−0.1414***	−0.0808***
	(0.0127)	(0.0148)	(0.0145)
Access to Farm Machinery	−0.0465***	0.0438***	0.0564***
	(0.0132)	(0.0131)	(0.0133)
Land Ownership	−0.0896***	0.0558***	0.0426***
	(0.0135)	(0.0151)	(0.0152)
Varietal Attribute-Specific Factors			
Early Maturity	−0.0309*	0.0269	0.0527***
	(0.0164)	(0.0168)	(0.0177)
High Yielding	0.0294*	−0.0061	0.0545***
	(0.0178)	(0.0185)	(0.0194)

Standard errors in parentheses
FBO denotes Farmer Based Organization
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

this context; rather, farmers may rely more heavily on external information sources or recent knowledge interventions when considering newer varietal technologies (D. et al., 2021). The negative impact observed for Digang could reflect an inclination among more experienced farmers to avoid technologies perceived as high-risk or resource-intensive, especially where adaptation to existing practices might be challenging (Muriithi et al., 2020). This aligns with Otsuka & Yamano (2023), who emphasized that years of experience do not always equate to higher adoption of newer agricultural innovations, especially when such technologies involve complex adjustments in existing farming routines.

The marginal effect of formal education further displayed mixed results, being negative but statistically

insignificant for AGRA and Digang varietal seed technologies, yet positive and highly significant at 1% level for Jasmine-85. This result underscores the potential role of education in enhancing farmers' capacity to comprehend and adopt Jasmine-85 technology, possibly due to its relatively higher complexity or input requirements compared to AGRA and Digang. Such findings align with Abay et al. (2023), who documented that formal education enhances farmers' capacity to assimilate technical information, increasing the likelihood of adopting knowledge-intensive technologies. However, the negative and insignificant effect of education on AGRA and Digang varietal seeds may reflect a preference among educated farmers for varieties that align more closely with their perception of cost-effectiveness and sustainability. This interpretation is supported by Iddrisu et al. (2019), who reported that educated farmers often exhibit selective adoption patterns based on perceived utility and compatibility with their financial resources.

In summary, the adoption of rice varietal seed technologies in the Northern Region of Ghana is significantly influenced by household head gender, household size, farming experience, and education level, with each variable exerting differential effects on distinct seed varieties. The findings underscore the importance of context-specific approaches in promoting rice varietal seed technology adoption, suggesting that policy interventions aimed at enhancing adoption rates should consider the unique demographic and socioeconomic characteristics of farming households.

4.2.2 Institutional and Farm-Specific Factors Influencing Adoption of Varietal Seed Technology

Following Issa & Kagbu (2017), access to credit, FBO membership, access to extension services, farm sizes, use of chemical fertiliser, access to farm machinery, and land ownership were identified as key institutional and farm-specific factors that can influence the adoption of rice varietal seed technologies in the Northern Region's Kumbungu, Tolon, and Savelugu districts. The analysis indicates that access to finance had a slightly negative effect on the likelihood of adopting both AGRA and Digang varietal seed technologies, with these marginal effects being statistical significance at 5% and 10% levels, respectively. This finding, which seems counterintuitive, could suggest that available financing is often directed towards less capital-intensive inputs or used to address immediate household needs rather than technology adoption, as documented by Gebre et al. (2020). Moreover, limited financial resources may prompt risk aversion among smallholders, leading them to forgo investment in potentially higher-yielding, yet costlier, seed technologies (Baiyegunhi & Fraser, 2022). This is corroborated by insights from Focus Group Discussions (FGDs), where participants emphasized the financial barriers to adopting improved seed technologies. One participant from Savelugu noted,

> *"In this district, we do not have any financial support to buy the seeds and other inputs we need to produce to improve our lives. The new seeds are there. But it is not easy to get them because they are expensive. Sometimes, we use the little money on us to buy the seeds because*

> *we know the seeds are good. But, after buying the seeds we do not get money to buy other inputs. Because as for these seeds, if you don't get other inputs like fertilizer and other needed materials, they cannot do well and so because of this we try to use our little money on our local seeds which we know how to handle very well even if we do not have a lot of money. I think governments and NGOs who are in the North here should help us"* ***(FGD participant C in the Savelugu district).***

The influence of FBO membership on rice varietal seed technology adoption appears mixed. Membership in an FBO was found to negatively influence AGRA varietal seed adoption, significant at 1% level, while positively influencing the adoption of Jasmine-85 at a similarly high level of statistical significance. However, FBO membership did not produce a statistically significant effect on Digang adoption. This pattern may indicate that while FBOs facilitate knowledge exchange and social capital—factors known to promote technology adoption (Houssou & Zeller, 2023)—their specific role varies by seed variety, with Jasmine-85 potentially perceived as more beneficial within FBO networks. FBO membership has often been associated with higher adoption rates due to improved access to collective resources and bargaining power, as well as reduced input costs, factors shown to be critical in technology adoption studies (Mwangi & Kariuki, 2021). Insights from FGDs further confirm these findings. A participant from the Tolon district noted,

> *"It is not easy to get the seed if you are not a member of a group. Because as a group, we support each other to acquire the seeds. We always use our contributions to buy the improved seeds in bulk and distribute it to our members and so even if you do not have money during the season, we help you get the seeds for your production, and we also help you sell your produce so that we can help you pay for the seeds and other inputs we supplied you. Let me say it for my colleagues who don't want to join a group that they will struggle and most of the times even get the fake improved seeds if they don't take advantage of joining a group. As for me and my members we are really benefiting a lot from our group in terms of things like what we are talking about here when it comes to getting the right and authentic improved seeds to buy for your farming even if you do not have enough money"* ***(FGD participant A in the Tolon district).***

Access to extension services significantly affected varietal seed technology adoption. The findings reveal a negative effect on AGRA varietal seed technology adoption, statistically significant at 1% level, contrasted by positive and highly significant effects on Jasmine-85 and Digang varietal seed technologies. This divergence could reflect differing levels of technical support or perceived suitability among the technologies, as indicated in studies such as that of Marenya et al. (2020), which highlighted the importance of targeted extension services in promoting crop-specific technologies. The positive impact of extension access on Jasmine-85 and Digang adoption aligns with findings by Asfaw et al. (2022b), who demonstrated that targeted extension interventions are critical for enabling smallholders to adopt knowledge-intensive agricultural innovations.These findings are further substantiated by insights from in-depth conversational interviews. An extension officer from the Tolon district remarked,

> *"We have been visiting some of the farmers especially those in groups. They organize themselves in their meetings and we go there to educate them about these improved varieties.*

> *So I can tell you that those farmers who have been receiving us in their membership group meetings are really using these improved varieties and it is helping them because they tell us whenever we visit them."* ***(In-depth Interview participant A in the Tolon district).***

This statement underscores the effectiveness of targeted outreach efforts among organized farmer groups in promoting the adoption of improved seed varieties. The officer also highlighted a key challenge in reaching farmers outside organized groups, noting,

> *"In the case of farmers who are doing their own thing, I mean those who do not belong to any farmer group, it is difficult to reach them because you know our region, the communities in the hinterlands require much more resources to get there and currently MOFA does not provide those resources needed in adequate quantities."* ***(In-depth Interview participant A in the Tolon district).***

This limitation, attributed to resource constraints, explains the lower adoption rates of AGRA varietal seeds, which may require tailored technical support unavailable to dispersed individual farmers. Additionally, the officer emphasized the potential for increased adoption if extension services could be expanded, stating,

> *"If we reach more farmers in the region, the use of the improved varieties will go up and that will go a long way to help our farmers improve their well-being and also curb this household food insecurity situation in the region."* ***(In-depth Interview participant A in the Tolon district).***

This observation reinforces the critical role of extension services in enabling smallholders to overcome adoption barriers, particularly for Jasmine-85 and Digang, which are perceived as more accessible and beneficial within existing extension frameworks.

Land size emerged as a critical determinant, with its marginal effect being positive and significant at 1% level for Jasmine-85 adoption, yet negative and significant at the same level for Digang. The adoption decision for AGRA was not significantly influenced by land size. The positive association for Jasmine-85 may be indicative of the economies of scale attainable on larger plots when using this seed variety, consistent with findings by Bekele et al. (2021). Conversely, the negative impact on Digang adoption could suggest a preference for this variety among smallholders with limited land resources, who may prioritize varieties that demand fewer resources or are better suited to intensive farming on smaller plots (Ullah et al., 2023). The marginal effect of fertilizer use presented another dichotomy. Fertilizer use positively and significantly influenced AGRA varietal seed adoption at the 1% level, while its effect was negative and statistically significant for both Jasmine-85 and Digang. The positive relationship with AGRA aligns with the characteristics of high-input, high-yield varieties, for which fertilizer application optimizes productivity (Ahmed et al., 2022). However, the negative effect for Jasmine-85 and Digang suggests that farmers adopting these varieties may opt for varieties that perform well under lower-input conditions, as documented by Asiedu et al. (2021). The findings show that access to farm machinery had a negative and highly significant impact on AGRA varietal seed adoption, while positively influencing Jasmine-85 and Digang,

each at the 1% significance level. This mixed effects may be attributed to variations in the labour intensity and mechanization compatibility of these seed varieties. As indicated by studies on mechanization and crop choice, farmers often align seed selection with available machinery resources to optimize production efficiency (Larson et al., 2023). The positive effect on Jasmine-85 and Digang, in particular, aligns with findings that mechanized farming practices can enhance adoption rates for technology-intensive varieties (Mwale et al., 2022). Finally, land ownership displayed a critical role in adoption choices. The marginal effect was negative and highly significant for AGRA adoption at 1% level, while positively and highly significant at the same level for Jasmine-85 and Digang. This result underscores the importance of tenure security in technology adoption, particularly for varieties perceived as high-return investments like Jasmine-85 (Kamau et al., 2023). This aligns with studies indicating that secure land tenure encourages farmers to invest in higher-yielding technologies due to the reduced risk of land appropriation or insecurity (Murendo & Wollni, 2020).

In summary, these findings reflect the complex interplay of institutional and farm-specific factors influencing the adoption of rice varietal seed technologies in the Northern Region of Ghana. Key institutional and farm-specific factors—including access to finance, FBO membership, and land ownership—highlight the need for targeted policies that address the specific constraints and motivations of smallholders in technology adoption.

4.2.3 Varietal Attributes Factors Influencing Rice Varietal Seed Technology Adoption

Varietal traits, specifically early maturity and high-yielding characteristics, emerged as critical determinants influencing the adoption of rice varietal seed technologies. The findings reveal a nuanced pattern: the marginal effect of the early maturity quality was negative and statistically significant at 10% level for the AGRA and Jasmine-85 varietal seed technologies but positive and highly significant at 1% level for the Digang varietal seed technology. These results suggest that rice-farming households in Northern Ghana perceive the Digang variety to be more early maturing compared to AGRA and Jasmine-85, a trait that significantly enhances its likelihood of adoption. The preference for Digang due to its early maturity and yield-enhancing characteristics was corroborated by qualitative evidence from Focus Group Discussions (FGDs). One participant remarked,

> *"As for me, my friends may say it is my opinion but I am telling you that I have experienced it for the past two seasons that since a friend told me about the Digang variety and I starting planting that one, I have seen that I harvest earlier and receive more yield than when was growing Jasmine-85. As for AGRA I cannot say because I have not planted that one before. But for the remaining two, I will say that for with my experience, the Digang gives early harvest and more yield than when I was growing Jasmine-85"* ***(FGD participant C in Kumbungu district).***

This testimony highlights how first-hand experience with Digang's performance reinforces its appeal among smallholder farmers. The centrality of early maturity in adoption decisions aligns with recent

literature emphasizing the role of varietal attributes in shaping farmers' technology preferences. For instance, Wossen et al. (2019) found that early-maturing seed technologies significantly reduce the risks associated with climate variability, enabling farmers to achieve timely harvests and secure income stability. Similarly, evidence from Mottaleb et al. (2020) underscores the positive association between early-maturity traits and the adoption of stress-tolerant rice varieties in resource-constrained environments. The higher likelihood of adopting Digang may also reflect its alignment with smallholder farmers' dual objectives of optimizing productivity and ensuring food security. Early-maturing varieties are particularly advantageous for households facing seasonal food shortages or market fluctuations, as they provide timely harvests for both household consumption and market sale. This observation aligns with findings by Tambo & Matimelo (2022), who report that the adoption of early-maturing rice varieties among sub-Saharan African farmers mitigates food insecurity while enhancing market participation. However, the negative association between early-maturity traits and the adoption of AGRA and Jasmine-85 suggests that other varietal attributes, such as grain quality or aroma, may overshadow early maturity in farmers' decision-making for these varieties. This nuance underscores the need for a targeted approach in agricultural extension services, ensuring that varietal promotion strategies address the specific priorities and constraints of diverse farmer groups.

The findings reveal that the high-yielding characteristics of rice varietal seed technologies significantly influence adoption decisions among rice farming households in Northern Ghana. Specifically, the marginal effects for high-yielding attributes were positive and statistically significant at 10% level for AGRA varietal seed technology and at 1% level for the Digang varietal seed technology. These results suggest that the preference for AGRA and Digang varieties is primarily driven by their superior yield potential, positioning them as favorable options for smallholder farmers aiming to maximize production outcomes. Qualitative evidence from Farmer-Based Organizations (FBOs) further corroborates these findings. Participants in the Tolon and Savelugu districts emphasized the practical benefits of AGRA and Digang varieties in enhancing productivity. Two participants observed,

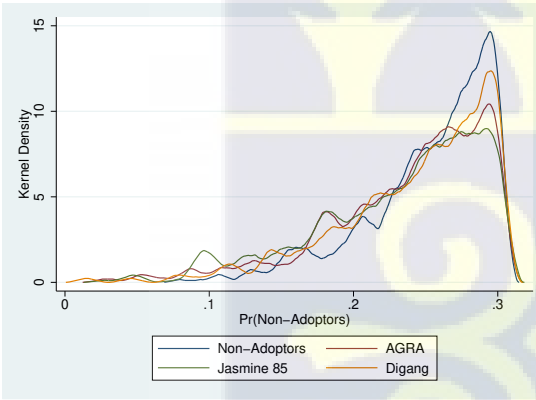
> *"When it comes to higher yield, you cannot deny the AGRA and Digang varieties. Personally, we have been growing these two varieties for almost five years now, and they have helped improve our production and even helped us expand our farms"* ***(FGD participants D and K from Tolon and Savelugu districts respectively).***

This experiential evidence underscores the transformative potential of high-yielding seed technologies in improving both productivity and the livelihoods of rice farmers. These findings are consistent with recent empirical studies that highlight the role of yield-enhancing varietal traits in driving adoption. According to Wossen et al. (2020a), high-yielding seed varieties are often perceived as essential tools for addressing food security and income generation challenges in resource-constrained agricultural systems. Similarly, Kariyasa & Dewi (2021) demonstrate that yield potential remains a critical determinant of varietal choice, particularly in regions where land and labor productivity are fundamental to household welfare. The preference for

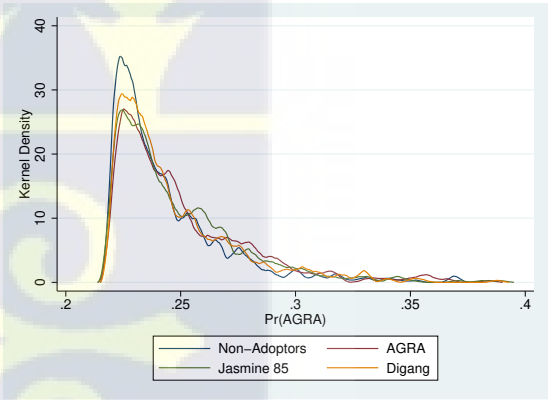
AGRA and Digang varieties may also reflect their adaptability to local agro-ecological conditions, enabling farmers to achieve higher outputs with minimal adjustments to existing farming practices. High-yielding traits not only enhance productivity but also facilitate farm expansion, as indicated by farmers who reported acquiring additional land to capitalize on the varieties' performance. This observation aligns with findings by Arouna et al. (2022b), who argue that high-yielding seed technologies contribute to both horizontal (area expansion) and vertical (yield improvement) growth in rice production systems. However, it is important to note the relative underperformance of Jasmine-85 in this context, which suggests that factors other than yield, such as grain quality or taste preferences, may play a more significant role in its adoption. This complexity reinforces the need for nuanced policy interventions that account for the heterogeneity of farmer preferences and constraints.

4.3 Test of the Overlap Assumption

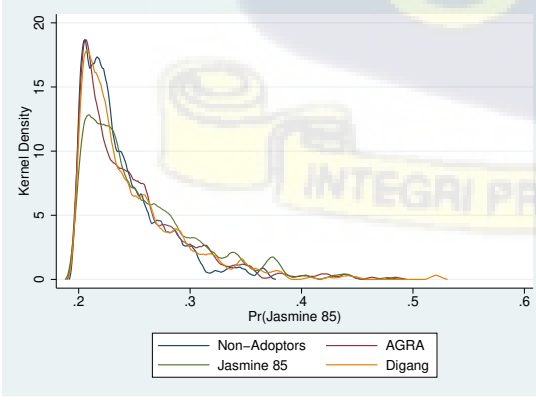
The overlap assumption, which posits that each household within the study sample possesses a positive probability of adopting any of the technologies, serves as a fundamental prerequisite for the application of the doubly robust estimation framework. This assumption ensures the reliable computation of average treatment effects, facilitating robust inference regarding the impact of varietal seed technology adoption on the outcomes of interest.



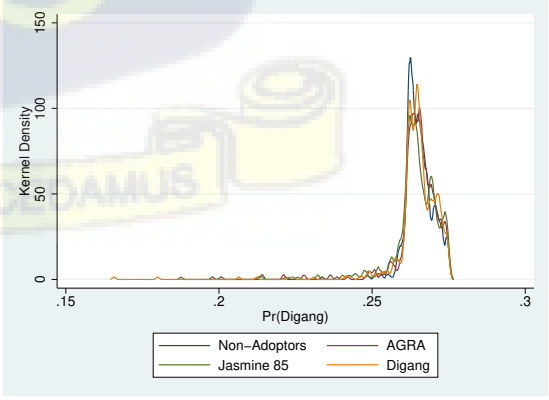
(a) The probability of assignment to non-adopters is shown by this overlap graph.



(b) The probability of assignment to AGRA adoption is shown by this overlap graph.



(c) The probability of assignment to Jasmine-85 adoption is shown by this overlap graph.



(d) The probability of assignment to Digang adoption is shown by this overlap graph.

Figure 4.1: Overlap Graph of the Adoption Group Assignment Probability

In this study, the overlap assumption—a critical condition for the validity of propensity score-based methods such as GPS and doubly robust estimation—was rigorously assessed using Kernel Density Estimations (KDEs) of the GPS for each technology adoption group. This approach aligns with the methodological framework outlined by Busso et al. (2014) and Silverman (1986), which underscores the importance of examining the distributional overlap of propensity scores to ensure credible treatment effect estimations.

Figures 4.1a to 4.1d present the KDEs of GPS for the four adoption groups analyzed in the study. The results demonstrate that none of the density distributions exhibit a probability mass concentrated at or near 0 or 1, indicating that the propensity scores are well-distributed across all groups. Moreover, the KDEs for each adoption group display substantial regions of overlap, suggesting that the overlap assumption holds for the sample under investigation. This finding is pivotal, as it implies that all adoption groups share a common support region, thereby ensuring that valid counterfactual comparisons can be made across the treatment groups.

These results corroborate the theoretical underpinnings and empirical requirements for applying advanced causal inference techniques to evaluate the impact of varietal seed technology adoption on outcomes such as productivity and household welfare. Similar studies have emphasized the significance of confirming the overlap assumption to mitigate bias and improve the robustness of treatment effect estimates. For instance, Asfaw et al. (2022a) demonstrated the importance of overlap in analyzing smallholder adoption of sustainable agricultural practices, while Wossen et al. (2020b) highlighted the methodological necessity of overlap in propensity score-based impact evaluations within the agricultural sector. In this context, the absence of violations to the overlap assumption strengthens the reliability of the results and ensures the robustness of the estimated treatment effects. This finding aligns with contemporary best practices in agricultural technology impact evaluations and supports the methodological integrity of this study's causal analysis framework.

4.4 Impact of Rice Varietal Seed Technology on Productivity and Household Income

This section provides the estimated doubly robust potential outcome means corresponding to each adoption status. It further presents the estimated average treatment effects, reflecting the impacts of rice varietal seed technology adoption on productivity and household income. The estimated average treatment effects are derived by comparing the average effects of treatment m on productivity and household income against those observed in the comparison group l, thereby providing robust insights into the differential outcomes attributable to technology adoption.

4.4.1 Potential Outcome Means for Each Treatment Level: Productivity and Household Income

Table 4.2 presents the estimated Potential Outcome Mean (POM) for each adoption status, where the potential mean outcome represents the outcome for a rice-farming household under a potential treatment.

The results underscore significant implications for both productivity and household income, highlighting the transformative potential of varietal seed technology adoption. These findings align with the findings of Essilfie (2018), who employed the doubly robust estimation technique to evaluate the impact of maize varietal seed technologies on household income, thereby corroborating the robustness of the methodological approach and the broader relevance of seed technology adoption in enhancing household welfare.

Table 4.2: Potential Outcome Means for Each Adoption Group: Productivity and Income

	Productivity (Kg/ha)		Annual Household Income (GHS)	
Treatment Levels	Mean	Std. Error	Mean	Std. Error
Non-Adoptors	1597.394***	67.301	1062.891***	57.276
AGRA	2293.840***	53.360	1860.163***	68.585
Jasmine-85	2009.029***	65.263	1552.099***	67.149
Digang	1916.407***	46.373	1517.762***	40.843

Source: Field Survey (2021)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The estimated Potential Outcome Means (POMs) provide critical insights into the productivity and income outcomes associated with different adoption scenarios of rice varietal seed technologies. The results demonstrate that if all rice-farming households remained non-adopters, the average productivity would be at 1,597.39 kg/ha, while annual household income would remain at GHS 1,062.89. These findings align with the observations of Kusum & Nyarko (2023), who noted that non-adoption of agricultural innovations often leads to suboptimal outcomes in farm productivity and income levels, perpetuating economic vulnerability among smallholder farmers. In contrast, the adoption of AGRA varietal seed technology shows a transformative potential, with average productivity increasing significantly to 2,293.84 kg/ha and annual household income rising to GHS 1,860.16. This underscores the substantial economic benefits of adopting high-yielding and resilient seed technologies, corroborating the findings of Abdulai et al. (2021), who reported that access to improved agricultural technologies substantially enhances farm productivity and economic returns among rural households. Similarly, households adopting Jasmine-85 varietal seed technology would achieve an average productivity of 2,009.03 kg/ha and an income level of GHS 1,552.10. Although these outcomes are lower than those associated with AGRA technology, they still signify a notable improvement compared to non-adopters. This observation reflects the moderate but significant role Jasmine-85 plays in boosting household welfare, as noted by Asare et al. (2023), who highlighted its adaptability to certain agro-ecological zones and its market acceptability. Adopters of the Digang variety would attain productivity levels of 1,916.41 kg/ha and annual household incomes of GHS 1,517.76. While these outcomes are slightly lower than those for Jasmine-85, the results still demonstrate the economic advantage of adopting this variety compared to non-adoption. These findings are consistent with Asare et al. (2023), who emphasized that the choice of varietal technologies often depends on farmer-specific preferences, including traits such as grain quality and production cost considerations. Overall, the results reinforce the critical role of varietal seed technology adoption in enhancing the productivity and income of

rice-farming households. These findings advocate for strengthened policy interventions aimed at improving smallholder access to high-performing seed technologies, alongside complementary inputs and extension services, to maximize agricultural productivity and household welfare in Northern Ghana.

4.4.2 Estimated Treatment Effect Parameters: Average Effects on Productivity

Table 4.3 shows the estimated treatment effect parameters for the adoption of rice varietal seed technologies on productivity.

Table 4.3: Average Effects of m relative to l on Productivity

		Productivity (Kg/ha)		
m	l	$\hat{\gamma}^{ml}$	$\hat{\tau}^{ml}$	$-\hat{\gamma}^{lm}$
AGRA	Non-Adoptors	580.599***	696.446***	457.503***
		(105.945)	(85.406)	(43.070)
Jasmin-85	Non-Adoptors	277.632**	411.635***	372.692***
		(115.746)	(93.645)	(31.167)
Digang	Non-Adoptors	254.658**	319.013***	180.07**
		(110.357)	(80.373)	(50.056)
Jasmine-85	AGRA	737.574	-284.811***	255.181**
		(890.874)	(83.793)	(95.811)
Digang	AGRA	490.280***	-377.434***	177.943*
		(109.354)	(69.987)	(74.099)
Digang	Jasmine-85	517.221*	-92.622	62.369
		(209.612)	(79.317)	(55.921)

Standard errors in parentheses

Note: m denotes treatment group and l denotes the comparison group.
$\hat{\gamma}^{ml}$ denotes ATT; $\hat{\tau}^{ml}$ denotes ATE and $-\hat{\gamma}^{lm}$ denotes ATU.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The study examined all possible pairwise comparisons for all four levels of adoption. The values presented represent treatment gains m relative to l. The average treatment effect of m relative to l is calculated for three groups, as described in Section 3.12: (i) the subpopulation $T_i = m(\hat{\gamma}^{ml})$; (ii) the total population ($\hat{\tau}^{ml}$); and (iii) the subpopulation $T_i = l(-\hat{\gamma}^{lm})$. The model in Equation (3.13) is used to calculate $\hat{\tau}^{ml}$, based on the weights in Equation (3.21). For all values of m and l based on the model in Equation (3.16), $\hat{\gamma}^{ml}$ is calculated using weighted regression with the weights supplied in Equation (3.23).

The findings presented in Table 4.3 reveal the substantial productivity gains achieved by rice-farming households that adopted the AGRA, Jasmine-85, and Digang varietal seed technologies. Specifically, households adopting the AGRA variety experienced the highest productivity gain of 580.60 kg/ha, followed by adopters of the Jasmine-85 variety with 277.63 kg/ha, and the Digang variety with 254.66 kg/ha, relative to non-adopters. This result further underscores the superior performance of the AGRA variety in enhancing productivity, likely due to its higher yield potential and adaptability to agro-ecological conditions. Similar

trends were observed across the entire population of rice-farming households, where adopters of AGRA, Jasmine-85, and Digang varieties recorded productivity gains of 696.45 kg/ha, 411.64 kg/ha, and 319.01 kg/ha, respectively.

For non-adopters, the analysis revealed potential productivity gains of 457.50 kg/ha, 372.70 kg/ha, and 180.07 kg/ha had they adopted the AGRA, Jasmine-85, and Digang varietal seed technologies, respectively. These findings emphasize the substantial opportunity cost associated with non-adoption, particularly for the AGRA variety, which provides the greatest yield advantage. Furthermore, productivity comparisons among adopters reveal a statistically insignificant difference of 737.57 kg/ha between Jasmine-85 and AGRA adopters. However, across the entire population, adopting Jasmine-85 over AGRA resulted in a significant negative yield difference of 284.81 kg/ha, underscoring the consistent superiority of AGRA technology in maximizing productivity.

The comparison of Digang with AGRA further highlights a negative productivity difference of 377.43 kg/ha for adopters across the entire population, despite a modest gain of 490.28 kg/ha among adopters versus non-adopters. Similarly, the adoption of Digang over Jasmine-85 yielded productivity gains of 517.22 kg/ha for adopters compared to non-adopters. These inter-varietal comparisons illustrate the trade-offs in productivity outcomes associated with adopting different technologies, which may reflect variation in input requirements, pest resistance, and climatic suitability of the varieties.

These results are consistent with findings from recent studies. Assaye et al. (2022) reported that the adoption of improved rice varieties in Ethiopia resulted in a productivity increase of 0.564 tons/ha, along with significant impacts on household commercialization and poverty reduction. Bello et al. (2021) observed productivity gains of 452 kg/ha among adopters of improved rice varieties in Nigeria, emphasizing the role of varietal technologies in enhancing smallholder welfare. Similarly, Dendup et al. (2021) reported higher productivity among Bhutanese farmers adopting improved varieties, albeit with a reduction in varietal diversity. In Bangladesh, Rahman & Connor (2022) identified a 35% increase in rice yield and a 76% rise in profitability among adopters of high-yielding varieties, further validating the economic benefits of varietal seed technology adoption. Finally, Tsinigo et al. (2017) highlighted a 46% productivity increase among adopters of improved rice varieties in Ghana, corroborating the transformative potential of these technologies in improving agricultural productivity.

These findings collectively underscore the critical importance of promoting adoption of high-performing varietal seed technologies like AGRA, Jasmine-85, and Digang to address productivity challenges in rice farming systems. Policy interventions aimed at improving access to these technologies, coupled with complementary inputs and extension support, are essential to achieving sustainable productivity gains and enhancing household welfare in Northern Ghana.

4.4.3 Estimated Treatment Effect Parameters: Average Effects on Household Income

The estimated treatment effect parameters for the adoption of varietal seed technologies on annual household income, presented in Table 4.4, demonstrate substantial income gains for rice-farming households adopting AGRA, Jasmine-85, and Digang varietal seed technologies. Specifically, households that adopted the AGRA variety experienced the highest increase in annual income, amounting to GHS 699.68, followed by Jasmine-85 adopters at GHS 414.60, and Digang adopters at GHS 357.69, compared to non-adopters. These results highlight the superior economic benefits of the AGRA variety, attributed to its higher productivity and profitability under prevailing agro-ecological and socio-economic conditions in Northern Ghana.

Table 4.4: Average Effects of m relative to l on Income

		Annual Household Income (GHS)		
m	l	$\hat{\gamma}^{ml}$	$\hat{\tau}^{ml}$	$-\hat{\gamma}^{lm}$
AGRA	Non-Adoptors	699.681***	797.273***	694.349***
		(107.849)	(88.5214)	(16.129)
Jasmin-85	Non-Adoptors	414.599***	489.209***	386.285***
		(105.548)	(87.559)	(17.56537)
Digang	Non-Adoptors	357.692***	454.872***	351.948***
		(93.138)	(69.536)	(43.873)
Jasmine-85	AGRA	510.969***	-308.064***	218.039**
		(109.999)	(95.271)	(97.991)
Digang	AGRA	43.789	-342.401***	49.915*
		(34.188)	(79.710)	(24.226)
Digang	Jasmine-85	37.242	-34.337	19.116
		(45.816)	(78.310)	(29.310)

Standard errors in parentheses

Note: m denotes treatment group and l denotes the comparison group.

$\hat{\gamma}^{ml}$ denotes ATT; $\hat{\tau}^{ml}$ denotes ATE and $-\hat{\gamma}^{lm}$ denotes ATU.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Across the entire population of rice-farming households, income gains associated with the adoption of AGRA, Jasmine-85, and Digang varieties were GHS 797.27, GHS 489.21, and GHS 454.87, respectively. For non-adopters, the income increases had they adopted these varietal technologies were estimated at GHS 694.35, GHS 386.29, and GHS 351.95 for AGRA, Jasmine-85, and Digang varieties, respectively. These findings underscore the significant opportunity costs of non-adoption, with AGRA adopters consistently achieving the highest income gains.

The comparative analysis of income gains between varietal technologies further underscores the economic trade-offs associated with adoption decisions. For instance, households that adopted Jasmine-85 over AGRA achieved an additional income gain of GHS 510.97; however, across the entire population,

this choice resulted in a negative income gain of GHS 308.06, reinforcing the financial superiority of AGRA. Similarly, choosing Jasmine-85 over AGRA among non-adopters would have yielded savings of approximately GHS 218.04, reflecting the economic disadvantage of non-adoption.

In the case of Digang adoption relative to AGRA, households recorded a modest income gain of GHS 43.79 among adopters, while non-adopters would have achieved GHS 49.92 had they adopted Digang. Nonetheless, across the entire population, the adoption of Digang over AGRA led to a significant negative income effect of GHS 342.40. These results suggest that while Digang adoption can generate moderate income benefits, its financial returns are consistently inferior to those of AGRA, likely due to differences in yield potential and market demand.

These findings are consistent with recent empirical evidence on the economic impacts of improved rice variety adoption. Bannor et al. (2020) demonstrated that the adoption of modern rice varieties in Eastern India significantly increased household income, thereby reducing poverty. Similarly, Budhathoki & Bhatta (2019) highlighted the substantial income gains achieved by rice-farming households in Nepal following the adoption of improved rice varieties. Chandio & Yuansheng (2020) observed that rice farmers in Pakistan who adopted improved rice varieties experienced higher income gains than non-adopters, reinforcing the financial viability of varietal technology adoption. Moreover, Varma (2019) reported significant welfare improvements, including higher household income, among adopters of improved rice varieties in South Asia. Wang et al. (2020) corroborated these findings in their econometric analysis in Yunnan, China, revealing that upland rice farmers who adopted improved varieties experienced significant household income increases.

In summary, the adoption of improved rice varietal seed technologies, particularly the AGRA variety, holds immense ability for improving household income and welfare among rice-farming households in Northern Ghana. These findings underscore the importance of promoting access to high-performing varietal technologies, coupled with targeted extension services and input subsidies, to maximize the economic benefits of adoption and enhance the livelihoods of smallholder farmers.

4.5 Impact of Rice Varietal Seed Technology on Household Food Security

This section presents the findings on the average treatment effect estimates of varietal seed technology adoption on household food security outcomes. The analysis encompasses three critical dimensions of food security: food availability, food accessibility, and food utilization. To operationalize the nutrition dimension, the study employed Household Dietary Diversity (HDD), Women Dietary Diversity (WDD) and Child Dietary Diversity (CDD) as key indicators. Additionally, the section provides comprehensive estimates of the potential outcome means associated with each adoption level. The estimated impacts are derived from the average treatment effects of adopting varietal seed technologies (treatment group m)

relative to the corresponding non-adopting comparison group (l) on food availability, food accessibility, and dietary diversity indicators, namely HDD, WDD and CDD. These results provide critical insights into the nuanced impacts of varietal technology adoption on various dimensions of household food security.

4.5.1 Potential Outcome Means for Each Treatment Level: Food Security

The Potential Outcome Mean (POM) for various adoption levels of rice varietal seed technologies on household food security indicators are presented in Tables 4.5 to 4.6. These results offer critical insights into the role of improved seed technologies in enhancing food availability, accessibility, and utilization. The findings reveal that all food security indicators demonstrate significant potential outcome means across adoption levels.

Table 4.5 highlights the potential outcomes for household food availability and accessibility under different adoption scenarios. If all households were non-adopters of improved rice varietal seed technologies, the average food availability and accessibility would remain at 11.8% and 35.0%, respectively. These outcomes are consistent with earlier findings by Adato & Hoddinott (2019), who emphasized the limited capacity of traditional farming practices to improve food security indicators. In contrast, if all rice-farming households adopted the AGRA varietal seed technology, average food availability would increase to 15.7%, and food accessibility would rise to 41.5%. This underscores the positive role of technology adoption in enhancing household welfare, corroborating findings by Fadare et al. (2020), which demonstrated the transformative effects of agricultural innovation on food security.

Table 4.5: Potential Outcome Means for Each Adoption Group: Food Security[a]

	Food Availability		Food Accessibility	
Treatment Level	Mean	Std. Error	Mean	Std. Error
Non-Adoptors	0.118***	0.009	0.350***	0.017
AGRA	0.157***	0.010	0.415***	0.018
Jasmine-85	0.183***	0.015	0.437***	0.024
Digang	0.141***	0.009	0.432***	0.017

Source: Field Survey (2021)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Similarly, adoption of the Jasmine-85 variety would further improve average food availability to 18.3% and food accessibility to 43.7%, while adoption of the Digang variety would result in average food availability of 14.1% and food accessibility of 43.2%. These outcomes align with Chirwa et al. (2021a), who reported substantial gains in food security from adopting improved rice varietal technologies in Southern Africa.

Table 4.6 presents the POM results for Household Dietary Diversity (HDD), Women Dietary Diversity (WDD) and Child Dietary Diversity (CDD), providing a comprehensive understanding of the nutritional

diversity dimension of food security. If all households were non-adopters, average HDD, WDD and CDD would be at 41.2%, 25.3%, and 8.1%, respectively. These findings are consistent with Chirwa et al. (2021a), who highlighted the limited nutritional diversity associated with traditional farming systems. Conversely, adoption of AGRA varietal seed technology would result in substantial improvements, with average HDD rising to 46.3%, WDD to 28.1%, and CDD to 10.2%. These findings align with Fadare et al. (2020), who emphasized the link between technology adoption and enhanced nutritional outcomes at the household level. Adoption of the Jasmine-85 variety would lead to an average HDD of 41.8%, WDD of 30.2%, and CDD of 15.3%, while adoption of the Digang variety would result in average HDD of 45.3%, WDD of 33.5%, and CDD of 13.2%. These varietal-specific impacts align with the findings of Kwakwa et al. (2022), which demonstrated that adoption of improved rice varieties contributes to substantial gains in dietary diversity, albeit with variations across varietal types.

Table 4.6: Potential Outcome Means for Each Adoption Group: Food Security[b]

	HDD		WDD		CDD	
Treatment Level	Mean	Std. Error	Mean	Std. Error	Mean	Std. Error
Non-Adoptors	0.412***	0.007	0.253***	0.011	0.081***	0.012
AGRA	0.463***	0.009	0.281***	0.013	0.102***	0.010
Jasmine-85	0.418***	0.012	0.302***	0.016	0.153***	0.013
Digang	0.453***	0.008	0.335***	0.010	0.132***	0.009

Source: Field Survey (2021)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The results underscore the significant potential of improved rice varietal seed technologies to enhance household food security rural rice-farming households in Northern Ghana. The findings highlight the importance of promoting targeted adoption strategies to optimize food availability, accessibility, and nutritional diversities. Future policy interventions should consider the differential impacts of varietal technologies to maximize the welfare gains for smallholder rice farmers in Ghana and beyond.

4.5.2 Estimated Treatment Effect Parameters: Average Effects on Food Availability

The treatment effect parameters for the adoption of improved rice varietal seed technologies on household food availability are presented in Table 4.7. The findings provide robust evidence on the differential impacts of adopting different varietal seed technologies. These impacts are explored for three varietal seed AGRA, Jasmine-85, and Digang.The adoption of AGRA and Jasmine-85 varietal seed technologies significantly increased household food availability by 3.0% and 4.3%, respectively, compared to non-adopters of improved rice varietal technologies. Among the varieties assessed, Jasmine-85 demonstrated the greatest positive impact on food availability, highlighting its superior productivity-enhancing attributes. These findings align with the work of Fadare et al. (2020), which emphasized the substantial gains in household welfare resulting from the adoption of highly adaptable seed varieties. In contrast, the adoption of the

Digang variety did not yield any significant increase in household food availability, a result consistent with Kwakwa et al. (2022), who reported mixed impacts of certain rice varieties on household food outcomes.

The analysis further reveals that adopters of the AGRA and Jasmine-85 varieties outperformed non-adopters by 3.9% and 6.5%, respectively, across the entire population of rice-farming households. These significant increases in household food availability underscore the potential of varietal technologies to address food insecurity at scale. Specifically, if non-adopters were to adopt the AGRA variety, an increase of 2.2% in household food availability could be realized. Similarly, non-adopters could experience a substantial 4.8% gain in food availability if they adopted Jasmine-85. These findings reaffirm the technological superiority of Jasmine-85, consistent with Chirwa et al. (2021a), who highlighted varietal-specific impacts on agricultural productivity and household food security.

Table 4.7: Average Effects of m relative to l Food Security[a]

		Household Food Availability		
m	l	$\hat{\gamma}^{ml}$	$\hat{\tau}^{ml}$	$-\hat{\gamma}^{lm}$
AGRA	Non-Adoptors	0.030*	0.039**	0.022*
		(0.017)	(0.014)	(0.011)
Jasmin-85	Non-Adoptors	0.043**	0.065***	0.011
		(0.021)	(0.018)	(0.018)
Digang	Non-Adoptors	0.016	0.022	0.022
		(0.018)	(0.013)	(0.016)
Jasmine-85	AGRA	0.035**	0.026	0.048***
		(0.012)	(0.018)	(0.010)
Digang	AGRA	0.030**	-0.016	0.006***
		(0.011)	(0.014)	(0.001)
Digang	Jasmine-85	0.033	-0.042*	0.016
		(0.027)	(0.017)	(0.0134)

Standard errors in parentheses

Note: m denotes treatment group and l denotes the comparison group.

$\hat{\gamma}^{ml}$ denotes ATT; $\hat{\tau}^{ml}$ denotes ATE and $-\hat{\gamma}^{lm}$ denotes ATU.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The comparative effects of varietal adoption provide additional insights. Adopting Jasmine-85 over AGRA results in a statistically significant gain of 3.5% in household food availability for adopters, while non-adopters could achieve an even higher gain of 4.8% by switching to Jasmine-85. Conversely, the adoption of Digang over AGRA results in a modest gain of 3.0% for adopters but only a marginal increase of 0.6% for non-adopters, indicating limited scalability of the Digang variety. Moreover, the adoption of Digang instead of Jasmine-85 results in a negative gain of 4.2% in household food availability for adopters. These results are consistent with the findings of Okoruwa et al. (2023), who emphasized that not all improved seed varieties are equally effective across diverse agro-ecological contexts.

These results underscore the critical importance of promoting targeted varietal seed technology adoption

based on their specific impacts on food availability. Jasmine-85 stands out as the most promising technology for enhancing household food security, particularly in Northern Ghana. However, the mixed results for the Digang variety indicate the need for careful varietal selection and contextual evaluation. Policymakers should focus on scaling up the adoption of high-performing varieties like Jasmine-85 while providing technical support to maximize their benefits.

4.5.3 Estimated Treatment Effect Parameters: Average Effects on Food Accessibility

The estimated treatment effect parameters presented in Table 4.8 provide robust insights into the impacts of adopting improved rice varietal seed technologies on household food accessibility. The results highlight the differential effects of three prominent varietal technologies: AGRA, Jasmine-85, and Digang. Adoption of the AGRA varietal technology significantly increased household food accessibility by 14.6%, making it the most impactful among the three technologies evaluated. Jasmine-85 and Digang varieties also contributed positively, with significant gains of 10.9% and 9.2%, respectively, compared to households that did not adopt any improved varieties. These findings align with the conclusions of Fadare et al. (2020), who documented that varietal seed adoption leads to substantial welfare improvements, particularly in food accessibility. The superior performance of AGRA in improving food accessibility underscores its adaptability to local agro-climatic conditions and the relative efficiency of its productivity-enhancing traits, as also reported by Chirwa et al. (2021a).

Table 4.8: Average Effects of m relative to l: Food Security[b]

		Household Food Accessibility		
m	l	$\hat{\gamma}^{ml}$	$\hat{\tau}^{ml}$	$-\hat{\gamma}^{lm}$
AGRA	Non-Adoptors	0.146***	0.065*	0.072***
		(0.030)	(0.025)	(0.020)
Jasmin-85	Non-Adoptors	0.109***	0.087**	0.006***
		(0.036)	(0.030)	(0.002)
Digang	Non-Adoptors	0.092***	0.082***	0.027**
		(0.032)	(0.024)	(0.011)
Jasmine-85	AGRA	0.087**	0.022	0.004
		(0.034)	(0.030)	(0.011)
Digang	AGRA	0.098*	0.017	0.039***
		(0.048)	(0.024)	(0.013)
Digang	Jasmine-85	0.089*	-0.005	0.010
		(0.047)	(0.030)	(0.014)

Standard errors in parentheses

Note: m denotes treatment group and l denotes the comparison group.

$\hat{\gamma}^{ml}$ denotes ATT; $\hat{\tau}^{ml}$ denotes ATE and $-\hat{\gamma}^{lm}$ denotes ATU.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Across the entire population of rice-farming households, the gains in household food accessibility due to the adoption of AGRA, Jasmine-85, and Digang varieties were 6.5%, 8.7%, and 8.2%, respectively. Notably,

non-adopters of these technologies could achieve a 7.2% increase in food accessibility if they adopted the AGRA variety. Similarly, the adoption of Jasmine-85 and Digang varieties by non-adopters could yield potential increases of 0.6% and 2.7%, respectively. These results resonate with Kwakwa et al. (2022), who found that varietal-specific interventions can narrow food accessibility gaps for vulnerable households.

When comparing the performance of varietal technologies, Jasmine-85 offered an 8.7% increase in food accessibility over AGRA for adopters, whereas Digang demonstrated a 9.8% increase over AGRA for the same group. However, for non-adopters, switching to Digang from AGRA would yield a gain of 3.9% in food accessibility. Finally, a notable increase of 8.9% in food accessibility was observed for adopters who chose Digang over Jasmine-85, suggesting that Digang may exhibit higher benefits in specific household contexts despite its lower baseline performance relative to AGRA. These findings are consistent with Okoruwa et al. (2023), who emphasized the importance of varietal specificity in achieving optimal impacts on household welfare metrics.

These findings provide valuable insights for policy-makers and development practitioners. The significant gains observed across all three technologies affirm the critical role of varietal adoption in enhancing household food accessibility in rice-farming households. Policies aimed at scaling up the adoption of AGRA and Jasmine-85 varietal seed technologies should be prioritized to maximize food accessibility improvements. Additionally, targeted interventions to improve the performance and adoption of the Digang variety could further optimize its potential benefits, especially for non-adopters transitioning to improved varieties.

4.5.4 Estimated Treatment Effect Parameters: Average Effects on HDD, WDD and CDD

The findings in Table 4.9 underscore the substantial and multidimensional impact of varietal seed technology adoption on dietary diversity and household welfare, as reflected in Household Dietary Diversity (HDD), Women Dietary Diversity (WDD) and Child Dietary Diversity (CDD). These results contribute significantly to the discourse on how agricultural innovations, particularly the adoption of improved seed varieties, can enhance nutritional outcomes and household resilience among smallholder rice farmers in Northern Ghana. The adoption of AGRA and Digang varietal seed technologies was associated with significant increases in HDD. Specifically, households adopting AGRA and Digang technologies experienced gains of 4.0% and 4.3%, respectively, compared to non-adopters. These gains were consistent across the entire population of rice-farming households, where the adoption of AGRA and Digang varieties yielded increases in HDD by 5.2% and 4.1%, respectively. For non-adopters, the gains in HDD, had they adopted these technologies, were estimated at 3.3% and 2.2%, respectively. Interestingly, the adoption of Jasmine-85 relative to AGRA revealed mixed outcomes. While adopters of Jasmine-85 experienced a 4.0% improvement in HDD compared to AGRA adopters, a negative gain of 4.5% was

observed across the entire population of adopters. However, non-adopters would have realized a positive HDD gain of 1.9% had they chosen Jasmine-85 over AGRA. This suggests heterogeneity in the benefits derived from Jasmine-85 adoption, which may be contingent on other contextual or household-specific factors. Comparatively, choosing Digang over Jasmine-85 led to a consistent gain in HDD for adopters (3.6%) and non-adopters (3.1%), indicating that Digang is potentially more effective at enhancing household dietary outcomes. These findings align with the conclusions of recent studies on the role of improved seed varieties in enhancing dietary diversity. For example, Lu et al. (2021) demonstrated that the adoption of improved rice varieties significantly improved household food security in Northern Ghana, highlighting the role of such technologies in diversifying diets and enhancing nutritional outcomes.

Women Dietary Diversity (WDD), a critical indicator of nutritional security and gendered welfare outcomes, also benefited significantly from varietal seed adoption. Households adopting Digang varietal seed technology recorded a WDD gain of about 6.5%, relative to non-adopters. Across the entire population, adopting Jasmine-85 and Digang resulted in 4.9% and 8.1% increases, respectively, in WDD for adopters and a 5.2% increase for non-adopters had they adopted Digang. When comparing the gains associated with different varieties, Jasmine-85 over AGRA observed a 7.3% WDD improvement for adopters, with a further 2.9% gain for non-adopters had they adopted Jasmine-85 over AGRA. Furthermore, adopting Digang over AGRA resulted in a 5.2% increase in WDD for adopters and 6.2% for non-adopters, emphasizing Digang's superior performance in enhancing women's dietary outcomes. Again, the adoption of Digang over Jasmine-85 resulted in gains of 6.7% for adopters and 4.0% for non-adopters. These findings reflect the importance of varietal characteristics and household adoption decisions in shaping nutritional outcomes for women. These results are consistent with Mansaray & Jin (2020), who observed significant improvements in food security and dietary outcomes among rice-farming households in Sierra Leone adopting improved rice varieties. They highlighted the gendered dimensions of food security, where women disproportionately benefit from technological adoption due to their role in household food management and consumption.

The adoption of varietal seed technologies also demonstrated significant positive impacts on child nutrition, as measured by CDD. Adopters of Jasmine-85 experienced a 5.3% increase in CDD compared to non-adopters, with gains increasing to 7.3% across the entire population of adopters. Non-adopters could have improved their children's dietary diversity by 6.3% had they adopted Jasmine-85. Similarly, adopting the Digang varietal seed technology increased CDD by 5.8% for adopters relative to non-adopters. Across the entire population, the adoption of Digang resulted in a 5.1% increase in CDD for adopters, while non-adopters could have realized a 4.0% improvement in CDD had they adopted Digang. Comparative analyses revealed that adopting Jasmine-85 over AGRA led to a 3.9% increase in CDD for adopters, with gains for non-adopters reaching 4.6%. Likewise, Digang adoption over AGRA resulted in a 4.5% increase in

Table 4.9: Average Effects of m relative to l: Food Security[c]

m	l	$\hat{\gamma}^{ml}$	$\hat{\tau}^{ml}$	$-\hat{\gamma}^{lm}$
Household Dietary Diversity (HDD)				
AGRA	Non-Adoptors	0.040***	0.052***	0.033***
		(0.014)	(0.011)	(0.027)
Jasmin-85	Non-Adoptors	-0.012	0.007	-0.012
		(0.017)	(0.014)	(0.011)
Digang	Non-Adoptors	0.043***	0.041***	0.022***
		(0.015)	(0.011)	(0.004)
Jasmine-85	AGRA	0.040**	-0.045**	0.019**
		(0.015)	(0.015)	(0.007)
Digang	AGRA	0.032	-0.011	0.040
		(0.025)	(0.012)	(0.035)
Digang	Jasmine-85	0.036*	0.034*	0.031**
		(0.019)	(0.014)	(0.013)
Women Dietary Diversity (WDD)				
AGRA	Non-Adoptors	0.007	0.028	0.001
		(0.022)	(0.018)	(0.014)
Jasmin-85	Non-Adoptors	0.022	0.049*	0.020
		(0.025)	(0.020)	(0.020)
Digang	Non-Adoptors	0.065***	0.081***	0.052***
		(0.021)	(0.016)	(0.007)
Jasmine-85	AGRA	0.073***	0.021	0.029***
		(0.023)	(0.021)	(0.006)
Digang	AGRA	0.052*	0.053**	0.062*
		(0.029)	(0.017)	(0.028)
Digang	Jasmine-85	0.067**	0.032	0.0370**
		(0.031)	(0.019)	(0.011)
Child Dietary Diversity (CDD)				
AGRA	Non-Adoptors	0.017	0.021	0.011
		(0.022)	(0.015)	(0.008)
Jasmin-85	Non-Adoptors	0.053**	0.073***	0.063**
		(0.025)	(0.018)	(0.022)
Digang	Non-Adoptors	0.058**	0.051***	0.040*
		(0.023)	(0.015)	(0.021)
Jasmine-85	AGRA	0.039**	0.052**	0.046*
		(0.019)	(0.017)	(0.025)
Digang	AGRA	0.045*	0.030	0.054*
		(0.028)	(0.014)	(0.028)
Digang	Jasmine-85	0.049*	-0.022	0.011
		(0.027)	(0.016)	(0.008)

Standard errors in parentheses

Note: m denotes treatment group and l denotes the comparison group.

$\hat{\gamma}^{ml}$ denotes ATT; $\hat{\tau}^{ml}$ denotes ATE and $-\hat{\gamma}^{lm}$ denotes ATU.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

CDD for adopters and a 5.4% increase for non-adopters. Finally, adopting Digang over Jasmine-85 was associated with a 4.9% gain in CDD for adopters and a 4.0% gain for non-adopters.

These findings corroborate those of Lu et al. (2021), who reported that improved rice varieties significantly enhanced child dietary outcomes by increasing household food availability and access. The study underscores the potential of such technologies to address child malnutrition and improve overall household welfare.

4.6 Test of Covariate Balance for Selection Bias Reduction

The analysis of covariate balance in the adoption of rice varietal seed technologies provides significant insights into the robustness of the propensity score weighting approach used. The pre-adoption characteristics of rice-farming households in the four groups—non-adopters and adopters of AGRA, Jasmine-85, and Digang varieties—revealed considerable imbalances before weighting, as indicated by absolute standardized mean differences (see Table 4.10). Specifically, 13 of the 42 covariates exceeded the 0.25 threshold recommended by Rubin (2001), signifying notable disparities. These imbalances underscore the potential biases in comparing groups without adjusting for confounding factors, as noted in agricultural technology adoption literature (Ali et al., 2020a; Rayhan et al., 2023).

Table 4.10: Unadjusted Pre-Adoption Covariates for Adoptors and Non-Adoptors of IRV Technology

Variables	Control	AGRA	Jasmine-85	Digang	Absolute Standardized Difference		
					AGR vs. Control	Jasmine-85 vs. Control	Digang vs. Control
Gender	0.900	0.900	0.960	0.927	0.000	**0.236**	0.095
Age	42.153	41.353	41.400	41.067	0.056	0.052	0.073
Household Size	5.800	6.513	6.413	6.080	**0.202**	0.182	0.080
Experience	14.093	14.573	14.320	14.867	0.042	0.020	0.065
Education	0.327	0.313	0.287	0.300	0.028	0.087	0.057
Credit	0.073	0.073	0.053	0.127	0.000	0.082	0.178
FBO	0.213	0.260	0.227	0.260	0.110	0.032	0.110
Extension	0.353	0.620	0.587	0.440	**0.552**	**0.479**	0.177
Farm Size	4.377	6.800	4.667	5.466	**0.551**	0.079	**0.260**
Fertilizer Use	0.673	0.213	0.313	0.400	**1.041**	**0.769**	**0.568**
Machinery	0.367	0.493	0.493	0.393	**0.257**	**0.257**	0.055
Owns Land	0.660	0.780	0.773	0.727	**0.269**	**0.253**	0.144
Early Maturity	0.480	0.520	0.540	0.487	0.080	0.120	0.013
High Yielding	0.300	0.273	0.287	0.253	0.059	0.029	0.104

Source: Field Survey (2021)

Post-weighting results in Table 4.11, however, reveal substantial improvements in covariate balance, with all absolute standardized mean differences reduced to below the 0.25 threshold. This aligns with recommendations by Linden & Samuels (2013), who emphasized the importance of achieving covariate balance in propensity score analyses for valid causal inferences. Such improved balance enhances the reliability of the estimated treatment effects, as supported by recent studies evaluating agricultural interventions (Kondylis et al., 2022). The findings are consistent with recent research on the adoption

of high-yielding varieties and other agricultural technologies. For instance, a study in Bangladesh found that interventions incorporating proper balancing methods effectively eliminated biases in estimating the impact of rural credit on the adoption of rice varieties (Rayhan et al., 2023). Similarly, Ali et al. (2020a) highlighted the importance of balancing covariates to accurately assess the impact of fertilizer adoption programs in sub-Saharan Africa.

Table 4.11: Adjusted Pre-Adoption Covariates for Adoptors and Non-Adoptors of IRV Technology

					Absolute Standardized Difference		
Variables	Control	AGRA	Jasmine-85	Digang	AGR vs. Control	Jasmine-85 vs. Control	Digang vs. Control
Gender	0.953	0.940	0.953	0.952	0.057	0.006	0.004
Age	41.758	41.550	41.758	41.770	0.015	0.023	0.001
Household Size	6.008	6.352	6.008	6.102	0.099	0.123	0.027
Experience	15.380	14.646	15.380	15.997	0.061	0.052	0.049
Education	0.292	0.381	0.292	0.303	0.189	0.035	0.024
Credit	0.059	0.045	0.059	0.071	0.061	0.066	0.049
FBO	0.253	0.221	0.253	0.246	0.074	0.056	0.016
Extension	0.502	0.558	0.502	0.558	0.112	0.038	0.112
Farm Size	5.203	6.615	5.203	5.552	0.098	0.180	0.078
Fertilizer Use	0.397	0.413	0.397	0.393	0.031	0.004	0.009
Machinery	0.385	0.455	0.385	0.419	0.140	0.146	0.069
Owns Land	0.764	0.752	0.764	0.731	0.028	0.018	0.076
Early Maturity	0.487	0.552	0.487	0.493	0.131	0.124	0.012
High Yielding	0.307	0.253	0.307	0.223	0.119	0.075	0.191

Source: Field Survey (2021)

The implications of these results are far-reaching. They not only validate the methodological rigour of using propensity score weighting but also emphasize the critical role of balanced covariates in deriving reliable policy insights. Given the strong covariate balance achieved, the subsequent impact evaluation of rice varietal adoption on productivity and household welfare yielded credible and actionable findings.

4.7 Key Constraints Affecting Adoption of Varietal Rice Seed Technology

The constraints to the adoption of varietal rice seed technology in the Northern Region of Ghana provide a comprehensive understanding of the barriers limiting the productivity and welfare benefits associated with improved rice varieties. This study identified and ranked 11 constraints using Garrett's Ranking Technique, which prioritizes constraints based on their perceived severity by rice farming households. Table 4.12 highlights the rankings, with high input costs emerging as the most pressing constraint, followed by lack of financing, unclear government policies, inadequate markets, insufficient access to extension services, and lack of access to farm machinery. These constraints resonate with findings in recent agricultural research, illustrating the systemic challenges in the adoption of agricultural innovations.

High input costs emerged as the most significant constraint with a mean score of 67.29. The predominance of imported inputs such as agrochemicals and fertilizers, coupled with exchange rate fluctuations, exacerbates the financial burden on rice farmers. This finding aligns with recent studies in similar

contexts. For instance, Ouma et al. (2022) reported that input price volatility significantly constrained smallholder farmers' adoption of climate-resilient seed varieties in sub-Saharan Africa. Addressing input cost challenges requires concerted efforts, such as subsidies or price stabilization policies, to make inputs more affordable and accessible.

The second-ranked constraint, with a mean score of 58.51, highlights the critical role of access to finance in agricultural technology adoption. Limited access to credit impedes farmers' ability to procure essential inputs, resulting in suboptimal productivity. This finding is consistent with Asamoah et al. (2022), who reported that financial constraints significantly hinder technology uptake among smallholder farmers in Ghana. Policy interventions such as microfinance programs tailored to rice farmers' needs and crop insurance schemes could mitigate this challenge, enabling greater adoption rates.

Table 4.12: Major Constraints Affecting Adoption of Varietal Rice Seed Technology

Constraints	Mean Score	Rank
High cost of Inputs	67.29	1
Lack of access to credit	58.51	2
Lack of clear government policies and incentives	54.17	3
Inadequate market for local rice	51.94	4
Inadequate access to extension services	48.50	5
Lack of access to farm machinery	47.91	6
Theft	47.15	7
Difficulty in accessing seeds	46.45	8
Human epidemic/disease (COVID-19)	46.26	9
Land turner challenges	45.11	10
Skilled labour unavailability	44.31	11

Source: Field Survey (2021)

The absence of clear and effective government policies was ranked third, with a mean score of 54.17. While the Ghanaian government provides fertilizer subsidies, their timing and delivery are often misaligned with farmers' needs, reducing their effectiveness. Farmers emphasized the need for more comprehensive policy support, including financial assistance to upgrade operations. Similar concerns were highlighted by Zakaria et al. (2021), who emphasized the importance of coherent policy frameworks in fostering the adoption of improved rice varieties in sub-Saharan Africa. Strengthening subsidy programs and integrating them with broader support mechanisms could enhance policy impact.

Ranked fourth, with a mean score of 51.94, the limited market for locally produced rice poses a significant challenge to adoption. Farmers face difficulties in marketing their rice due to competition from imported varieties and insufficient post-harvest infrastructure. As emphasized by Nyamekye et al. (2023), investments in grain quality improvement and marketing infrastructure are critical to enhancing the competitiveness of local rice. Initiatives such as government procurement programs targeting local rice and collaborative efforts with value chain actors can expand market opportunities and incentivize adoption.

With a mean score of 48.50, inadequate extension services were identified as the fifth most significant barrier. Extension agents play a crucial role in disseminating knowledge about improved agricultural practices, but the low extension worker-to-farmer ratio in Ghana's Northern Region limits their reach. Anang & Asante (2020a) also reported similar findings, emphasizing the need for increased investment in extension services to promote the adoption of modern agricultural technologies. Strengthening extension systems through digital platforms and community-based approaches could address these challenges.

The sixth-ranked constraint, with a mean score of 47.91, reflects the mechanization gap in the region. Rice farming households rely heavily on manual labour, which increases production costs and limits scalability. Access to machinery such as tractors, harvesters, and dryers is critical for improving productivity and grain quality. As highlighted by Asante et al. (2018a), the mechanization of rice farming can significantly reduce labour costs and enhance competitiveness. Policy initiatives promoting shared access to machinery through cooperatives or rental schemes could alleviate this barrier.

Other constraints include theft (ranked seventh) and difficulty in obtaining seeds (ranked eighth). External shocks such as pandemics, land tenure issues, and skilled labor shortages were also identified. Short-term land leases restrict farmers' long-term planning, affecting their ability to adopt and sustain improved technologies. Addressing land tenure security is critical, as highlighted by Agyei-Holmes & Boakye-Yiadom (2023), who found that secure land rights significantly influence technology adoption in Ghanaian agriculture.

The findings underscore the multifaceted barriers to adopting rice varietal seed technologies. High input costs and financial constraints require coordinated interventions, including subsidies, affordable credit facilities, and exchange rate stabilization measures. Enhancing access to markets through infrastructure development and institutional procurement policies can boost local rice competitiveness. Strengthening extension services and promoting mechanization through public-private partnerships are also critical. Addressing systemic issues such as land tenure security and farmer cooperatives will ensure the sustainability of these interventions.

CHAPTER FIVE

SUMMARY, CONCLUSION AND POLICY RECOMMENDATIONS

5.1 Introduction

This chapter summarises the study and draws conclusions from the major findings based on the study's hypothesis. It also includes policy recommendations for policy interventions based on the major findings.

5.2 Summary of the Study

Rural poverty is exacerbated by low agricultural productivity, high post-harvest losses, and poor farm product marketing. Low productivity is exacerbated by the use of traditional farming methods or technologies, poor soil fertility, unreliable rainfall patterns, high input costs, poor seed quality, and a lack of credit facilities. These major impediments have resulted in food shortages, underdevelopment of farms or agribusinesses, low farm incomes, food insecurity, and poor nutritional status, particularly among children, increasing the vulnerability of the rural farm household population to poverty. The transition from traditional rice varieties to improved rice varieties represents a technological shift in rural smallholder rice production. However, available technologies and resource constraints limit the options available to rural rice-farming smallholder households. Agriculture technology, such as high-yielding seed varieties, is critical to reducing poverty, hunger, and ensuring food security in developing countries where agriculture is the primary source of income. This study examined the impact of rice varietal seed technology adoption on the productivity, annual household income, and household food security of rural rice-farming households in Ghana's Northern Region by testing the following underlying hypotheses:

i. Household, institutional, and farm-specific factors, as well as varietal attributes, significantly influence the adoption of improved rice seed technologies.

ii. Adopting rice varietal seed technology significantly enhances productivity and household income of smallholder rice farmers in the region.

iii. Improved rice varietal seed technology adoption enhances household food security.

iv. Adoption of rice varietal seed technology in the region is not hindered by financial, policy, or market constraints.

The study employed survey data obtained from rice-farming households in Ghana's northern districts of Kumbungu, Tolon, and Savelugu, where the indicator variable is a nominal multivalued treatment indicator.

The estimation approach used in this research is an extension of the doubly robust ATE and TT estimation methods from a binary treatment situation to a multivalued treatment case with the Conditional

Independence Assumption (CIA). It combines the regression correction and weighting approaches. Model specifications for the conditional mean functions are required for the regression adjustment, and model specifications for the Generalized Propensity Scores (GPS) are required for the weighting technique. The combination of the two techniques has the benefit of consistently estimating the treatment parameter of interest even if one of the models is misspecified. The work specifies the estimation technique explicitly and obtains the parameters' asymptotic distribution. The findings generalise Hirano & Imbens (2001); Wooldridge (2007)'s investigations on multivalued treatment variables.

It is more common to assess the impact of improved rice varietal seed technology adoption as a binary treatment effect. However, the study anticipated that accounting for the multivalued nature of varietal seed technology adoption (where a rice-farming household could adopt AGRA rice, Jasmine-85, Digang, or choose not to adopt any at all) can provide additional insights on the impact of improved varieties on productivity, income, and household food security.

To ensure that the overlap assumption was not broken, a test was run. Furthermore, the study investigated covariate balancing and selection bias reduction. After weighing, the test confirmed that all absolute standardised mean differences of the pre-adoption characteristics or covariates were significantly closer to zero, with no standardised mean difference value exceeding 0.25.

Given the treatment indicator's nominally multivalued nature, a multinomial logistic regression model was used to build the GPS and the marginal probabilities of the factors identified to influence the adoption of improved varietal rice seed technologies. For each treatment arm, the Potential Outcome Mean (POM) was calculated. In order to determine the impacts, pairwise comparisons were performed between all adoption groups.

The study found that household-specific factors such as the gender of the household head influenced adoption of the Jasmine-85 variety while positively influencing adoption of the Digang variety. Household size influenced AGRA variety adoption negatively while positively influencing Digang variety adoption. Experience in rice production had a negative impact on the adoption of the Digang variety but had no effect on the adoption of the AGRA and Jasmine-85 varieties. Finally, the household head's formal education status was found to positively influence the adoption of the Jasmine-85 variety but had no significant influence on the adoption of the AGRA and Digang varieties. According to the study's findings, institutional and farm-specific factors such as credit availability influenced the adoption of the AGRA and Digang varieties, respectively. Again, FBO membership had a negative impact on AGRA variety adoption while having a positive impact on Jasmine-85 variety adoption. Access to extension influenced Jasmine-85 and Digang variety adoption positively, but negatively influenced AGRA variety adoption. Furthermore, farm size influenced Jasmine-85 variety adoption while negatively influencing Digang variety adoption.

According to the study's findings, fertiliser use by rice farming households influenced adoption of the AGRA variety positively but negatively influenced adoption of the Jasmine-85 and Digang varieties. Finally, the study's findings on institutional and farm-specific factors revealed that access to farm machinery and land ownership positively influenced adoption of the Jasmine-85 and Digang varieties, but negatively influenced adoption of the AGRA variety. In terms of varietal attributes or trait-specific factors, the study found that the early maturity trait positively influenced Digang variety adoption and negatively influenced AGRA variety adoption. Finally, the results show that the high yielding trait influenced the use of AGRA and Digang varieties.

The study found that adopters of the AGRA, Jasmine-85, and Digang varieties experienced productivity and annual household income gains of approximately 580.60 kg/ha, 277.63 kg/ha, and 254.66 kg/ha, respectively, when compared to their counterpart rice farming households who did not adopt any of the varietal technologies at all. Similarly, adopters of AGRA, Jasmine-85, and Digang varietal technologies received approximately GHS 699.68, GHS 414.60, and GHS 357.69 more in annual household income than counterpart rice farming households who did not adopt any of these improved varietal rice seed technologies. According to these findings, adopters of the AGRA variety gained the most in productivity and annual household income, followed by Jasmine-85, and Digang adopters gained the least in productivity and annual household income.

Concerning the effects of variety adoption on household food security, the study's findings show that adopting the AGRA and Jasmine-85 varieties increased adopters' household food availability by 3.0% and 4.3%, respectively, compared to non-adopters. Adoption of the AGRA, Jasmine-85, and Digang varieties, on the other hand, increased adopters' household food accessibility by 14.6%, 10.9%, and 9.2%, respectively, compared to non-adopters. It is worth noting that adopters of the AGRA variety experience the greatest increase in household food accessibility, followed by adopters of the Jasmine variety, with Digang adopters experiencing the least increase in household food accessibility.

Adoption of the AGRA and Jasmine-85 varieties increased adopters' HDD by 4.0% and 4.3%, respectively, compared to non-adopters of the improved varietal seed technologies, while only adoption of the Digang variety increased adopters' WDD by 6.5% compared to non-adopters. In terms of the impact of variety adoption on CDD, evidence from the study shows that only Jasmine-85 and Digang adopters experienced a CDD gain of about 5.3% and 5.8%, respectively, when compared to non-adopters of the improved varietal seed technologies.

Finally, the study discovered that the top six most important constraints preventing rice-farming households in the three districts from adopting rice varietal seed technologies were high input costs, a lack of access to credit, a lack of clear government policies and incentives, an inadequate market for local rice, insufficient

access to extension services, and a lack of access to farm machinery, while theft and difficulty in accessing seeds were the seventh and eighth most important constraints. Other barriers to the adoption of improved varietal seed technologies identified by rice farming households as less important included human epidemics and diseases (e.g., the COVID-19 pandemic), land tenure issues, and a lack of skilled labour.

5.3 Conclusion of the Study

The study established that the adoption of improve varietal seed technologies by rice-farming households is significantly influenced by specific household characteristics, including the gender of the household head, household size, years of experience in rice production, and the formal education level of the household head. These characteristics shape the decision-making processes and readiness of households to adopt these improved technologies. Furthermore, factors related to accessibility and resources, such as access to financing, membership in Farmer-Based Organizations (FBOs), access to extension services, land size or farm size, use of fertilizer, access to farm machinery, and farmland ownership, were identified as key in determining the likelihood of adoption. Varietal attribute characteristics, particularly early maturity and high yield traits, were also found to play a significant role in influencing these decisions.

The analysis further revealed that households adopting enhanced varietal seed technologies such as AGRA, Jasmine-85, and Digang achieved higher outcomes in terms of productivity and annual household income compared to non-adopters. Notably, these gains were observed both within specific adopter groups and across the general population of rice-farming households in the Northern Region, encompassing the districts of Kumbungu, Tolon, and Savelugu. Additionally, adopters of AGRA and Digang improved varietal seeds demonstrated enhanced household food availability, with these benefits surpassing those experienced by non-adopters. Across the population, households employing AGRA and Digang varieties consistently exhibited greater improvements in food security metrics than their counterparts who did not adopt these improved technologies.

Household food accessibility also saw substantial gains among adopters of the enhanced varietal seed technologies. Specifically, users of AGRA, Jasmine-85, and Digang varieties experienced notable improvements in food accessibility compared to non-adopters, with consistent performance advantages observed across the entire population of rice-farming households. Evaluating dietary diversity outcomes, the study highlighted that households adopting AGRA and Digang varieties recorded significant improvements in Household Dietary Diversity (HDD). These gains were not only evident within the specific groups of adopters but also observed relative to the broader population of non-adopters. Furthermore, the adoption of the Digang variety was particularly instrumental in improving Women Dietary Diversity (WDD), with adopters consistently outperforming non-adopters in this regard.

Similarly, significant improvements in Child Dietary Diversity (CDD) were associated with the adoption of

Jasmine-85 and Digang varieties. Households employing these technologies achieved superior outcomes in CDD compared to non-adopters, both within the selected study group and across the entire population of rice-farming households in the Northern Region. The study's findings underscore the critical role of these improved varietal technologies in advancing dietary diversity metrics, thereby contributing to broader food security and nutritional goals.

Despite the evident benefits of adopting enhanced varietal seed technologies, the study identified six primary constraints that hinder their widespread adoption among rice-farming households in the study districts. These include the high cost of inputs, limited access to credit facilities, the absence of clear governmental policies and incentives to support adoption, an inadequate market for locally produced rice, lower access to extension services, and limited access to agricultural machinery. Among these, high input costs emerged as the most significant barrier, reflecting broader structural and financial challenges faced by farmers. Conversely, less critical constraints included theft, difficulties in acquiring seeds, human epidemics and illnesses such as the COVID-19 pandemic, land tenure issues, and a shortage of skilled labour.

The overarching conclusion of the study aligns with the broadly held view that the adoption of improved rice varieties is a cornerstone for enhancing productivity, food security, and income generation among rice farmers in Ghana and other developing economies. The observed positive impacts on productivity, income, and food security metrics underscore the transformative potential of these technologies. These findings reinforce the necessity of prioritizing policies and interventions that support the adoption of improved rice varietal seed technologies. Specifically, addressing the key constraints identified in the study is critical to enabling broader adoption and ensuring the sustainability of these benefits.

The study's results further emphasize the importance of government support in fostering an enabling environment for the adoption of enhanced varietal technologies. Increased investment in agricultural extension services, provision of financial incentives, and development of markets for local rice are crucial to addressing the barriers faced by farmers. Such efforts would not only enhance the adoption rates of improved rice varieties but also contribute to the broader goals of agricultural transformation, poverty reduction, and food security in Ghana.

In conclusion, the study provides robust evidence supporting the adoption of improve rice varietal seed technologies as a viable strategy for addressing productivity and food security challenges among rice-farming households. The findings highlight the multifaceted benefits of these technologies, while also underscoring the need for targeted interventions to address the systemic constraints impeding their adoption. By fostering a supportive policy and institutional environment, stakeholders can unlock the full potential of these technologies to drive sustainable agricultural development and improve the livelihoods of rural households.

5.4 Policy Recommendations

The study strongly advocates for targeted government interventions through the Ministry Of Food and Agriculture (MOFA) and other agricultural development organizations to address farm-specific and institutional determinants that influence the adoption of varietal seed technologies by rice-farming households. These interventions should aim to build upon the positive trends in varietal seed adoption, thereby fostering improvements in rice productivity across the Northern Region and beyond. Enhanced focus on these factors will ensure a more systematic promotion of technological adoption tailored to the specific needs and conditions of rice-farming households.

Expanding access to extension services is paramount, as these services play a critical role in equipping rice-farming households with the requisite knowledge to make informed production decisions. To this end, the grain development division of MOFA should prioritize increasing the number of extension agents dedicated to rice production in each district. This expansion should be accompanied by intensive capacity-building initiatives to equip extension agents with the skills to provide both technical and educational support. Extension officers must focus on disseminating improved rice farming techniques and the importance of Farmer-Based Organization (FBO) membership. Their role as educational facilitators is critical in bridging knowledge gaps, enabling farming households to adopt better management practices that optimize productivity and income.

The study underscores the need for extension agents and stakeholders to intensify efforts in sensitizing rice-farming households about the benefits of adopting technologies that enhance productivity and income. Specifically, MOFA extension agents should actively support farmers in the appropriate application of recommended quantities of improved varietal seeds and complementary inputs. Empirical evidence from this study suggests that such practices significantly bolster productivity, annual household incomes, and food security outcomes for farming households. Strategic capacity-building and demonstration programs can enhance farmers' understanding of these technologies, ensuring their effective application.

Encouraging membership in self-help groups and FBOs is a pivotal recommendation derived from the findings. Membership in these organizations provides access to essential resources, including technical support, credit facilities, and pooled resources, which are instrumental in facilitating the acquisition of improved seeds and inputs. The positive association between FBO membership and improved adoption rates of enhanced varietal technologies highlights the critical role of collective action in overcoming adoption barriers.

Rice-farming households must also be incentivized to scale up their production levels by adopting productivity-enhancing methods. This involves the integration of effective management practices designed to optimize resource utilization and achieve higher yields. The study emphasizes the importance of

continuous engagement with crop research institutes and development organizations to create and disseminate varietal seed technologies aligned with national agricultural development initiatives. These institutions should focus on developing adaptive seed varieties that address the unique agro-ecological challenges faced by rice farmers, thereby enhancing resilience and productivity.

The persistent challenges faced by rice farmers in adopting advanced agricultural technologies require robust policy measures to mitigate these barriers. MOFA should implement targeted policies aimed at improving access to critical assets, including financial capital, markets, extension services, farm machinery, and infrastructure. Promising policy initiatives could encompass subsidized credit schemes, investment in rural market infrastructure, and the establishment of mechanization centres to ensure the availability and affordability of farm machinery. Such measures are instrumental in fostering an enabling environment that supports the widespread adoption of improved varietal seed technologies.

Additionally, the study highlights the necessity for integrated policy frameworks that address both price and non-price constraints. Financial incentives, coupled with improved market access and enhanced service delivery mechanisms, can significantly influence adoption rates. Policymakers must also consider the socio-economic diversity among farming households to tailor interventions that are inclusive and equitable. Strengthening institutional frameworks to streamline the provision of extension services and ensuring the alignment of agricultural policies with farmer needs are critical steps in this direction.

Ultimately, the study affirms that the adoption of enhanced varietal seed technologies holds transformative potential for rice farming in Ghana. By addressing the multifaceted barriers to adoption, government and institutional stakeholders can unlock the full potential of these technologies, contributing to sustainable agricultural development and improved livelihoods for rice-farming households.

5.5 The Study's Contributions to Knowledge

This study contributes significantly to the discourse on agricultural technology adoption by providing a nuanced understanding of the direct impact of improved rice varietal seed adoption on both productivity and household welfare in Northern Ghana. Through a region-specific lens, it offers critical insights into how rice farmers in this area engage with modern agricultural practices, thereby contributing to the broader conversation about technology adoption in low-income, developing economies.

The study's primary contribution lies in its examination of the specific factors that influence the adoption of rice varietal seed technology in Northern Ghana. By focusing on the socio-economic, institutional, and environmental characteristics unique to the region, it provides empirical evidence that helps identify the barriers and facilitators to the widespread use of improved seed varieties. These findings fill a crucial gap in the literature by offering context-specific data that are often absent in studies that generalize adoption

trends across diverse regions. This regional specificity enhances the relevance and applicability of the study's results to the particular challenges faced by farmers in Northern Ghana, such as inconsistent rainfall, limited access to inputs, and insufficient extension services (Adams & Smith, 2019; Owusu et al., 2020).

Additionally, the study highlights the key challenges impeding the adoption of improved rice seed technologies in the Northern Region, particularly the high costs of seed and the inadequacy of support systems, such as extension services and access to credit. These challenges are critical determinants of the extent to which technology adoption can occur, and the study provides empirical evidence to support this assertion. By identifying these constraints, the research calls attention to the pressing need for policy interventions that address these barriers, particularly through mechanisms that can reduce the cost of inputs, enhance the accessibility of support services, and ensure the long-term sustainability of rice production in the region (Ali et al., 2020a).

One of the study's notable contributions is its provision of valuable context-specific evidence that can guide policy formulation and inform the design of interventions tailored to the needs of rice farmers in the Northern Region of Ghana. Given the region's unique agricultural challenges and its significance to the national economy, the study offers a critical foundation for developing targeted interventions that can effectively increase rice productivity and improve household welfare. For example, findings regarding the challenges related to seed costs and limited support systems suggest that government policies should prioritize initiatives aimed at reducing seed costs, improving access to financing, and enhancing the reach of agricultural extension services (Nyantakyi-Frimpong et al., 2019). Moreover, by contextualizing the findings within the specific socio-economic environment of Northern Ghana, the study provides an evidence-based framework for designing regionally tailored programs that can lead to better adoption outcomes and higher agricultural productivity.

Furthermore, the study's contribution extends beyond the immediate context of Northern Ghana. By demonstrating the impact of improved seed adoption on agricultural productivity and household welfare, it offers a model for similar regions facing analogous challenges. The findings can inform broader policy discussions on the adoption of agricultural technologies in sub-Saharan Africa, where many farmers still rely on traditional seed varieties. This study thus enriches the literature on agricultural innovation, adoption, and development by providing an empirical example of how region-specific factors influence the outcomes of technology adoption in a rural African context (Asare et al., 2020; Essilfie, 2018).

In summary, this study's contribution is twofold: it offers in-depth, region-specific insights into the factors that influence the adoption of rice varietal seed technology and its outcomes on productivity and welfare, and it identifies the key barriers that hinder technology uptake. The study's findings provide a foundation for designing targeted policy interventions aimed at improving adoption rates, which, in turn, can enhance

agricultural productivity and household welfare in Northern Ghana. By situating these findings within the broader discourse on agricultural technology adoption, the study provides valuable evidence that can inform both local and national policy decisions, with implications for other regions facing similar challenges.

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APPENDICES

APPENDIX I: Household Questionnaire

Rice Varietal Seed Technology Adoption on Improving Productivity and Household Welfare, Northern Region, Ghana

PhD Applied Agricultural Economics and Policy
Department of Agricultural Economics and Agribusiness, University of Ghana, Legon.

CONSENT FORM

This study aims to understand how varietal seed technologies can enhance productivity and household welfare in Ghana. This study will particularly look at the role of varietal seed in improving productivity and household welfare in rice production in the Northern Region of Ghana. The study is being conducted by a student from the Department of Agricultural Economics and Agribusiness at the University of Ghana, in partial fulfillment for the award of a PhD degree in Applied Agricultural Economics and Policy.

We kindly ask for your support by responding to the questions as honestly and fully as possible. This is not an assessment of your efforts and there are no right or wrong answers. We just would want to know your actual practices and the challenges you face in order to understand how we can improve the technologies and services we develop and promote. We are also not part of any scheme, program or project, so your answers will not affect in any way with your relationships with your aggregators, creditors or input dealers. Your answers will be extremely important for our breeders and agronomists who make sure that they develop varieties and agricultural management practices that solve your constraints and technological challenges. Your responses are very useful to this study and will be KEPT STRICTLY CONFIDENTIAL. Your responses will be summarized along with other 600 farmers in the Northern Region of Ghana.

If you have questions about this survey, you may contact the PhD candidate's Supervisory Team Lead, Prof. Daniel Bruce Sarpong at dbsarpong@ug.edu.gh or by phone at 0244737745, or Mr. Felix Larry Essilfie, the PhD candidate, at flessilfie@st.ug.edu.gh or by phone at 0243179345. You can ask questions concerning the study, both before agreeing to be involved and during the course of the interview.

Do you indicate your voluntary consent to participate in this interview: may we begin? _____

NOTE: This is the paper-based version of the questionnaire. This is modified and programmed to a computer-assisted and mobile-based interviewing. This Module is a farm household-level questionnaire and is to be administered to household head, spouse or jointly, or any knowledgeable member about rice production activities of the household. This questionnaire is complemented by a consent form that needs to be read to the respondents before starting the interview and a detailed study manual for enumerators.

Contents

MODULE I. HOUSEHOLD-LEVEL QUESTIONNAIRE

[Enum: To be administered to single or two members in the household who are most knowledgeable about the household's rice production activities]

SECTION A. HOUSEHOLD IDENTIFICATION

Questions to be answered by enumerator		**Answer**	**Codes**
A1. What sampling group does the HH belong to?			1=AGRA Growers, 2=Jasmine 85 Growers, 3=Digang Growers, 4=Traditional Variety Growers
A2. GPS coordinates of homestead:			
A3. Respondent's status			1=Consented to interview 2=Refusal (replaced) 3= Non-contact (replaced); 4=Replacement household
A4. Name of Enumerator:		A5. Date of Interview:	/ / 2021
A6. Village (see code)		A7. District (see code)	
A8. Region (see code)			
A9. Start time of Interview:		A10. End time of Interview:	
Questions to be answered by respondents *(this questionnaire can be answered by HH head, spouse or jointly, or any member/s knowledgeable about rice production)*		**Answer**	**Codes**
A10. Respondent 1 Name			
A11. Respondent tel. number			
A12. What is the respondent 1's gender?			1=Male, 0=Female
A13. Relationship with household head?			1= HH head, 2=spouse, 3=child, 4=Other (specify)
A14. Respondent 2 Name			
A15. Respondent 2 tel. number			
A16. What is the respondent 2's gender?			1=Male, 0=Female
A17. Relationship with household head?			1= HH head, 2=spouse, 3=child, 4=Other (specify)
Questionnaire checked by supervisor:		Name of supervisor:	

SECTION B. HOUSEHOLD SOCIO-ECONOMIC CHARACTERISTICS

Table BA. Please list the HH head, the spouse/s and all other **ADULT** HH members who are **16 years and older** (from oldest to youngest) (*HH members = people who live, sleep and eat in the household as well as people who lived, slept and are in the household for at least 6 months for at least 3 days a week in the past year)*

B1.	B2.	B3.	B4.	B5.	B6	B7	B8	B9.	B10.
HH member	**Name**	**Age**	**Gender**	**Relation to HH head**	**Marital status**	**What is the highest level of schooling [NAME] has attended?**	**Can [NAME] read or write in English?**	**Primary Occupation/Type of Work**	**Secondary Occupation/ Type of Work**
ID Code		In years	0 = male 1 = female	RELATE CODE	1 = Married/ consensual union 2 = Single 3 = Separated 4 = Divorced 5 = Widowed	EDUCATION CODE	1 = Cannot read and write 2 = Can write only 3 = Can read only 4 = Can read and write	OCCUPATION CODE	OCCUPATION CODE
1									
2									
3									
4									
5									
6									
7									
8									
9									
10									

RELATE CODE: 1 = HH head / 2 = Spouse / 3 = child (including in-law) / 4 = Brother or sister (and in-law) / 5 = Father or mother (and in-law) / 6 = Niece or nephew (and in-law) / 7 = Cousin (and in-law)/ 8 = Grandchild / 9= Other (specify)

SCHOOL CODE: 1 = No schooling / 2 = Primary school / 3 = Junior Secondary School / 4 = Senior Secondary School / 5 = Polytechnic / 6 = Undergraduate / 7 = Postgraduate / 8 = Doctorate Degree / 9 = Other (specify)

OCCUPATION CODE: 1 = None / 2 = Rice farming / 3 = Farming other crops / 4 = Agro-processing / 5 = Trading or aggregation of crops / 6 = Paid employment on other HH's farm / 7 = Paid employment off-farm (civil service, private INSTpany) / 8= Self-employed or business ventures / 9 = others (specify)

Table BB. How many children are living in the household?

	B11.	B12.
Age group	**Female**	**Male**
Age 0-5		
Age 6-15		

B13. Since when has the HH head lived in this village? 1=Since_____ (year) 2=Since birth **>>> *skip to B15.***

B14. Where is the HH head originally from? _____ (district) _____ (region) _____ (country)

B15. What is main ethnicity within the HH? _____

1=Akan; 2= Dagao (Dagarti); 3=Ewe; 4=Ga-Adangbe; 5=Guan; 6 = Gurma; 7=Mole-Dagbane; 7 = Sissaala; 8= Waala; 9= Other _____(specify)

B16. What is the main religion in the HH? 1=Christian-Protestant (incl. Methodist, Anglican and Baptist) 2=Christian-Catholic 3=Christian-Pentecostal 4=Seven Day Adventist 5=Muslim 6=Traditional 7=Other _____(specify)

B17. Did you or any household member ever held a political office? 1=Yes 0=No

B18. Did you or any household member ever held a traditional office (paramount chief, sub-chief, queen mother, family head, Tendana, other)? 1=Yes 0=No

B19. Do you or any household member has relatives that held a political office? 1=Yes 0=No

B20. Do you or any household member has relatives that held a traditional office (paramount chief, sub-chief, queen mother, family head, Tendana, other)? 1=Yes 0=No

SECTION C: KNOWLEDGE ABOUT RICE VARIETIES

Table C. Please list all the varieties of rice that you know of (either you planted in the past or have heard about from others) ***[Enum: Make sure the main rice grower or the manager of the rice plots under consideration will answer this question. List all varieties they mention, then ask questions for each variety.]***

ID	Variety (see VARIETY CODE)	How long you have known them (number of years)	Did you ever plant them? 1=Yes, 0=No	If C3=1, what years did you grow this variety?		If C3=0 or C5 is not present, main reason for not growing it or not growing it anymore (see REASON CODE)
				Year started growing	Year ended growing (if still growing, please indicate "present")	
	C1.	C2.	C3.	C4.	C5.	C6.
1						
2						
3						
4						
5						
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19						
20						

VARIETY CODE: 1=AGRA rice; 2= JASMINE 85 (SAR-RICE 2; Gbewaa; Lapez); 3= DIGANG (also called Abirikukuo or Aberikukugo); 4=NERICA 1; 5=NERICA 2; 6= NABOGO RICE; 7= KATANGA RICE; 8= OTOOMU (TOX 3377); 9= GRUG7; 10= EMO TEAA (IDSA85); 11=Marshall (Amankwatia); 12=Wakatsuki (Bouake 189); 13= Bodia (ITA-320); 14= Sakai (ITA-324); 15=FARO 15; 16=GR 17 (IET 2885); 17=GR 18 (Afife); 18=GRUG7; 19=GR 19 (C168); 20=GR 20 (IR 1750-F5-B5) SR; 21= GR 21 (TOX 515-19-SLR); 22= TOX 3108 (Sikamo; GR 22); 23=indigenous/local/traditional; 24=do not know; 25=Other (specify)

REASON CODE: 1=low yield performance; 2=not drought resistant; 3=has some characteristics that I do not like; 4=difficult to get seed or do not know where to find seed; 5=expensive seed; 6=do not know much about it; 7=I am waiting for my neighbors or other farmers to try it first before I try it; 8=poor germination; 9=other (specify)

C7. Did you grow more than one variety in the last 3 years? Yes = 1; No = 0 (If No, go to C.9)

C8. If you grew more than one variety in the last 3 years, what was the most important reason for doing so? _____ (MULTIPLE CODE)

MULTIPLE CODE: 1 = to experiment with or tray a new variety / 2 = Could not obtain enough seeds of just one variety / 3 = Learnt that better varieties are available / 4 = the new variety was given to me for free or as a gift / 5 = the cost of seed of the previous variety was too expensive / 6 = the seed of the previous variety was of poor quality / 7 = the previous variety gave a poor

yield / 8 = the previous variety was susceptible to disease / 9 = the previous variety was not resistant to flood / 10 = the previous variety was not resistant to drought / 11 = the previous variety spoiled easily when stored / 12 = minimize risk by growing multiple varieties / 13 = Other (specify)

C9. In the past 5 years, were there field trials or farm demonstrations of rice in your area or that you have participated in or observed? Yes = 1 No = 0 **>>>** ***if No, proceed to C11***

C10. Kindly describe the farm demos or field trials you are aware of or that you have participated in in the past 10 years.

Trial	Year	Plot area	Plot area unit	What technologies or management practices were tested? (see TECHNOLOGY CODE)			Name all rice varieties used (see VARIETY CODE)				
			(see AREA UNIT CODE)	***[Enum: Do not read out choices; choose the one closest to respondents' description, if not, choose "other" and specify]***			***[Enum: Do not read out choices; make sure to have least 2 varieties per trial (at least 1 treatment and 1 control)]***				
				Tech. 1	Tech. 2	Tech. 3	Var. 1	Var. 2	Var. 3	Var. 4	Var. 5
1											
2											
3											
4											
5											
6											
7											
8											
9											
10											

AREA UNIT CODE**:** 1=Acres; 2=Hectares; 3=Poles; 4=Rope; 5=Arm stretch; 6=Square meters; 7=Square yards; 8=Square feet; 9=Others (specify)

VARIETY CODE: 1=AGRA rice; 2= JASMINE 85 (SAR-RICE 2; Gbewaa; Lapez); 3= DIGANG (also called Abirikukuo or Aberikukugo); 4=NERICA 1; 5=NERICA 2; 6= NABOGO RICE; 7= KATANGA RICE; 8= OTOOMU (TOX 3377); 9= GRUG7; 10= EMO TEAA (IDSA85); 11=Marshall (Amankwatia); 12=Wakatsuki (Bouake 189); 13= Bodia (ITA-320); 14= Sakai (ITA-324); 15=FARO 15; 16=GR 17 (IET 2885); 17=GR 18 (Afife); 18=GRUG7; 19=GR 19 (C168); 20=GR 20 (IR 1750-F5-B5) SR; 21= GR 21 (TOX 515-19-SLR); 22= TOX 3108 (Sikamo; GR 22); 23=indigenous/local/traditional; 24=do not know; 25=Other (specify)

TECHNOLOGY CODE: 1=crop rotation; 2=minimum tillage; 3=zero tillage; 4=conservation agriculture; 5=organic farming; 6=fertilizer use; 7= burying of fertilizer; 8=intercropping with leguminous crops; 9=integrated soil fertility management; 10=new variety; 11=row planting; 12=pest management; 13=weed management; 14=other (specify)_____

C11. What do you know about "hybrid seed" or "hybrid rice"? Please tell us things you have heard or know about hybrid rice. ***[Enum: Do not read out choices. Choose the codes closest to the responses. Check all that applies]***

1. _____
2. _____

3. _____

HYBRID CODE: 1=high yield; 2=cannot be recycled or reused for next season (or if it is recycled, yield will be very low); 3=rich in nutrients; 4=expensive; 5= harmful to the environment; 6= [Enum: if 2 is selected, proceed to C15]

C12. Can you reuse the seed of hybrid rice for next season or next year's planting? Yes = 1; No = 0

C13. Are hybrid rice varieties harmful to the environment (soil, other crops, animals or humans)? Yes = 1; No = 0

C14. When did you first hear about hybrid rice? _____ (number of years ago)

C15. From whom did you learn about hybrid rice? _____ (SOURCE OF INFORMATION CODE)

SOURCE OF INFORMATION CODE: 1=lead farmer or model farmer in the village; 2=another farmer/relative/friend, 3=farmer organization or association, 4= aggregator, 5=MoFA extension agent; 6=input or seed dealer, 7=grain market, 8=radio; 9=TV ; 10=newspaper; 11=Masara scheme; 12=other outgrower schemes; 13=ADVANCE project; 14=other projects/programs; 15=other (specify _____))

C16. Of the varieties you know of or have planted in the plant, please identify which ones are hybrid rice? [check all that applies IN Table C] [***Enum: CAPI to show filled out Table C]***

SECTION D. RICE PLOTS

Table DA. Please list all the plots on which you grew rice in 2020 or 2021 (from largest to smallest plot). ***[Enum: Plot=parcel of land in a given location. Plots may be subdivided into distinct sections, distinguishable by different crops, varieties, inputs, and management practices. If there are distinct sections in a plot, please record them separately]***

	2020												2019									
ID	Plot area	Plot area unit (see code)	Rice on this plot? 1=Yes 2=No (If No go to D.13)	Is this inter-cropped? 1=Yes 2=No	If D4=1 (intercropped), please estimate % of plot size allotted for rice	Number of varieties planted in this plot/ section	Main rice varieties planted (see VARIETY CODE)		Color (see COLOR CODE)		Is this plot/ section under a project, program or scheme? 1=Yes, 0=No	If D11=1, what program, project or scheme? (see SCHEME CODE)	Rice on this plot? 1=Yes 2=No (If not >> next line)	Was this inter-cropped? 1=Yes 2=No	If D14=1, estimate % of plot size allotted for rice	Number of varieties planted in this plot/ section	Main rice varieties planted (see variety code)		Color (see COLOR CODE)		Was this plot/ section under a project, program scheme? (1=Yes, 0=No)	If D21=1, what program, project or scheme? (see scheme code)
							1	2	1	2							1	2	1	2		
	D1.	D2.	D3.	D4.	D5.	D6.	D7.	D8	D9	D10	D11.	D12.	D13.	D14.	D15.	D16.	D17	D18	D19	D20	D21.	D22.
1																						
2																						
3																						
4																						
5																						
6																						
7																						
8																						
9																						
10																						

AREA UNIT CODE: 1=Acres; 2=Hectares; 3=Poles; 4=Rope; 5=Arm stretch; 6=Square meters; 7=Square yards; 8=Square feet; 9=Others (specify)

COLOR CODE: 1=White; 2=Brown

VARIETY CODE: 1=AGRA rice; 2= JASMINE 85 (SAR-RICE 2; Gbewaa; Lapez); 3= DIGANG (also called Abirikukuo or Aberikukugo); 4=NERICA 1; 5=NERICA 2; 6= NABOGO RICE; 7= KATANGA RICE; 8= OTOOMU (TOX 3377); 9= GRUG7; 10= EMO TEAA (IDSA85); 11=Marshall (Amankwatia); 12=Wakatsuki (Bouake 189); 13= Bodia (ITA-320); 14= Sakai (ITA-324); 15=FARO 15; 16=GR 17 (IET 2885); 17=GR 18 (Afife); 18=GRUG7; 19=GR 19 (C168); 20=GR 20 (IR 1750-F5-B5) SR; 21= GR 21 (TOX 515-19-SLR); 22= TOX 3108 (Sikamo; GR 22); 23=indigenous/local/traditional; 24=do not know; 25=Other (specify)

SCHEME CODE: 1=Masara, 2=nucleus farmer or aggregator (specify name), 3=input or seed dealer (specify name), 4=Bank or financial institution (specify name), 5=project (specify name); 6=Other (specify)

Table DB. Please describe the source of information and seed for all rice plots/sections in 2020 and 2019.

Plot/ section ID	2020								2019						
	Is this for seed or for grain? (1=seed, 2=grain)	% of harvest that is sold?	Main rice variety planted **[Enum: copy]**	Where did you learn about this variety? (SOURCE OF INFORMATION CODE)	Where did you acquire the seed? (SOURCE OF SEED CODE)	If D27=1		Will you plant the same variety in the next season? 1=Yes, 0=No	Was this for seed or for grain? (1=seed, 2=grain)	% of harvest that was sold?	Main rice variety planted **[Enum: copy]**	Where did you learn about this variety? (SOURCE OF INFORMATION CODE)	Where did you acquire the seed? (SOURCE OF SEED CODE)	If D35=1	
						How many years have you been reusing it?	Where did you originally acquire the seed? (SOURCE OF SEED CODE)							How many years have you been reusing it?	Where did you originally acquire the seed? (SOURCE OF SEED CODE)
	D23.	D24.	D25.	D26.	D27.	D28.	D29.	D30.	D31.	D32.	D33.	D34.	D35.	D36.	D37.
1															
2															
3															
4															
5															
6															
7															
8															
9															
10															

SOURCE OF INFORMATION CODE: 1=Masara Outgrower; 2=Outgrower of Akati; 3=Outgrower of Dori; 4=Outgrower (do not know the scheme); 5=another farmer (not Outgrower), 6=farmer organization or association, 7=nucleus farmer/aggregator, 8=project/program officers/agents, 9=MoFA extension agent; 10=input or seed dealer, 11=grain market, 12=radio; 13=TV ; 14=newspaper; 15=other (specify _____)

SOURCE OF SEED CODE : 1=saved seeds from last season's harvest, 2=another farmer, 3=farmer organization or association, 4=nucleus farmer/aggregator, 5=project/program officers, agents, 6=MoFA extension agent; 7=input or seed dealer, 8=grain market, 9=other (specify _____)

D38. Compared to the total rice area cultivated now, what was the land area cultivated under rice five years ago? _____ Unit? ____

AREA UNIT CODE: 1=Acres; 2=Hectares; 3=Poles; 4=Rope; 5=Arm stretch; 6=Square meters; 7=Square yards; 8=Square feet; 9=Others (specify)

D39. Did you have enough land for growing rice in 2019? Yes=1; No=0

D40. Did you have enough land for growing rice in 2020? Yes=1; No=0

D41. If you would like to expand your rice farm for the next season, how easily can you find land to do so? 1=very easy, 2=easy; 3=difficult, 4=very difficult

SECTION E: PLOT-LEVEL INFORMATION

[Enum: please choose 1 largest rice plot or distinct section under scheme and 1 largest non-scheme rice plot or distinct section in 2020; if no plot or distinct section under scheme, choose 1 largest with hybrid rice and 1 largest non-hybrid rice plot or distinct section in 2020; if no plot or distinct section under scheme or with hybrid rice, choose 2 largest plots or distinct sections in 2020. Plots for 2019 are the same as plots for 2020]

Table EA. Please tell me who manages or make decisions about these rice plots.

	First plot		Second plot	
	2020	2019	2020	2019
Plot ID (copy plot ID from section D) **(CAPI programming)**				
E1. Who manages and decides on production and input use for this plot? (see HH member code)				
E2. Number of years in farming ***[Enum: Ask also for 2019 if plot manager is different]***				
E3. Number of years in rice production ***[Enum: Ask also for 2019 if plot manager is different]***				

Table EB. Please describe the plot characteristics.

	First plot	Second plot
Plot ID (copy plot ID from section D) **(CAPI programming)**		
GPS coordinates (CAPI – will be entered later)		
Size of plot based on GPS device measurements (CAPI – will be entered later)		
E4. Minutes from home to plot (*walking)*		
E5. Minutes from field to nearest motorable road (walking)		
E6. Minutes from field to nearest tarred road (walking)		
E7. When was the plot acquired? (year)		
E8. Who in the household acquired this plot? (see HH member code)		
E9. How was this plot acquired? (see land code)		
E10. What type of ownership document do you (or any member of your household) have for this land? (1=none; 2=registered deed; 3=unregistered deed; 4=invoice or sales; 5=indenture; 6=Other (specify)		
E11. In the last 5 years, was there any dispute or conflict on this plot? [1=Yes; 0=No)		
E12. How long do you think you could leave the land alone (i.e. fallow) without the risk of losing it? (In number of years)		
E13. What are the things that you are doing to ensure that you do not lose the land (ask all, check all the applies) (SECURITY CODE)		
E14. Before 2020, how many years this entire plot has been fallowed in the last 10 years? *(number)*		
E15.a Which year did the last fallow start?		
E15.b Which year did the last fallow end?		
E16. What is the previous year's crop (in 2019)? [See CROP CODE]		
E17. Before you had applied fertilizer, how would you rate the inherent soil fertility in this plot? from 1 to 5, 1=not fertile and 5=very fertile		
E18. Slope (1=flat, 2=gentle, 3=steep, 4=undulating, 888=do not know) (show illustration)		
E19. % of plot area that is considered steep?		
E20. Is waterlogging a problem? 1=YES 0=NO (If no >>> E22)		
E21. % of plot area where waterlogging is a problem?		
E22. Is erosion a problem? 1=YES 0=NO (If no >>> E.24)		
E23. % of plot area where erosion is a problem?		
E24. Source of water? (1=permanent stream, 2=dugout /tubewell, 3=irrigation scheme, 4=water reservoir, 5=direct rain, 6=from homestead for water of spraying; 7=other)		

LAND CODE: 1=Inherited land;2 = Outright purchase; 3=Given free from chief (allocated skin land or community land) 4=Given free by relatives (allocated family land); 5= Given free by government (allocated government land); 6=rented (with rental fee); 7=borrowed (for free use); 8=Sharecropping agreement with landowner; 9=just walked in (e.g., cleared virgin land); 10=Other (specify)_____

SECURITY CODE

1=Stumping the land

2=Do not leave land under fallow

3=Give a share of harvest to chief/village authorities

4=Improved boundary demarcations

4=Others (specify_____)

CROP CODE

FIELD CROPS

1=Bambara beans	11=Kenaf	21=Sugarcane	31=Coconut	41=Plantain	51=Cabbage	61=Pepper (black)
2=Cassava	12=Rice	22 =Sweet potato	32=Coffee	42=Rubber	52=Carrots	62=Pepper (sweet)
3=Citronella	13=Millet	23=Tobacco	33=Cola	43=Shea-nut	53=Cucumber	63=Pumpkin leaves
4=Cocoyam/Taro	14=Pepper (hot)	24=Watermelon	34=Lime	44=Sweet berry	54=Garden eggs	64=Shallots
5=Cotton	15=Pigeon peas	25=Yam	35=Mango	45=Dawadawa	55=Groundnuts, fresh	65=Talinum leaves
6=Cowpeas	16=Pumpkin	26=potato	36=Nutmeg	46=Neem	56=Lettuce	66=Tomato
7=Flowers	17=Rice	**TREES**	37=Oil-palm	47=Fig	57=Rice, fresh	67=Yellow melon
8=Ginger	18=Sisal	27=Avocado	38=Oranges	48=Kapok	58=Melon (agusi)	68=Henna
9=Groundnuts	19=Sorghum	28=Banana	39=Paw-paw	49=Acacia	59=Okra	69=Hibiscus
10=Jute	20=Soyabean	29=Cashew	40=Pineapples	**VEGETABLES**	60=Onions	70=Other crops (specify
		30=Cocoa		50=Asian vegetables		

SECTION F. LAND PREPARATION AND PLANTING PRACTICES

Please tell me about your land preparation and planting practices.

	Fist plot (section)		Second plot	
	2020	2019	2020	2019
Plot ID (CAPI copy plot ID) (CAPI programming)				
F1. What are the land preparation practices for this plot? (choose all that applies) (see PREPARATION CODE) ***[Enum: please read all choices to respondents]***				
F2. When you needed tractor or power tiller, did you have it the time you needed it? 1=Yes 0=No				
F3. If no, how many days did you have to wait?				
F4. What land management practices were adopted in to this plot? [check all that applies] (see MANAGEMENT CODE)				
F5. Did you use or retain vegetative cover, crop residue or mulch (green manuring)? 1=YES, 0=NO				
F6. Did you plant in rows or line? 1=YES, 0=NO				
F7. How many seeds planted per hole?				
F8. Did you practice crop relay or planted cover crop (such as mucuna)? 1=YES, 0=NO				
F9. Did you grow other crops (such as vegetables) during dry season? 1=Yes 0=No (If no >>> to F.11)				
F10. What crop/s were planted during dry season? (see CROP CODE) (check all the applies)				

PREPARATION CODE
1=Slash&burn
2=Herbicide application
3=Ploughing with power tiller or tractor
4=Ploughing with ox
5=Tilling land with hoe
6=Harrowing
7=Zero tillage (no disturbance of the soil)
8=Minimum tillage (little disburbance of the soil)
9=Other (specify)_____

MANAGEMENT CODE
1=Ridging
2=Mounding
3=Bunding
4=Pit planting
5=Flat (no ridges, no mounds, no pits)
6=Other (specify)_____

SECTION G. INPUT USE AND COST

Table GA. How much inputs were used and how much were the costs per acre of this plot? ***[Enum: Record ACTUAL quantity of input applied and actual payment (in cash or in-kind). Record in acre. For Column B (COST), if payment was done in-kind (e.g., bag of grain harvested), estimate value using actual output price received. If inputs are bundled (cannot estimate cost per input), please record the quantity and unit, and write "B" under cost, then proceed to G2 after filling out G1.]***

	First plot					First plot				
	2020					2019				
	Quantity	**Unit (UNIT CODE)**	**Cost per unit (cedi)** ***[Enum: Write B if input is bundled, and record terms of repayment in G2]***	**Total cost PER ACRE (cedi)**	**Did you receive part or all of this on credit? Yes = 1 No = 0**	**Quantity**	**Unit**	**Cost per unit (cedi)** ***[Enum: Write B if input is bundled, and record terms of repayment in G2]***	**Total cost PER ACRE (cedi)**	**Did you receive part or all of this on credit? Yes = 1 No = 0**
	A		**B**	**A x B**		**A**		**B**	**A x B**	
Plot ID (copy from section D) CAPI										
Seed										
- Subsidized seed										
- Commercial										
- Seed provided by scheme										
Fertilizer application 1 (specify type _____) (see code)										
- Subsidized fertilizer										
- Commercial										
- Fertilizer provided by scheme										
Fertilizer application 2 (specify type _____) (see code)										
- Subsidized fertilizer										
- Commercial										
- Fertilizer provided by scheme										
Fertilizer application 3 (specify type _____) (see code)										
- Subsidized fertilizer										
- Commercial										
- Fertilizer provided by scheme										
Herbicide										
- Commercial										
- Herbicide provided by scheme										
Pesticide/insecticide										
Manure										
Land rental (including payment for sharecropping)										
Materials (sacks, others)										
- Commercial										
- Provided by scheme										

Rental of power tiller/tractor/animal traction										
- Commercial										
- Provided by scheme										
Rental for transportation from plot to home										
Rental for transportation from home to market										
Other marketing costs (trader, market tax, loading of shelled rice into trucks, etc.)										
Shelling/milling										
- Commercial										
- Herbicide provided by scheme										

Fertilizer code: 1=NPK15-15-14; 2=NPK20-20-20; 3=Sulphate of ammonia; 4=Urea; 5=Sulfan; 6=Foliar; 7=Winner; 8=Actyva 9=Others (specify)

	Second plot					**Second plot**				
	2020					**2019**				
	Quantity	**Unit (UNIT CODE)**	**Cost per unit (cedi)** ***[Enum: Write B if input is bundled, and record terms of repayment in G2]***	**Total cost PER ACRE (cedi)**	**Did you receive part or all of this on credit? Yes = 1 No = 0**	**Quantity**	**Unit**	**Cost per unit (cedi)** ***[Enum: Write B if input is bundled, and record terms of repayment in G2]***	**Total cost PER ACRE (cedi)**	**Did you receive part or all of this on credit? Yes = 1 No = 0**
	A		**B**	**A x B**		**A**		**B**	**A x B**	
Plot ID (copy from section D) CAPI										
Seed										
- Subsidized seed										
- Commercial										
- Seed provided by scheme										
Fertilizer application 1 (specify type) (see code)										
- Subsidized fertilizer										
- Commercial										
- Fertilizer provided by scheme										
Fertilizer application 2 (specify type _____) (see code)										
- Subsidized fertilizer										
- Commercial										
- Fertilizer provided by scheme										
Fertilizer application 3 (specify type _____) (see code)										
- Subsidized fertilizer										
- Commercial										
- Fertilizer provided by scheme										
Herbicide										
- Commercial										

- Herbicide provided by scheme										
Pesticide/insecticide										
Manure										
Land rental (including payment for sharecropping)										
Materials (sacks, others)										
- Commercial										
- Provided by scheme										
Rental of power tiller/tractor/animal traction										
- Commercial										
- Provided by scheme										
Rental for transportation from plot to home										
Rental for transportation from home to market										
Other marketing costs (trader, market tax, loading of shelled rice into trucks, etc.)										
Shelling/milling										
- Commercial										
- Herbicide provided by scheme										

Fertilizer code: 1=NPK15-15-14; 2=NPK20-20-20; 3=Sulphate of ammonia; 4=Urea; 5=Sulfan; 6=Foliar; 7=Winner; 8=Actyva 9=Others (specify)

G1. Did you received inputs in bundle and the required repayment is also in bundle (cannot separate cost for each input) on one of these two rice fields in 2020 or 2019? ____
1=Yes, 0=No (If No >>>> to Table GC)

Table GB. Which inputs were provided under scheme for these rice plots? ***[Enum: Only for rice plots in Table GA with inputs provided under scheme]***

	First plot				Second plot			
	2020		2019		2020		2019	
Plot ID (copy plot ID) CAPI								
[Enum: make sure that the inputs recorded here are only those that cannot be costed since they were provided in bundle]	Quantity	Unit (unit code)	Quantity	Unit (unit code)	Quantity	Unit (unit code)	Quantity	Unit (unit code)
G2. Seed								
G3. Fertilizer 1 (specify type _____) (see fertilizer code)								
G4. Fertilizer 2 (specify type _____) (see fertilizer code)								
G5. Fertilizer 3 (specify type _____) (see fertilizer code)								
G6. Herbicide								
G7. Others (specify) _____								
G8. What is the required repayment for this bundle of inputs?								

Fertilizer code: 1=NPK15-15-14; 2=NPK20-20-20; 3=Sulphate of ammonia; 4=Urea; 5=Sulfan; 6=Foliar; 7=Winner; 8=Actyva 9=Others (specify)

Unit code: 1=kg, 2=liter, 3=bottle, 4=gram, 5=50-kg bag of fertilizer; 6=50-kg bag of rice grain; 7=100-kg bag of rice grain, 8=other (specify)

Table GC. How did you experience access to inputs for your rice production in 2020 and 2019?

		2020						2019					
		Seeds	**Herbicides, pesticides**	**Mineral fertilizer**	**Manure**	**Tractor services**	**Labor**	**Seeds**	**Herbicides, pesticides**	**Mineral fertilizer**	**Manure**	**Tractor services**	**Labor**
G9.	Was the [input] available at the time you needed it? Yes= 1 ; No = 0												
G10.	Were you able to buy as much [input] you needed and could pay for? Yes= 1 ; No = 0												
G11.	Were you able to buy as little [input] as you wanted? Yes= 1 ; No = 0												
G12.	Were you able to buy the type of [input] you wanted? Yes= 1 ; No = 0												
G13.	How would you rate the quality of [input] available? 1. Good, no problem; 2. Some problems; 3. Poor, serious problems												

Table GD. Please rate how serious you experience constraints for your rice production concerning:

Constraint number	**Constraint**	**Is this a serious constraint for you?** (rate 1=not serious; 5=very serious)
GD1	Lack of clear government policies and incentives	
GD2	Inadequate market for local rice	
GD3	High cost of inputs	
GD4	Lack of access to credit	
GD5	Theft	
GD6	Inadequate access to extension services	
GD7	Difficulty in accessing seeds	
GD8	Lack of access to farm machinery	
GD9	Difficulty in accessing land (i.e., land tenure challenges)	
GD10	Skilled labour unavailability	
GD11	Human epidemic/disease (e.g., COVID-19)	

G14. From all the constraints mentioned above (table GD, can you name the six most pressing constraints (in order of importance)?

1.
2.
3.
4.
5.

SECTION H: HIRED LABOR

H1. Did you hire labor for your rice plots (= people paid in cash or in-kind) in 2020 or 2019? 1=YES, 0=NO **>>>>>>** ***If NO, proceed to SECTION I***

[Enum: Make sure to include family members that receive a payment in cash or in kind for their work on the farm. DO NOT include exchange labor]

[Enum: Values are total for this plot]	**First plot (2020)**					**First plot (2019)**				
	How many people did you hire?	How many days did those people take to Complete ___?	On average, how many hours did they work per day?	In total, how much did you pay to Complete this activity? (cedi) ***[Enum: if in-kind, ask respondent to estimate the value]***		How many people did you hire?	How many days did those people take to Complete ___?	On average, how many hours did they work per day?	In total, how much did you pay to Complete this activity?? (cedi) ***[Enum: if in-kind, ask respondent to estimate the value]***	
				Cash	In-kind				Cash	In-kind
	H2.	H3.	H4.	H5.	H6.	H7.	H8.	H9.	H10.	H11.
Plot ID (Copy from section D) CAPI										
Plot acreage (copy from section D and remind interviewee) CAPI										
Land preparation										
Planting										
Fertilizer applications										
Herbicide application										
Pesticide application										
Manure application										
Weeding										
Harvesting										
Transporting										
Drying and other postharvest activities										

[Enum: Values are total for this plot]	**Second plot (2020)**					**Second plot (2019)**				
	How many people did you hire?	How many days did those people take to Complete ___?	On average, how many hours they worked per day?	In total, how much did you pay to Complete this activity? (cedi) ***[Enum: if in-kind, ask respondent to estimate the value]***		How many people did you hire?	How many days did those people take to Complete ___?	On average, how many hours they worked per day?	In total, how much did you pay to Complete this activity? (cedi) ***[Enum: if in-kind, ask respondent to estimate the value]***	
				Cash	In-kind				Cash	In-kind
	H12.	H13.	H14.	H15.	H16.	H17.	H18.	H19.	H20.	H21.
Plot ID (Copy from section D) CAPI										
Plot acreage (copy from section D and remind interviewee) CAPI										
Land preparation										
Planting										
Fertilizer applications										
Herbicide application										
Pesticide application										

Manure application										
Weeding										
Harvesting										
Transporting										
Drying and other postharvest activities										

SECTION I: FAMILY LABOR

I1. Did you use (free) family labor for your rice plots in 2020 or 2019? 1=YES, 0=NO, ***>>>>if NO, proceed to SECTION J***

[Enum: Values are total for this plot]	**First plot (2020)**			**First plot (2019)**			**Second plot (2020)**			**Second plot (2019)**		
	How many people did you hire?	How many days did those people take to Complete ___?	On average, how many hours they worked per day?	How many people did you hire?	How many days did those people take to Complete ___?	On average, how many hours did they work per day?	How many people did you hire?	How many days did those people take to Complete ___?	On average, how many hours did they work per day?	How many people did you hire?	How many days did those people take to Complete ___?	On average, how many hours did they work per day?
	I2.	I3.	I4.	I5.	I6.	I7.	I8.	I9.	I10.	I11.	I12.	I13.
Plot ID (Copy from section D) CAPI												
Plot acreage (copy from section D and remind interviewee) CAPI												
Land preparation												
Planting												
Fertilizer applications												
Herbicide application												
Pesticide application												
Manure application												
Weeding												
Harvesting												
Transporting												
Drying and other postharvest activities												

SECTION J: COMMUNAL/EXCHANGE LABOR

J1. Did you use Communal/exchange labor for your rice plots in 2020 or 2019? 1=YES, 0=NO, ***>>>>If NO, proceed to SECTION K***

Enum: Values are total for this plot]	**First plot (2020)**	**First plot (2019)**	**Second plot (2020)**	**Second plot (2019)**

	How many people did you hire?	How many days did those people take to Complete ___?	On average, how many hours they worked per day?	How many people did you hire?	How many days did those people take to Complete ___?	On average, how many hours they worked per day?	How many people did you hire?	How many days did those people take to Complete ___?	On average, how many hours they worked per day?	How many people did you hire?	How many days did those people take to Complete ___?	On average, how many hours they worked per day?
	J2.	J3.	J4.	J5.	J6.	J7.	J8.	J9.	J10.	J11.	J12.	J13.
Plot ID (Copy from section D) CAPI												
Plot acreage (copy from section D and remind interviewee) CAPI												
Land preparation												
Planting												
Fertilizer applications												
Herbicide application												
Pesticide application												
Manure application												
Weeding												
Harvesting												
Transporting												
Drying and other postharvest activities												

SECTION K: HARVEST AND UTILIZATION

	[Enum: Values are total for the plot]	First plot		Second plot	
		2020	2019	2020	2019
	Plot ID (copy here) CAPI				
	Plot acreage (copy here and remind respondent) CAPI				
K1	Total output of rice grain : _____ (quantity)				
K2	Total output of rice grain: _____ Unit (1=50-kg bag; 2=100-kg bag; 3=Other (specify)				
K3	How was the actual rice yield INSTpared to your expectations at the start of the season? (CODE APPRECIATION)				
	How was the rice grain harvest utilized? Please estimate %:				
K4	% sold				
K5	% consumed as food				
K6	% used of livestock				
K7	% used as seed for next planting				
K8	% used as gifts				
K9	When did you harvest your rice? (MONTH CODE – select all that apply)				
K10	When did you sell your rice? (MONTH CODE – select all that apply)				
K11	Price of output during month 1 (cedi per unit)				
K12	To whom/where did you sell? (SALES CODE – select all that apply)				
K13	Price of output during month 2 (cedi per unit)				
K14	To whom/where did you sell? (SALES CODE – select all that apply)				
K15	Price of output during month 3 (cedi per unit)				
K16	To whom did you sell the rice grain? (SALES CODE – select all that apply)				
K17	How were the actual prices of rice per bag INSTpared to your expectations at the start of the season? (CODE APPRECIATION)				
K18	Average distance to the buyer/s above? (Quantity)				
K19	Unit of distance (1= km, 2 = mile, 3 = minutes walking , 4 = hours walking)				
K20	Was the rice grain picked-up at homestead or farm by the buyer or you transported to the buyer? 1=picked-up; 2=transported;3=both; 4=other (specify)				
K21	If you did not sell to the above current buyers, who would be the alternative buyer of your rice grain? (SALES CODE – select all that apply)				
K22	Distance to this alternative buyer? (Quantity)				
K23	Distance unit (1= km, 2 = mile, 3 = minutes walking , 4 = hours walking)				
K24	How did you bag/package the harvest? (PACKAGE CODE)				
K25	Did you store rice? 1=Yes, 0=No (If No >>>> to K34)				
K26	If YES, what is the storage space? (STORAGE CODE – select all that apply)				
K27	Did you treat stored rice with chemical? 1=YES, 0=NO				
K29	Did you pay for storage? 1=YES, 0=NO				
K30	If YES, how much did you pay for storage? (cedi)				
K31	For how many months did you store rice?				
K32	Is this intercropped? Yes or no				
K33	If yes, what crops? (see crop codes)				
K34	What is the estimated proportion of land cultivated with intercrop 1?				
K35	What is the total output for the intercrop 1 (kg/plot)				
K36	% sold				
K37	Price sold to (cedi/kg)				

K38	What is the estimated proportion of land cultivated with intercrop 2?					
K39	What is the total output for the intercrop 2? (kg/plot)					
K40	% sold					
K41	Price sold to (cedi/kg)					
K42	What is the estimated proportion of land cultivated with intercrop 3?					
K43	What is the total output for the intercrop 3? (kg/plot)					
K44	% sold					
K55	Price sold to (cedi/kg)					

SALES CODE: 1=Masara association; 2=Cooperatives or farmers' organizations; 3=Aggregators/traders; 4=Processors; 5=Projects/programs; 6=MOFA; 7=Other farmers; 8=Consumers; 9=Others (specify) _____

STORAGE CODE
1=Own traditional crib or silo
2=Own narrow-wooden crib
3=Barn
4=Ordinary room at homestead (with bare floor)
5=Ordinary room at homestead (concrete)
6=Store
7=MOFA storage facility
8=Certified warehouse
9=Other warehouses (not certified)
10=Other (specify) _____

PACKAGE CODE
1=Single bagging
2=Double bagging
3=Triple bagging
4=Drums
5=Bottles
6=Others (specify) _____

MONTH CODE: 1= January; 2= February; 3= March; 4 = April; 5=May; 6=June; 7=July; 8=August; 9=September; 10=October; 11=November; 12= December

APPRECIATION CODE: 1. Much better than expected; 2. Somewhat better than expected; 3. About what I expected; 4. Somewhat less than expected; 5. Much less than expected.

SECTION L: PARTICIPATION IN OUTGROWER SCHEMES

L1. Have you ever participated in any Outgrower scheme or contract farming for any crop with aggregator, company, bank or buyer? 1=Yes, 0=No >>> if No, proceed to L3

L2. For which crop? (see CROP CODE)

L3. Have you ever tried to join a scheme / contract farming arrangement, but were refused? 1=Yes, 0=No

L4. Why were you refused? _____ (REFUSAL CODE)

REFUSAL CODE: 1= Past history of default ; 2= the size of rice farm is not large enough; 3= my total production of rice is not large enough; 4= no other farmers to form a joint liability group; 5= no or not enough collateral; 6= located too far from scheme or contract farmer; 7= other (specify _____)

L5. For rice, have you ever participated in any Outgrower scheme with aggregator, company, bank or buyer? 1=YES, 0=NO >>>> if No, proceed to section M

Please mention all the schemes related to rice that you have participated in during the past 3 years.

		Scheme 1	Scheme 2	Scheme 3	Scheme 4	Scheme 5
L6	Name of scheme/aggregator/INSTpany/buyer (see scheme code)					
L7	Contact details (phone number):					
L8	When did you start with this project or scheme? _____					
	What encouraged you to participate in the scheme at the start**? (see participation reason code) (list first three)**					
L9	1.					
L10	2.					
L11	3.					
L12	Were you required to form a group with other farmers to be able to participate in this scheme?					
L13	How many acres of land was used for this scheme?					
L14	Are you still participating in this scheme? 1=Yes, 0=No					
L15	If yes, please record/link to plot ID					
L16	If No, when did you exit? (year)					
L17	Why did you exit? (see code)					
L18	Written or oral contract? 1=written, 2=oral contract					
L19	What inputs were provided? (see input code)					
L20	Are the prices in inputs provided fixed before the start of the season? 1=YES 0=No					
L21	Are the prices of output/grain harvest fixed before the season starts (1), variable according to market prices (2), or variable depending on quality (3)?					
L22	Are you required to sell all output to scheme? 1=Yes 0=No					
L23	If no, Is there a minimum quantity you must sell to scheme? 1=Yes 0=No					
L24	If yes, what is the minimum quantity?					
L25	If no, if you would want to, can you sell all your output to the scheme? 1=Yes 0=No					
L26	Is there a quality requirement? 1=Yes 0=No					
L27	If yes, what is the quality requirement? (see quality code) (check all)					
L28	Are technical assistance or extension services provided under this scheme? 1=Yes 0=No					
L29	How often were technical assistance or agricultural advice provided last 2 year (2019-2020)?					
L30	If yes, what technologies or management practices were promoted? (see technology code)					
L31	What are the terms of default or inability to repay under the project or scheme? (see default) (check all)					
L32	Since you started with the project or scheme, were there periods of loan default or inability to pay back? 1=YES 1=No					
	If YES, for how many years (since you started with the project or scheme)? _____					
L33	If YES, what were the reasons for the default or inability to pay?					
L34	1					
L35	2					
L36	3					
L37	Do you plan to continue with this scheme in 2016? 1=YES, 0=No					
L38	How long you would like to remain in the scheme?					
L39	How long you expect you would be allowed or be able to participate in the scheme?					
L40	How long he/she expects the scheme in the village?					
L41	Rate your satisfaction with this scheme? 1=not satisfied, 2=somewhat satisfied; 3=satisfied; 4=very satisfied					
	What are the areas/aspects of the scheme that can currently be improved?					

L42	1					
L43	2					
L44	3					

INPUT CODE: 1=fertilizer; 2=seed; 3=herbicide; 4=tractor services; 5=shelling services; 6=technical assistance/extension services; 7=Other (specify) _____

TECHNOLOGY CODE: 1=crop rotation; 2=minimum tillage; 3=zero tillage; 4=conservation agriculture; 5=organic farming; 6=fertilizer use; 7= burying of fertilizer; 8=intercropping with leguminous crops; 9=integrated soil fertility management; 10=new variety; 11=row planting; 12=pest management; 13=weed management; 14=other (specify)_____

QUALITY CODE: 1=well-dried rice; 2=uniform color; 3=brown color; 4=white color; 5=other (specify)

DEFAULT CODE: 1=pay in cash that same year; 2=pay in other crops that same year; 3=pay in rice the following year; 4=pay in rice grain the following year; 5=non-renewal of contract or agreement the following year; 6=pay in terms of household assets; 7=resort to court; 8=other (specify)

PARTICIPATION REASON: 1=access to fertilizer through credit; 2=access to preferred seed; 3=have buyers or market for rice grain; 4=stable price of rice grain; 5=timely delivery of inputs; 6=timely access to tractor services; 7=access to technical assistance or extension services; 8=other (specify) _____

L44. Are there any other schemes that you know of but that you were not part of? Yes=1; No = 0 if no, proceed to section N

L45. If yes, please name the schemes:

	Name of scheme	Things you know of heard of about . . .	Are you thinking of participating in this scheme in the future? 1=Yes 0=No
1			
2			
3			

>>>>> proceed to Section N

SECTION M. KNOWLEDGE ABOUT OUTGROWER SCHEMES

[Enum; To be answered only if L5=0]

M1. Do you know or heard of any Outgrower scheme or contract farming for any crop? 1=Yes 0=No (If no >>>> to section N)

M2. Do you know or heard of any Outgrower scheme or contract farming for rice? 1=Yes 0=No (If no >>>> to section N)

Table MA. Please list which Outgrower schemes you know of:

	Name of scheme	Crop	Things you know of heard of about . . .	Are you thinking of participating

				in this scheme in the future? 1=Yes 0=No
1				
2				
3				
4				

SECTION N. PROJECTS/PROGRAMS

N1. Have there been any projects or programs implemented in this village in the past 3 years? Yes = 1 No = 0 (If no >>>> to Section O)

Table NA. Please name all projects and programs implemented in village during the past 3 years:

Project/program (name, title, general description)	Name the implementing or funding organization/s	Description of the project/ program (check all that applies) (see PROJECT CODE)	Year the project/ program started	Year the project/ program ended	Is it related to rice? (Yes = 1; No = 0) If No, go to next line	Did it promote hybrid rice varieties?	Are inputs or services provided? 1=Yes, through grant or free inputs provided; 2= Yes, through credit; 3=No	How relevant were the inputs/services provided (1=not relevant, 2 somewhat relevant; 3=relevant, 4=very relevant)	Rate how you or your household benefitted from this project or program. (1=no benefit; 2=some benefit; 3= benefitted; 4= benefitted a lot)

PROJECT CODE: 1=agriculture; 2=livelihoods; 3=sanitation; 4=water; 5=health and nutrition, 6=education, 7=road, 8=other infrastructure; 9=training and capacity building; 10=other (specify) _____

SECTION O. SOCIAL NETWORKS AND SOURCES OF INFORMATION

O1. Where do you get most of your farming advice from? _____ (ADVICE CODE)

ADVICE CODE: 1= MOFA; 2= lead or model farmer in the village; 3=Other farmers (small-scale, <5 ha) 4= Other farmer (medium scale, 5-50 ha); 5=Other farmers (large scale, >50 ha) 6=FBO/Cooperative; 7=input dealers; 8=Masara scheme 9=aggregators, 10=ADVANCE; 11 =other NGO/Project; 12=radio; 13=TV; 14=print media; 15=other (specify)

O2. How many hybrid rice farmers do you know? _____

Table OA. Kindly describe distance to nearest MOFA extension agent, Outgrower technical officer and nucleus farmer/aggregator, and technical advice provided.

		2020	2019	2015 (5 years ago)
	MOFA extension agent			
O3	Distance to nearest MOFA extension agent?			
O4	Distance unit? (1=km; 2=mile)			
O5	Did you receive advice on rice? 1=Yes; 0=No >>> if no, proceed to O10			
O6	How often did you receive advice in the year [...]?			
O7	On which technology or subject did you receive advice? (TECHNOLOGY CODE)			
O8	Rate the usefulness of the information provided. (1=not useful; 2= somewhat useful; 3=useful; 4=very useful)			
O9	Did you act on it? 1=YES 0= NO			
	Outgrower technical officer			
O10	Distance to nearest Outgrower officer?			
O11	Distance unit? (1=km; 2=mile)			
O12	Did you receive advice on rice? 1=Yes; 0=No >>>if no, proceed to O17			
O13	How often did you receive advice in the year [...]?			
O14	On which technology or subject did you receive advice? (TECHNOLOGY CODE)			
O15	Rate the usefulness of the information provided . (1=not useful; 2= somewhat useful; 3=useful; 4=very useful)			
O16	Did you act on it? 1=YES 0= NO			
	Nucleus farmer/aggregator			
O17	Distance to nearest nucleus farmer/aggregator?			
O18	Distance unit? (1=km; 2=mile)			
O19	Did you receive advice on rice? 1=Yes; 0=No >>>if no, proceed to O24			
O20	How often did you receive advice in the year [...]?			
O21	On which technology or subject did you receive advice? (TECHNOLOGY CODE)			
O22	Rate the usefulness of the information provided . (1=not useful; 2= somewhat useful; 3=useful; 4=very useful)			
O23	Did you act on it? 1=YES 0= NO			

TECHNOLOGY CODE: 1=crop rotation; 2=minimum tillage; 3=zero tillage; 4=conservation agriculture; 5=organic farming; 6=fertilizer use; 7= burying of fertilizer; 8=intercropping with leguminous crops; 9=integrated soil fertility management; 10=new variety; 11=row planting; 12=pest management; 13=weed management; 14=weather; 15=land rights/tenure; 16=INSTmunal labor; 17=ploughing/tractor services; 18=water/irrigation; 19=storage; 20=harvesting method; 21=market information or prices; 22= other (specify)_____

O24. How many rice Outgrower do you know in your village or other villages? What varieties, technologies or management practices have you followed/adopted from them?

	Number of Outgrower that you know of	What rice varieties did you follow/adopt from any of them? (check all)	Since when? (year)	What rice technologies or management practices did you follow or adopt from any of them? (check all)	Since when? (year)
Outgrower of scheme 1 (Please state name)					
Outgrower of scheme 2 (Please state name)					
Outgrower of scheme 3					
Other (specify)					

VARIETY CODE: 1=AGRA rice; 2= JASMINE 85 (SAR-RICE 2; Gbewaa; Lapez); 3= DIGANG (also called Abirikukuo or Aberikukugo); 4=NERICA 1; 5=NERICA 2; 6= NABOGO RICE; 7= KATANGA RICE; 8= OTOOMU (TOX 3377); 9= GRUG7; 10= EMO TEAA (IDSA85); 11=Marshall (Amankwatia); 12=Wakatsuki (Bouake 189); 13= Bodia (ITA-320); 14= Sakai (ITA-324); 15=FARO 15; 16=GR 17 (IET 2885); 17=GR 18 (Afife); 18=GRUG7; 19=GR 19 (C168); 20=GR 20 (IR 1750-F5-B5) SR; 21= GR 21 (TOX 515-19-SLR); 22= TOX 3108 (Sikamo; GR 22); 23=indigenous/local/traditional; 24=do not know; 25=Other (specify)

TECHNOLOGY CODE: 1=crop rotation; 2=minimum tillage; 3=zero tillage; 4=conservation agriculture; 5=organic farming; 6=fertilizer use; 7= burying of fertilizer; 8=intercropping with leguminous crops; 9=integrated soil fertility management; 10=new variety; 11=row planting; 12=pest management; 13=weed management; 14=weather; 15=land rights/tenure; 16=INSTmunal labor; 17=ploughing/tractor services; 18=water/irrigation; 19=storage; 20=harvesting method; 21=market information or prices; 22= other (specify)_____

Table OB. Name a maximum of three persons to whom you talk frequently about agricultural decisions

		Contact 1	Contact 2	Contact 3
O25	Name			
O26	What is the relation of this person to you? (1) Family / extended family, (2) other farmers / friends, (3) aggregator (specify), (4) others (specify)			
O27	Does this person belong to the same cooperative or association as you? 1=Yes, 0=No			
O28	Does this person belong to the same church or faith as you? 1=Yes, 0=No			
O29	Does this person participate in contract farming or Outgrower scheme? 1=Yes, 0=No (If no, go to O30)			
O30	If yes, when did that person join the contract or scheme? 1=Before, 2=simultaneously or 3=after you?			
O31	Does this person grow hybrid rice?			
O32	If yes, when did that person started growing hybrid rice? 1=Before, 2=simultaneously or 3=after you?			
O33	Is s/he adopting improved technologies or management practices? 1=Yes, 0=No			
O34	Did s/he change technologies/practices in the last 5 years? 1=YES 0=NO			
O35	Do you seek advice from this person? 1=Yes, 0=No			
O36	How often do you communicate with this person? (times per month)			
O37	What things have you learned from him/her? Referring to technologies or practices? (TECHNOLOGY CODE)			
O38	What is the main thing that you would like to emulate from this farmer? TECHNOLOGY CODE			
O39	What topics you discuss? TECHNOLOGY CODE			

TECHNOLOGY CODE: 1=crop rotation; 2=minimum tillage; 3=zero tillage; 4=conservation agriculture; 5=organic farming; 6=fertilizer use; 7= burying of fertilizer; 8=intercropping with leguminous crops; 9=integrated soil fertility management; 10=new variety; 11=row planting; 12=pest management; 13=weed management; 14=weather; 15=land rights/tenure; 16=INSTmunal labor; 17=ploughing/tractor services; 18=water/irrigation; 19=storage; 20=harvesting method; 21=market information or prices; 22= other (specify)_____

Table OC. Please mention all associations or organizations in which you or anyone in the household are or were a member of in the past 3 years:

Name	Type (association code - Check all that apply)	First year of membership	Last year of membership (if still member, please write 9999)	Reason for joining (see reason code)	Membership fee		Services derived (see service code)	Satisfaction: 1=not satisfied, 2=somewhat satisfied; 3=satisfied; 4=very satisfied
					GHC	Frequency (1=monthly, 2=yearly; 3=one-time membership fee)		

ASSOCIATION code: 1=cooperative; 2= farmer-based organization; 3=women's group; 4=youth group; 5=church-based or faith-based organization; 6=water-user association; 7=village savings and loans association; =8=other (specify)

Reason code: 1=information; 2=marketing; 3=credit; 4=outgrower scheme; 5=easier access to inputs; 6=access to farm labor; 7=social learning/social capital; 8=training; 9=others (specify)

Services code: 1=information/training; 2=marketing; 3=credit; 4=fertilizer; 5=seed; 6=other inputs; 7=labor; 8=others (specify)

SECTION P. OTHER CROPS

P1. In 2020 or 2019, were there any other plots/sections that you cultivated, owned or controlled, but that were not mentioned above as rice fields? Yes=1. No=0
(If No, to P.2)

Table PA. Please list all the plots/ sections that you cultivated in 2020 and/or 2019, but that were not mentioned above as rice fields.

					2020	**2019**
	Total Area	Unit (see code)	Mode of acquisition (LAND CODE)	When did you acquire this land (year)	Crops (CROP CODE - check all)	Crops (CROP CODE - check all)
Plot A1						
Plot A2						
Plot A3						
Plot A4						
Plot A5						
Plot A6						
Plot A7						
Plot A8						
Plot A9						
Plot A10						

Area Unit: 1=Acres; 2=Hectares; 3=Poles; 4=Rope; 5=Arm stretch; 6=Square meters; 7=Square yards; 8=Square feet; 9=Others (specify)

LAND CODE: 1=Inherited land;2 = Outright purchase; 3=Given free from chief (allocated skin land or INSTmunity land) 4=Given free by relatives (allocated family land); 5= Given free by government (allocated government land); 6=rented (with rental fee); 7=borrowed (for free use); 8=Sharecropping agreement with landowner; 9=just walked in (e.g., cleared virgin land); 10=Other (specify) _____

P2. What is the % of rice in all the land/plot cultivated in 2020? ____ 2019? _____

P3. In 2020 or 2019, were there any other plots/sections that you owned or controlled, but did not cultivate (including land rented out, sharecropped out, borrowed out, left under fallow, and excluding the rice plots and other crops listed above) ? Yes=1; No=0
(If No, to P.5)

P4. What is the total land area of these other plots/sections that you owned or controlled, but did not cultivate? _____

Area Unit: 1=Acres; 2=Hectares; 3=Poles; 4=Rope; 5=Arm stretch; 6=Square meters; 7=Square yards; 8=Square feet; 9=Others (specify)

P.5 Was there any other land that you were cultivating or controlling in the past 5 years, but that you were not cultivating in 2020 or 2019? Yes=1. No=0
(If No, to Section Q)
Other land cultivated in 2010: _____ (quantity) _____ (UNIT CODE)
Other land controlled but not cultivated in 2010: _____ (quantity) _____ (UNIT CODE)

SECTION Q: HOUSEHOLD INCOME DURING LAST 12 MONTHS

Table QA. Please provide an estimation of other income sources for your household during the past 12 months

	income sources	Q1. Did you receive any income from [Source] 1 = Yes 0 = No >> next source	Q2. What was the **total annual** income from [income source] for your household over the **last 12 months**? Ghana Cedi
1	income from sales of other crops (not rice)		
2	Livestock/fisheries income		
3	income from forest products (timber, wild fruits …)		
4	Labour income (agriculture)		
5	Labour income (non-agriculture)		
6	Salary employment (government or private sector)		
7	Artisan and other businesses and trade		
8	Remittances (foreign and domestic)		
9	Cash transfers		
10	Rent (Land, House, etc.)		
11	Other (please specify)		

Q3. For the income from crops, list the 3 most important crops, in order:

1.
2.
3.

CROP CODE						
FIELD CROPS						
1=Bambara beans	11=Kenaf	21=Sugarcane	31=Coconut	41=Plantain	51=Cabbage	61=Pepper (black)
2=Cassava	12=Rice	22 =Sweet potato	32=Coffee	42=Rubber	52=Carrots	62=Pepper (sweet)
3=Citronella	13=Millet	23=Tobacco	33=Cola	43=Shea-nut	53=Cucumber	63=Pumpkin leaves
4=Cocoyam/Taro	14=Pepper (hot)	24=Watermelon	34=Lime	44=Sweet berry	54=Garden eggs	64=Shallots
5=Cotton	15=Pigeon peas	25=Yam	35=Mango	45=Dawadawa	55=Groundnuts, fresh	65=Talinum leaves
6=Cowpeas	16=Pumpkin	26=potato	36=Nutmeg	46=Neem	56=Lettuce	66=Tomato
7=Flowers	17=Rice	**TREES**	37=Oil-palm	47=Fig	57=Rice, fresh	67=Yellow melon
8=Ginger	18=Sisal	27=Avocado	38=Oranges	48=Kapok	58=Melon (agusi)	68=Henna
9=Groundnuts	19=Sorghum	28=Banana	39=Paw-paw	49=Acacia	59=Okra	69=Hibiscus
10=Jute	20=Soyabean	29=Cashew	40=Pineapples	**VEGETABLES**	60=Onions	70=Other crops (specify
		30=Cocoa		50=Asian vegetables		

Q4. For income from other things (not cropping income), list the two most important sources

1.
2.

ININSTE CODE: 1= Selling animals (livestock or fishing), 2= salary, 3=hired labour, 4=trading, 5=food seller, 6=craft (carpenter, tailor, etc.), 7=remittances, 8=rents, 9=others (specify _____)

SECTION R. HOUSEHOLD FOOD SECURITY

Q No.	Question and filters		Code
AVAILABILITY [Months of Adequate Household Food Provisioning]			
R.1	Now I would like to ask you about your household's food supply during different months of the year. When responding to these questions, please think back over the last 12 months, from now to the same time last year. Were there months, in the past 12 months, in which you did not have enough food to meet your family's needs? PLACE 1 IN THE BOX IF THE RESPONDENT ANSWERS YES. PLACE 0 IN THE BOX IF THE RESPONSE IS NO.		[…..] IF NO, END HERE
R.2	If yes, which were the months in the past 12 months during which you did not have enough food to meet your family's needs? DO NOT READ THE LIST OF MONTHS ALOUD. PLACE 1 IN THE BOX IF THE RESPONDENT IDENTIFIES THAT MONTH AS ONE IN WHICH THE HOUSHOLD DID NOT HAVE ENOUGH FOOD TO MEET THEIR NEEDS. IF THE RESPONDENT DOES NOT IDENTIFY THAT MONTH, PLACE 0 IN THE BOX. USE A SEASONAL CALENDAR IF NEEDED TO HELP RESPONDENT REMEMBER THE DIFFERENT MONTHS. PROBE TO MAKE SURE THE RESPONDENT HAS THOUGHT ABOUT THE ENTIRE PAST 12 MONTHS.	A. January	[…..]
		B. February	[…..]
		C. March	[…..]
		D. April	[…..]
		E. May	[…..]
		F. June	[…..]
		G. July	[…..]
		H. August	[…..]
		I. September	[…..]
		J. October	[…..]
		K. November	[…..]
		L. December	[…..]

ACCESSIBILITY [Household Food Insecurity Access Scale]

Q No.	Questions	Response options	Code

R.3	In the past four weeks, did you worry that your household would not have enough food?	0=No (Skip to Q4) 1=Yes	[…..]
R.3a	How often did this happen?	1=Rarely (once or twice in the past 4 weeks) 2= Sometimes (3-10 times in the past 4 weeks 3= Often (more than 10 times in past 4 weeks)	[…..]
R.4	In the past four weeks, were you or any household member not able to eat the kinds of foods you preferred because of a lack of resources?	0=No (Skip to Q5) 1=Yes	[…..]
R.4a	How often did this happen?	1=Rarely (once or twice in the past 4 weeks) 2= Sometimes (3-10 times in the past 4 weeks 3= Often (more than 10 times in past 4 weeks)	[…..]
R.5	In the past four weeks, did you or any household member have to eat a limited variety of foods due to a lack of resources?	0=No (Skip to Q6) 1=Yes	[…..]
R.5a	How often did this happen?	1=Rarely (once or twice in the past 4 weeks) 2= Sometimes (3-10 times in the past 4 weeks 3= Often (more than 10 times in past 4 weeks)	[…..]
R.6	In the past four weeks, did you or any household member have to eat some foods that you really did not want to eat because of a lack of resources to obtain other types of food?	0=No (Skip to Q7) 1=Yes	[…..]
R.6a	How often did this happen?	1=Rarely (once or twice in the past 4 weeks) 2= Sometimes (3-10 times in the past 4 weeks 3= Often (more than 10 times in past 4 weeks)	[…..]
R.7	In the past four weeks, did you or any household member have to eat a smaller meal than you felt you needed because there was not enough food?	0=No (Skip to Q8) 1=Yes	[…..]
R.7a	How often did this happen?	1=Rarely (once or twice in the past 4 weeks) 2= Sometimes (3-10 times in the past 4 weeks 3= Often (more than 10 times in past 4 weeks)	[…..]
R.8	In the past four weeks, did you or any other household member have to eat fewer meals in a day because there was not enough food?	0=No (Skip to Q9) 1=Yes	[…..]
R.8a	How often did this happen?	1=Rarely (once or twice in the past 4 weeks) 2= Sometimes (3-10 times in the past 4 weeks 3= Often (more than 10 times in past 4 weeks)	[…..]
R.9	In the past four weeks, was there ever no food to eat of any kind in your household because of lack of resources to get food?	0=No (Skip to Q10) 1=Yes	[…..]
R.9a	How often did this happen?	1=Rarely (once or twice in the past 4 weeks) 2= Sometimes (3-10 times in the past 4 weeks 3= Often (more than 10 times in past 4 weeks)	[…..]
R.10	In the past four weeks, did you or any household member go to sleep at night hungry because there was not enough food?	0=No (Skip to Q11) 1=Yes	[…..]
R.10a	How often did this happen?	1=Rarely (once or twice in the past 4 weeks) 2= Sometimes (3-10 times in the past 4 weeks 3= Often (more than 10 times in past 4 weeks)	[…..]
R.11	In the past four weeks, did you or any household member go a whole day and night without eating anything because there was not enough food?	0=No (finished) 1=Yes	[…..]

R.11a	How often did this happen?	1=Rarely (once or twice in the past 4 weeks) 2= Sometimes (3-10 times in the past 4 weeks 3= Often (more than 10 times in past 4 weeks)	[…..]
ACCESSIBILITY [Reduced Coping Strategies Index]			
R.12	In the past 7 days, if there have been times when you did not have enough food or money to buy food, how often has your household had to:		
	a. Rely on less preferred and less expensive foods?		[…..]
	b. Borrow food, or rely on help from a friend/relative?		[…..]
	c. Limit portion size at mealtimes?		[…..]
	d. Restrict consumption by adults in order for small children to eat?		[…..]
	e. Reduce number of meals eaten in a day?		[…..]
UTILIZATION [Household Dietary Diversity Score]			
Q No.	**Questions and filters**		**Code**
R.13	I would like to ask you about the types of foods that you or anyone else in your household ate yesterday during the day and at night, whether at home or outside the home. READ THE LIST OF FOODS. PLACE 1 IN THE BOX IF ANYONE IN THE HOUSEHOLD ATE THE FOOD IN QUESTION, PLACE 0 IN THE BOX IF NO ONE IN THE HOUSEHOLD ATE THE FOOD.		
	A. CEREALS [corn/maize, rice, wheat, sorghum, millet or any other grains or foods made from these, e.g. bread, noodles, porridge or other grain products, or insert local foods e.g. porridge]		[…..]
	B. ROOTS AND TUBERS + PLANTAINS [cassava, yam, cocoyam, potatoes, plantain, or other foods made from roots or tubers]		[…..]
	C. VITAMIN A RICH VEGETABLES AND TUBERS [pumpkin, carrot, or orange flesh sweet potato, and other locally available vitamin A rich vegetables (e.g. red sweet pepper)		[…..]
	D. DARK GREEN LEAFY VEGETABLES [dark green leafy vegetables such as *nkontomire* and locally available vitamin A rich leaves such as cassava leaves, spinach, etc.]		[…..]
	E. OTHER VEGETABLES [other vegetables (e.g. tomato, onion, eggplant, cabbage, cucumbers, garlic, green pepper, mushroom, onion) and other locally available vegetables]		[…..]
	F. VITAMIN A RICH FRUITS [mango, pawpaw and 100% fruit juice made from these and other locally available vitamin A rich fruits]		[…..]
	G. OTHER FRUITS [other fruits: apple, pear, banana, cashew nut fruit, coconut flesh, guava, pineapple, tangerine, watermelon, including wild fruits and 100% fruit juice made from these]		[…..]
	H. FLESH MEAT [beef, pork, lamb, goat, rabbit, wild game, chicken, duck, other birds]		[…..]
	I. ORGAN MEAT [organ meat such as liver, kidney, heart, or other organ meat]		[…..]
	J. EGGS [eggs from chicken, ducks, guinea fowl or any other]		[…..]
	K. FISH AND SEAFOOD [fresh or dried or smoked fish or shellfish]		[…..]
	L. LEGUMES, NUTS AND SEEDS [dried beans, dried peas, lentils, nuts, egushie/melon seed, seeds or foods made from these (e.g. peanut butter)]		[…..]
	M. MILK AND MILK PRODUCTS [milk, yogurt, cheese or other milk products]		[…..]
	N. FATS AND OILS [oil, fats or butter added to food or used for cooking]		[…..]
	O. SWEETS [sugar, honey, sweetened juice drinks, sugary foods such as chocolates, candies, cakes and cookies]		[…..]
	P. SPICES, CONDIMENTS, BEVERAGES [spices (e.g. pepper and salt) condiments (e.g. hot sauce), coffee, tea, alcoholic beverages]		[…..]
Women Dietary Diversity Score			
R.14	I would like to ask you about the types of foods that **women between 15 – 49 years** in your household ate yesterday during the day and at night, whether at home or outside the home. READ THE LIST OF FOODS. PLACE A *1* IN THE BOX IF WOMEN IN THIS GROUP IN THE HOUSEHOLD ATE THE FOOD IN QUESTION, PLACE A *0* IN THE BOX IF OTHERWISE.		
	A. STARCHY STAPLES[Cereals and roots & tubers + plantain] *Refer to B.13 A & B for examples*		[…..]
	B. DARK GREEN LEAFY VEGETABLES [*nkontomire* and cassava leaves, spinach, etc.]		[…..]
	C. VITAMIN A RICH FRUITS AND VEGETABLES [Vitamin A rich vegetables and tubers and Vitamin A rich fruits + red palm oil] *Refer to B.13 C & F for examples*		[…..]

	D. OTHER FRUITS AND VEGETABLES [other fruits, including wild fruits and 100% fruit juice made from these and other vegetables (e.g. tomato, onion, eggplant, etc.)			[…..]
	E. ORGAN MEAT [organ meat such as liver, kidney, heart, or other organ meat]			[…..]
	F. MEAT AND FISH [beef, pork, lamb, goat, wild game, chicken, etc. and fish (fresh or smoked)]			[…..]
	G. EGGS [eggs from chicken, ducks, guinea fowl or any other]			[…..]
	H. LEGUMES, NUTS AND SEEDS [dried beans, dried peas, lentils, nuts, egushie/melon seed, seeds or foods made from these (e.g. peanut butter)]			[…..]
	I. MILK AND MILK PRODUCTS [milk, yogurt, cheese or other milk products]			[…..]
Children under 5 years [Ask only about children below the ages of 5 years]				
R.15		Child 1	Child 2	Child 3
	Sex of child [1=Male 2=Female]	|……|	|……|	|……|
	Age of child (in months)	|…..| months	|…..| months	|…..| months
	Did the child receive breast milk yesterday? [0=No 1=Yes]	|……|	|……|	|……|
	How many times did the child receive breast milk yesterday?	|……|	|……|	|……|
	How many times did the child receive food yesterday?	|……|	|……|	|……|
R.16	What food items did any of your children, below 5 years, eat yesterday during the day and at night, whether at home or outside the home? PLACE 1 IN THE BOX IF CHILDREN IN THIS GROUP ATE FOOD AND 0 IF OTHERWISE.			
	A. Cereals [bread, rice, maize, wheat, sorghum, millet, noodles, porridge, etc. + biscuits]			|……|
	B. Roots and tubers + plantain			|……|
	C. Milk and milk products, yogurt			|……|
	D. Legumes and nuts [beans, peas, nuts]			|……|
	E. Meat, liver, kidney, chicken and fish			|……|
	F. Eggs			|……|
	G. Vitamin A rich fruits and vegetables [mango, pawpaw, carrots, red sweet pepper]			|……|
	H. Other fruits and vegetables [Fruits: apple, pear, banana, coconut flesh, guava, pineapple, tangerine, watermelon + vegetables: cabbage, cucumbers, eggplant, garlic, green pepper, mushroom, onion, tomato]			|……|
	I. Tea			|……|
	J. Infant formula			|……|
	K. Vitamins and mineral supplements			|……|

SECTION S. ASSETS

[Enum: Read out list of assets and record a yes or no. Once all assets are recorded, ask the questions about each asset that follows.]

Table SA. Kindly describe your dwelling and source of drinking water, toilet, lighting and cooking fuel.

	Question	**Answer**	**Code**
S1.	How many bed/ living rooms does the house have? (*Note: include detached rooms in same household but not kitchen and bathrooms!*)		Numbers
S2.	What type of house does the HH occupy?		1 = Permanent house / 2 = Semi-permanent house / 3 = Temporary house / 4 = Other (specify)
S3.	When did the HH move into this dwelling?		Year
S4.	What is the ownership status of dwelling?		1 = Owned / 2 = Provided free by employer / 3 = Provided free by owner / 4 = Rented from private owner / 5 = Rented from govt. or public ownership / 6 = Subsidized by employer / 7 = Family house / 8= Other (specify)
S5.	Did you build the dwelling?		1 = Yes / 2 = No
S6.	What type of roofing material is used in main house?		1 = Wood / 2 = Corrugated metal sheets / 3 = Thatch or palm leaf / 4 = Concrete or cement / 5 = Slate or asbestos / 6 = Tiles / 7 = Other (specify)

S7.	What type of flooring does the dwelling have?		1 = Concrete or cement / 2 = tiles/ 3 = Earth or mud brick / 4 = Wood / 5 = Stones / 6 = Other (specify)
S8.	What is the main construction material for the main walls of the dwelling?		1 = Concrete or cement / 2= earth, mud or mud brick / 3 = wood / 4 = stones / 5 = Other (specify)
S9.	What is the main source of drinking water?		1 = Pipe inside house / 2 = Pipe outside house / 3 = Tanker service / 4 = River or stream / 5 = Bore hole / 6 = Well / 7 = Dugout or pond or dam / 8 = Other (specify)
S10.	What is the distance to the drinking water source?		In m maybe easier in minutes walking
S11.	What kind of toilet does the HH use?		1 = Flush toilet / 2 = Pit latrine / 3 = Ventilated Improved Pit Latrine (VIP) / 4 = Bucket latrine / 5 = Other (specify)
S12.	Where is the toilet located?		1 = Inside house (exclusive) / 2 = Inside house (shared) / 3 = Outside house (exclusive) / 4 = Outside house (shared) / 5 = Other (specify)
S13.	Main source of lighting?		1 = Kerosene / 2 = Electricity / 3 = Gas lamp / 4 = Solar energy / 5 = Lamp with battery / 6 = No light / 7 = Other (specify)
S14.	Main type of cooking fuel?		1 = Charcoal / 2 = Firewood / 3 = Gas / 4 = Electricity / 5 = Paraffin or Kerosene / 6 =Solar / 7 = Coconut husk / 8 = Millet straw / 9 = Other (specify)

Table SB. Which of the following assets does the household own?

		R15.	R16.	R17.			R15.	R16.	R17.
	Asset	Number owned in 2020	Number owned in 2019	Number owned in 2015 (5 years ago)			Number owned in 2020	Number owned in 2019	Number owned in 2010 (5 years ago)
1	Motor vehicle				16	Refrigerator			
2	Motorbike				17	Gas stove			
3	Bicycle				18	Microwave			
4	Farm equipm. (non-mechan.)				19	Sewing machine			
5	Farm equipm. (mechanized)				20	Generator			
6	Sprayer				21	Water pump			
7	TV Set				22	Water Tank			
8	Radio				23	Jewelry			
9	CD Player				24	Oxen and cattle			
10	Satellite dish				25	Other large livestock (donkey)			
11	Washing machine				26	Small livestock (goats, pigs, sheep)			
12	Telephone				27	Chicken, ducks, turkey			
13	Air con				28	Other			
14	Fan				29	Other			
15	Freezer				30	Other			

SECTION T. HOUSEHOLD EXPENDITURE

Table TA. Food consumption

	Food Item (eaten at home or outside)	How many days did your household consume [FOOD ITEM] in the last 7 days? [write 0 if they did not consume]	Have members of your household purchased or spent money on any [FOOD ITEM] in the last 4 weeks? 1=YES 0=No	How much did your household pay in total for [FOOD ITEM] in the last 4 weeks? (Ghana Cedi)
A	RICE			
B	OTHER CEREALS – rice, wheat, millet, sorghum, barley, oats/breakfast cereals, and other (include grains and flours)			
C	BREAD & PASTA – bread, cake, biscuits, buns, pasta/macroni, other			
D	CASSAVA			
E	OTHER ROOTS & TUBERS – potatoes, sweet potatoes, arrow roots, yams, crisps, cooking banana, other			
F	LEGUMES/PULSES/BEANS (fresh & tinned) –grams, black grams (njahi), peas, groundnut, cowpeas, other			
G	VEGETABLES (fresh & tinned) – leafy vegetable, onions/leeks, cabbages, carrots, tomatoes, spinach, kale-sukuma wiki, capsicums (pilipili hoho), cucmuber, french beans, lettuce, courgette, celery, mushrooms, cauliflower, aubergines (bringanya), pumpkins, okra, squashes, coriander leaves (dania), others			
H	MEAT (fresh & tinned) – beef, minced meat, pork, mutton/goat meat, chicken, camel meat, offals (liver, kidney, matumbo), sausage, bacon, ham/salami, corned beef, other			
I	FISH (fresh & tinned) – small or large fish, dried/smoked fish, prawns/sea foods, other			
J	DAIRY PRODUCTS – milk, UHT milk, milk (condensed/powder), yogurt, fresh cream, cheese, fresh cream, cheese, eggs, other			
K	OILS & FATS – butter, ghee from milk, margarine, cooking fat, cooking oil, lard, peanut butter, other			
L	FRUITS (fresh & tinned) – ripe banana, oranges, pawpaws, avocado, mangoes, pineapples, passion fruits, pears, plums, apples, lemons, grapefruit, strawberries, other berries, melons, grapes, coconut, fruit juices, other			
M	JAMS, HONEY, SWEETS AND CANDIES – jams, marmalade, honey, chocolate, sweets, candy, sugar cane, soda, chocolate or cocoa preparations, other			
N	BEVERAGES – coffee, tea			
O	Other (specify) _____			

Table TB. More frequent expenditure

	In the **last 30 days** did your household spend money on [item]? Yes = 1 ; No = 0	Amount spent on [item] in the **last 30 days**? (cedi)	Average monthly expenditure for the last 12 months (cedi)
Fuel (firewood, charcoal, kerosene, gas)			
Transport expenses			
Communication (cell phone, airtime, calling)			
Cultural/religious activities (e.g. church)			

Utilities and maintenance costs (electric bill, water)			
Other, specify			

Table TC. Less frequent expenditure

Expenditure item	In the **last 12 months**, did your household spend money on [item]? 1 = Yes 0 = No ***if No => next [item]***	What was your household's total expenditure on [item] over the **last 12 months**? (cedi)
Clothes and shoes (including school uniforms)		
School fees and other educational expenses		
Social events (wedding, funeral, etc)		
Housing improvement (latrine, new roof, etc)		
Human Health expenses (medication, consultation, hospitalization)		
Other 1, specify		
Other 2, specify		

SECTION U. SHOCKS IN THE PAST 3 YEARS

Shock		Did you experience any adverse shocks that affected crop production/livestock in the past 3 years? Such as ---------- *1=Yes 2=No → go to next shock*	In which year did you experience this shock (2018 to present)? (list all relevant years) *(Year)*		
	SHOCK	**T1.**	**T2.**	**T3.**	**T4.**
Drought/irregular rain	1				
Floods/landslide (due to heavy	2				
Human epidemic/disease	3				
Livestock disease	4				
Devastating crop pest/disease	5				
Death	6				
Theft	7				
Unusually high food prices	8				
Conflict/civil unrest/violence	9				
Earthquake	10				
Fire	11				
Other (specify) _____	12				

SECTION V. LOANS & CREDIT

V1.Did you ever apply for a loan or credit (in cash or in-kind) to support your farming activities in the last two years (2019-2020) including from outgrower schemes, friends, family, moneylenders, aggregator, buyers, association, bank, and other financial institutions? 1= Yes 0 =No (If yes >>> to Table UA, question U3)

V2. Why did you not try to obtain a loan in the last two years? _____ (LOAN CODE) (Go to section W)

LOAN CODE: 1= No need for loan; 2 = Inadequate collateral; 3= Had outstanding loan; 4=Past history of default ; 5=Interest rates too high; 6=Lenders not located nearby; 7=Procedures too cumbersome; 8= other (specify)

Table VA. Please list all persons, groups or institutions to whom you applied for a loan in 2020 or 2019

	From whom did you attempt to get loan or credit (in cash or in kind)? *(see lender code)*	When did you apply for this loan? **Month**	**Year**	Did you get the loan? ***1=Yes 2=No → go to next potential lender (next line)***	If U6=1, What was the **value of this loan/credit excluding interest** (**GHC equivalent** if it **was in-kind**)? *(GHC)*	Did you obtain the amount you wanted to? Yes= 1 (= the preferred amount) No = 0 (= less than the preferred amount)	What was the main use of the loan? *(see loan use codes)*	Was **collateral required** to obtain this loan/credit? 0 = No ; 1=Yes; 2=Group security
	U3	U4.	U5	U6	U7	U8	U9	U10
1								
2								
3								
4								
5								
6								
7								
8								

LENDER CODE:		**LOAN USE CODE:**
1=Friends or family		1=Purchase fertilizer
2=Cooperative/farmer organization		2=Purchase seed
3=Aggregator, trader, buyer (not under scheme)		3=Purchase herbicides/pesticides/other chemicals
4=Private moneylender		4=Purchase of farm equipment
5=Employer		5=Pay for tractor or shelling services
6=Commercial bank		6=Payment for labor (including food and labor related expenses)
7=Microfinance institution		7=Payment for land rental services
8=Non-governmental or faith-based organization / church		8=Home food consumption purchases
9=Government or district body-run program		9=Payment of school fees
10=Other projects		10=Medical expenditures
11=Masara Outgrower scheme		11=Other (specify)
12=Other Outgrower scheme		
13=Other (specify) _____		

SECTION W. SAVINGS HISTORY, TIME PREFERENCE, RISK AVERSION & ASPIRATION WINDOW

[Enum: To be asked separately to managers or decision makers of 2 focus rice plots, if two different persons] -> CAPI

W1. Respondent ID _____ (HH member ID code)

Reasons for saving
1= Day-to-day household expenses
2= Conducting business
3= Purchasing, constructing or improving housing
4= Education

W2. Do you save your money? *1=Yes 0= No → If no, Skip to V6*

SAVING Method		How do you save your money? Do you ……? *1=Yes* *2=No→go to next method*	What is the main purpose of this saving? *See reason codes*	What is the **approximate value of savings** which you currently have in this type of savings *(Enumerator: if respondent does not know, they should estimate approximate value)*
		W3.	**W4.**	**W5.**
Deposit money into a bank	1			
Save with a savings society or group in the Community	2			
Save with another financial institution	3			
Save with Susu collectors	4			
Purchase small animals	5			
Purchase large animals	6			
Keep money in the household	7			
Other (specify) _____	8			

W6. Imagine that someone gives you 500 New GHC, but you can only spend it one of four ways. Which of the following options would you choose?

1=You can spend it on immediate consumption

2=You can buy farm input B that assures you will get 550 New GHC after 1 year

3=You buy farm input C that assures you will get a total of 650 New GHC after 2 years

4=You buy a farm input D that assures you will get a total of 800 New GHC after 3 years

W7. Now suppose the extra 500 New GHC is from the sale of your own farm output, say due to a bumper harvest, but still you are only allowed to spend it in one of four ways: Which of the following options would you choose?

1=You can spend it on immediate consumption

2=You can buy farm input B that assures you will get 550 New GHC after 1 year

3=You buy farm input C that assures you will get a total of 650 New GHC after 2 years

4=You buy a farm input D that assures you will get a total of 800 New GHC after 3 years

W8. Suppose you are given two options of receiving income: either you choose receive it tomorrow or in a month. If you wait a month, you will receive more. Would you prefer to receive:

A 100 GHC tomorrow or 105 GHC in a month?

1. 100 tomorrow [go to B]
2. 105 in a month [go to V9]

(B) And if it was 100 GHC tomorrow or 110 GHC in a month?

1. 100 tomorrow [go to C]
2. 110 in one month[go to V9]

(C) And if it was 100 GHC tomorrow or 120 GHC in a month?

1. 100 tomorrow [go to D]
2. 120 in a month [go to V9]

(D) How much should we give you so that you can wait a month? _____ (GHC)

W9. Imagine that you could choose one of the following bags of rice seeds. Each bag contains rice seeds that will produce different harvest of rice the following year depending on the weather. Which seed would you choose? (use visual aids)

1. Seeds which can produce stable 10 bags per acre regardless of the weather
2. Seeds which can produce 7 bags per acre (during bad weather) or 20 bags per acre (during good weather)
3. Seeds which can produce 4 bags per acre (during bad weather) or 30 bags per acre (during good weather)
4. Seeds which can produce 0 bags per acre (during bad weather) or 40 bags per acre (during good weather)

Table WA. How connected are you outside of your village? ***[Enum: To be asked separately to managers or decisionmakers of 2 focus rice plots, if two different persons]***

			Decision maker 1	**Decision maker 2**
	Plot decision maker	*(see HH member ID)*		
W10	How often do you listen to the radio?	*1=Every day 2=At least once a week 3=At least once a month 4=At least once a year 5=Never*		
W11	how often do you watch television?	*1=Every day 2=At least once a week 3=At least once a month 4=At least once a year 5=Never*		
W12	How often do you go to nearest town?	*1=Every day 2=At least once a week 3=At least once a month 4=At least once a year 5=Never*		
W13	How often do you travel outside the District?	*1=Every day 2=At least once a week 3=At least once a month 4=At least once a year 5=Never*		
W14	How often do you travel outside the Region?	*1=Every day 2=At least once a week 3=At least once a month 4=At least once a year 5=Never*		
W15	Have you ever lived more than 6 months outside this District?	*1= Yes 0= No*		
W16	Have you ever lived more than 6 months outside this Region?	*1= Yes 0=No*		
W17	How often you talk on the telephone?	*1=Every day 2=At least once a week 3=At least once a month 4=At least once a year 5=Never*		
W18	How often you go to nearest market?	*1=Every day 2=At least once a week 3=At least once a month 4=At least once a year 5=Never*		

APPENDIX II: Focus Group Discussion Guide

SECTION A: Factors Affecting Adoption of Improved Varietal Rice Seed Technologies

1. Can you tell me about some of the:
   (a) Socio-economic factors that influence your decision to adopt improved varietal rice seed technologies?
   (b) Institutional and farm-specific factors that influence your decision to adopt improved varietal rice seed technologies?
   (c) Varietal trait attributes that affect your decision to adopt improved varietal rice seed technologies?
2. Can you share with me some of the key/major constraints that hinder your adoption of improved varietal seed technologies and how does each place a hindrance to adoption.?
3. Kindly tell me some of the coping strategies you have been using to manage these constraints/challenges.

SECTION B: Access to Seeds and other inputs, and institutional support

1. How do you manage to acquire the seeds you have been cultivating be it improved or local varietal seeds?
2. How easy or difficult it is for you to acquire seeds and other necessary inputs for your farming?
3. How do you mostly obtain assistance from your farmer groups (i.e., FBO) or any Outgrower scheme to acquire your seeds and other inputs for your production (if any)?
4. How have you been obtaining support from the extension service agents in your district/community. How often do you have the opportunity to engage with an extension agent?
5. Do you receive any form of education or training about the about agronomic practices for your rice farming activities?
6. What arrangement or mechanisms/avenues do farmers of your kind obtain easy and cheap credit support for your farming investment?
7. Do you have any means of obtaining information about how you can acquire improved seeds in your community/district?
8. Can you share with me some of the training(s) you have ever received about the best postharvest practices for the handling and storage of your rice farm produce (if any)?

9. Can you tell me some of the processing facilities or infrastructure in place for you to get your harvest well processed (if any)?

10. Let's talk about marketing. Can you share with me how you get your rice harvest marketed? Tell me how you get them transported to nearby potential markets.

11. Are there any information or concerns you would want to share with us about access to seeds, other inputs and institutional support you require for your rice farming activities?

SECTION C: Perceived Benefits from adopting improved varietal rice seeds (Adopters only)

1. Are there any perceived benefits you can share with me about the improved variety you are cultivating?

2. Specifically, can you share with me if you have been observing some positive difference in your harvest since you started cultivating the improved variety you are currently using?

3. What advice do you have for farmers who do not adopt improved rice varieties?

APPENDIX III: In-depth Interview Guide

University of Ghana, Legon

College of Basic and Applied Sciences

Department of Agricultural Economics and Agribusiness

Dear Sir/Madam,

This study aims to understand how varietal seed technologies can enhance productivity and household welfare in Ghana. This study will particularly look at the role of varietal seed in improving productivity and household welfare in the Northern Region of Ghana. The study is being conducted by a student from the Department of Agricultural Economics and Agribusiness at the University of Ghana, in partial fulfilment for the award of a PhD degree in Applied Agricultural Economics and Policy.

Your view or response as a research scientist, an extension agent, certified seed seller/supplier, input dealer, aggregator or a processor is highly needed to confirm or verify/authenticate findings from rice farming households. Your response or views will be extremely important for our breeders and agronomists who make sure that they develop varieties and agricultural management practices that solve the constraints and technological adoption challenges of rice farmers in the region. Your responses are very useful to this study and will be KEPT STRICTLY CONFIDENTIAL. Your responses will be summarized along with other 600 farming households in the Northern Region.

Thank you.

SECTION A: Factors Affecting Adoption of Improved Varietal Rice Seed Technologies

1. Can you tell me about some of the:
   (a) Socio-economic factors that influence farmers adoption decision of improved varietal rice seed technologies?
   (b) Institutional and farm-specific factors that influence farmers adoption decision of improved varietal rice seed technologies?
   (c) Varietal trait attributes that affect farmers adoption decision of improved varietal rice seed technologies?
2. Comparing the improved, and indigenous varieties, can share your view of which farmers are really using or cultivating and why do you think so?
3. Generally, what do farmers usually look for in rice varietal seeds before adopting any of them?

SECTION B: Access to Seeds and other inputs, and institutional support

1. Can you tell us how you think farmers access the improved rice seed for their production?
2. Do you educate them on where and how they can access these improved seeds, and possibly the original once?
3. Can you tell me about the measures you have put in place to enable farmers have easy access to these improved seeds.
4. Looking at the sparse nature of the northern region, can tell us how you are able to reach or visit farmers the way you would have wanted? And if so, can you share with us how you are able to manage that?
5. With your experience, are often able to reach individual farmers just us you are able to reach farmers that belong to farmer groups?
6. Can you tell us if your outfit has any challenges that inhibit you from doing your work the way it ought to be done? If any, can you tell us how you are able to manage the limited resources at your disposal to help these farmers the best way you can?
7. Do you have occasions you routinely meet farmers and educate or train them on how to acquire these improved seeds and other necessary complementary inputs for their production?
8. Considering the resource constraints you usually encounter, are you often able to visit rice farms in you district to share some good agronomic or cultural practices with farmers. If so, can you share with us how farmers usually receive these information you share with them?
9. Do you sometimes receive resource support from institutions or organizations other than government? If so, can you please share with us how often you receive these supports. Tell us also the primary purpose of these private institutions or organizations.
10. Do you receive any form of education or training about these improved varieties of which you also teach farmers about? If so, can you share with us how you think these trainings are benefiting you and your work duties?
11. Let's talk about marketing. Can you share with me how you might have been assisting your rice farmers to market their harvest?
12. Are there any information or concerns you would want to share with us about your work, and the support you think rice farmers jurisdiction require for them to achieve their optimum yield or productivity?

APPENDIX IV: An Estimate from the Statistical Power Analysis

alpha	power	N	N1	N2	N3	N4	delta	Var_m
.05	.8	600	150	150	150	150	.1352	8368
.05	.81	600	150	150	150	150	.1368	8564
.05	.82	600	150	150	150	150	.1384	8768
.05	.83	600	150	150	150	150	.1401	8981
.05	.84	600	150	150	150	150	.1418	9206
.05	.85	600	150	150	150	150	.1437	9442
.05	.86	600	150	150	150	150	.1455	9692
.05	.87	600	150	150	150	150	.1475	9958
.05	.88	600	150	150	150	150	.1496	10242
.05	.89	600	150	150	150	150	.1518	10547
.05	.9	600	150	150	150	150	.1542	10878