Institute for Food Economics and Consumption Studies

of the Christian-Albrechts Universität Kiel

Contribution of Climate-smart Agriculture to Farm Performance, Food and Nutrition Security and Poverty Reduction in Ghana

Dissertation

Submitted for Doctoral Degree

Awarded by the Faculty of Agricultural and Nutrition Sciences

of the

Christian-Albrechts Universität zu Kiel

Submitted

M. Sc. Gazali Issahaku

Born in Ghana

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Dedication

I dedicate this Thesis to my parents Alhaj Umar Alhassan and Hajia Amama Abdulai and to my lovely wife Warahamatu Adam for their unflinching support, encouragement and prayers

Acknowledgement

I render thanks and praises unto the Almighty Allah (SWT); for His Blessings and Grace. I heartily acknowledge the immeasurable support of my mentor Prof. Dr. Awudu Abdulai who supervised this work. Professor Abdulai's fatherly guidance and encouragement contributed immensely to the success of this study. I also extend a lot of thanks to members of the doctoral examination committee; Prof. Dr. Ulrich Orth, Prof. Dr. Sebastian Hess and Prof. Dr. Dr. Christian H. Henning. With gratitude, I acknowledge the financial support and opportunity afforded me by the management of University for Development Studies (UDS) and the Government of Ghana-DAAD collaboration. My appreciation also goes to my colleagues at the University of Kiel (Dr. Sascha Stark, Abdul-Rahman Awal, Abdul-Mumin Yazeed, Muhammad Faisal Shazad, Mohammed Sadick, Dubbert Caroline, Johanna Scholz, William Ali, Yitayew Asrezu, Zhao Jiajia, Richartz Christoph, Adam Baba and Anna Labohm) for their invaluable contributions to my work. I also extend my thanks to Miss Anett Wolf, Brix Fynn Christian, Hinrichsen Lea and Stupnicki Larissa, for their support during my study. I am eternally grateful for the prayers, understanding and unflinching support of my beloved parents, I pray to Allah (SWT) to reward them abundantly. To my benefactor Mba Issahaku Alhassan (deceased), mother and father- Hajia Amama Abdulai and Alhaj Umar Alhassan, I sincerely cherish your support and prayers. My dearest wife (Warahamatu Adam) and kids have been a source of courage for which I extend my affection. I share with you all the joy and success of this work.

Kiel, im January 2019 Gazali Issahaku

Abstract

The threats of climate change and land degradation continue to hamper food and nutrition security in many developing countries, especially among food crop farmers. To the extent that climate change and land degradation continue to conflict with people's livelihoods, information on climate climate-smart agriculture and adaptation impacts, drivers and challenges to adoption of climate-smart and sustainable agricultural technologies, will be useful to analysts and policy makers. Evidence from various sources indicates that agricultural production systems, including climate-smart agriculture technology has the potential to restore degraded farm lands and soils, reduce production risks under climate uncertainty and improve food productivity in a sustainable manner. To promote and motivate the adoption and scaling-up of climate-smart agriculture and sustainable land management technologies, or to sustain the use of these technologies in SSA requires a comprehensive study on the prospects of climate-smart agriculture to the awareness of the economic, environmental, as well as climate mitigation attributes of climate-smart agriculture. First, this study examines the drivers of individual and joint adoption of crop choice and soil and water conservation strategies and how adoption of these strategies impacts on farm performance and exposure to production risks, using a multinomial endogenous switching regression model to account for selectivity bias due to both observable and unobservable factors. Second, the study examines the factors that affect farmers' decisions to adopt climate-smart practices and how adoption affects food and nutrition security among farm households in three agro-ecological zones in Ghana, using an endogenous switching regression approach to account for selectivity bias. To the extent that adoption intensity could have poverty implications, the study further examines the impact of adoption of sustainable land management (SLM) practices on consumption and poverty outcomes using multivalued treatment effects and generalized propensity score (GPS) approaches, while considering adoption intensity within a continuum. Finally, the study assesses the impact of adoption of SLM practices on farm households' technical efficiency and environmental inefficiency using bias-corrected stochastic production frontier and data envelopment analysis models. The empirical results revealed that farmers' adoption of crop choice and soil and water conservation leads to higher crop yields and reduction in exposure to production risks, with the largest impact on yields coming from joint adoption, an indication of complementarity effects of crop choices and soil and water conservation strategies. The findings also showed that adoption of climate-smart practices had positive and significant impact on food and nutrition security in terms of household dietary diversity scores, household food insecurity access scores and farm revenues. The general pattern from a quantile analysis suggested that food and nutrition security improvement effect of adoption is more generally felt by poorer farm households, whose dietary diversity scores fall within lower quantiles. In addition, the treatment effect of adoption of SLM on per capita consumption and poverty outcomes is nonlinear and differed among adopters at different intensity levels of adoption. In addition, the group of farmers who adopted SLM technology exhibited higher levels of technical efficiency as compared to non-adopters, but they were also found to be using higher levels of herbicides that might have environmental implications. Furthermore, the findings revealed that household participation off-farm work positively influences their expenditure on SLM practices and also reduced household vulnerability to expected poverty. The findings also showed that farmers' education, extension services, access to weather information, access to credit and machinery, as well as soil quality positively influenced adoption of climate-smart agriculture and SLM. Thus, addressing challenges of farm households' adaptation to climate change can be enhanced through government interventions, including improved access to credit, improved and drought-tolerant seeds, access to up-to-date weather information, through improvement in extension, as well as investment in infrastructure, particularly irrigation.

Zusammenfassung

Der Klimawandel und die Bodendegradation erschweren die Sicherung der Ernährung in vielen Entwicklungsländern, vor allem für Getreidebauern. Diese Bedrohungen stehen im Konflikt mit den Lebensgrundladen der Menschen. Informationen über Einflussfaktoren und Herausforderungen bei der Implementierung von klimaschonenden- und nachhaltigen Agrartechnologien können für Forscher und politische Entscheidungsträger nützlich sein. Belege aus verschiedenen Quellen deuten darauf hin, dass klimaschonende Agrartechnologie das Potenzial haben, degradierte landwirtschaftliche Flächen und Böden wiederherzustellen, Produktionsrisiken unter klimatischen Unsicherheiten zu verringern und die Lebensmittelproduktivität nachhaltig zu verbessern. Um die Einführung und Verbreitung einer klimaschonenden- und nachhaltigen Landwirtschaft, sowie Landmanagement Technologien zu fördern und auszubauen, bedarf es einer umfassenden Studie. Ziel einer solchen Studie sollte sein, das Minderungspotenzial einer klimaschonenden Landwirtschaft auf wirtschaftliche, ökologische und klimatische Aspekte, herauszustellen.

Im Folgenden werden die verschiedenen Fragestellungen dieser Arbeit erläutert. Diese Studie untersucht, welche Faktoren die Einführung von nachhaltigen Anbaustrategien beeinflusst und wie sich die Einführung dieser Strategien auf die Betriebsleistung und die Gefährdung durch Produktionsrisiken auswirkt. Zu den Maßnahmen zählt die Auswahl der Getreideart, sowie Boden- und Wasserschutzstrategien. Gemessen wird der Effekt der Maßnahmen allein und bei gemeinsamer Durchführung. Zum anderen widmet sich diese Studie der Frage, welche Faktoren die Entscheidung der Landwirte zur Einführung klimaschonender Praktiken beeinflussen. Des Weiteren soll herausgestellt werden, wie sich die Einführung dieser Praktiken auf die Nahrungsmittel- und Ernährungssicherheit in landwirtschaftlichen Haushalten auswirkt. Hierfür werden drei agrar-ökologische Zonen in Ghana berücksichtigt. Außerdem untersucht diese Studie welche Auswirkungen die Einführung nachhaltiger Landmanagementpraktiken (SLM), auf den Konsum und die Armut von entsprechenden Haushalten, ausübt. Hierfür

wurden mehrwertige Behandlungseffekte und „generalized propensity score“ (GPS)-Ansätze verwendet, zugleich wurden verschiedene Implementierungs-Grade innerhalb eines Kontinuums berücksichtigt. Darüber hinaus bewertet die Studie die Auswirkungen der Einführung von SLM-Praktiken auf die technische Effizienz und die ökologische Ineffizienz der landwirtschaftlichen Haushalte. Zur Bewertung der Effizienz wurden eine Bias-korrigierte, stochastische Produktionsgrenze, sowie verschiedene Modelle nach der „Dateneinhüllanalyse“ verwendet. Schließlich untersucht die Studie den Zusammenhang zwischen landwirtschaftlich unabhängiger Arbeit, Grad der Implementierung der SLM und Armutsgefährdung. Die empirischen Ergebnisse zeigen, dass die Übernahme der Pflanzenauswahl und des Boden- und Wasserschutzes durch die Landwirte zu höheren Ernteerträgen und einer Verringerung der Exposition gegenüber Produktionsrisiken führt. Die größten Auswirkungen auf die Ernteerträge konnten bei der gemeinsamen Implementierung der beiden Maßnahmen betrachtet werden. Dies ist möglicherweise ein Hinweis für eine komplementäre Beziehung zwischen der Pflanzenauswahl und der Boden- und Wasserschutzstrategien. Die Ergebnisse zeigen auch, dass sich die Einführung klimaschonender Praktiken positiv und signifikant auf die Nahrungsmittel- und Ernährungssicherheit auswirkt. Die Effekte beziehen sich auf die Vielfalt der Ernährungsgewohnheiten der Haushalte, den Wert für die Unsicherheit beim Zugang zu Lebensmitteln und die Einnahmen der landwirtschaftlichen Betriebe. Das allgemeine Muster der Quantil-Analyse deutete darauf hin, dass die Verbesserung der Nahrungsmittel- und Ernährungssicherheit, durch die Maßnahmeneinführung, generell von ärmeren landwirtschaftlichen Haushalten stärker wahrgenommen wird. Der Wert für die Ernährungsvielfalt dieser Haushalte befindet sich innerhalb des unteren Quantils. Darüber hinaus ist der Behandlungseffekt der Einführung von nachhaltigen Methoden auf den jährlichen Konsum und die Armut nicht linear und unterscheidet sich je nach Grad der Methodeneinführung. Die Gruppe der Landwirte, welche die nachhaltigen Technologien annahmen und einsetzten, besaßen eine höhere technische Effizienz im Vergleich zu Nicht-

Verwendern, jedoch setzten die Anwender einen höheren Anteil an Herbiziden ein, was Auswirkungen auf die Umwelt haben könnte. Die Ergebnisse zeigen auch, dass die Ausbildung der Landwirte, die Beratungsdienste, der Zugang zu Wetterinformationen, der Zugang zu Krediten und Maschinen sowie die Bodenqualität positiv mit der Verwendung von klimaschonenden- und nachhaltigen Landwirtschaftspraktiken zusammenhängen. Durch staatliche Maßnahmen, wie ein verbesserter Zugang zu Krediten, verbessertem und dürrebeständigem Saatgut, Zugang zu aktuellen Wetterinformationen, sowie Investitionen in die Infrastruktur, insbesondere Bewässerung, können Landwirte bei den Herausforderungen, durch die Anpassung an den Klimawandel, unterstützt werden.

Chapter 1

General Introduction

1.0 Background

Extensive changes in patterns of precipitation and temperature threaten agricultural production and increase the vulnerability of farm households, particularly food crop farmers. Projections from various studies indicate that these changes in climate variables and their negative effects will be greater in locations that are already economically marginal and where livelihoods are precarious (IPCC, 2014; Tol, 2018; World Bank, 2010).

There is a global concerted effort to reduce the threats posed by climate change by enhancing the adaptive capacity of farmers, as well as increasing resilience and resource use efficiency in agricultural production systems. Climate-smart agriculture (CSA) is identified as a system for reorienting arable production to support sustainable food productivity and security under the increasing realities of climate change and land degradation (Food and Agriculture Organization [FAO] 2013). CSA together with sustainable land management (SLM) promote coordinated actions by farmers, researchers, private sector, civil society and policymakers towards climate-resilient and sustainable pathways through certain key action areas: (1) gathering and building evidence; (2) enhancing local institutional capacity and effectiveness; (3) fostering coherence among climate change and agricultural policies; and (4) linking climate adaptation and mitigation, SLM and agricultural financing. These will require emphasizing the capacity to implement flexible, context-specific and location specific solutions, supported by innovative policy actions (Castells-Quintana, Lopez-Uribe, & McDermott, 2018; Lipper et al., 2014).

The focus of this study is on the key factors influencing the adoption of climate-smart agricultural technology, as well as SLM practices in sub-Saharan African (SSA) countries, using Ghana as a case study. After introducing some conceptual issues, the study establishes the link between climate change and agricultural productivity, the role of CSA and SLM in mitigating the effects of climate change and variability, as well as reducing production risk and enhancing efficiency of farming systems.

1.1 Climate variability and agriculture nexus in Ghana

Achieving a more sustainable and resilient agricultural sector is paramount to economic development in SSA including Ghana. The sector in Ghana is made up predominantly of subsistence smallholders, with weak linkages to industry and other services, and employs about 75% of rural households and contributes about 22.0% of the country's gross domestic product (GSS 2015; MoFA 2017). It is therefore a major source of food and livelihood security. However, many challenges, together with climate change pose major threats to the agricultural sector, livelihoods and developmental aspirations of many countries including Ghana as shown by several studies (IPCC 2007 and 2014; Wossen et al. 2014; Adiku et al. 2015). Estimates of projected increases in temperature over the 21st century ranges between 1.8 and 4.9 degrees Celsius (IPCC 2007). The mean monthly temperature in the Savannah agro-ecological zones in Ghana has already increased by 2 degrees over the last few decades (Kunstmann and Yung 2005), and it is projected to reach +3 degrees by the year 2080 (Ghana Environmental Protection Agency [EPA] 2011).

Production trends of major food crops including maize, rice and sorghum indicate that on-farm productivity has remained stagnant due to use of inadequate yield enhancing technologies (e.g., quality seed, fertilizer), weak extension and market linkages etc. (Barrett et al. 2017; MoFA 2017). The low production trends are projected to worsen as a result of climate change and variability. Some crop yield trends as reported by the EPA (2008) indicate a negative relationship between major crop production and mean variations in climate variables. Using different climate scenarios, the EPA projected that cassava yields are expected to reduce by 3%, 13.5% and 53% in the years 2020, 2050 and 2080, respectively as a result of rise in mean temperature. Rice production in Ghana is expected to experience variations of up to -8% by 2080 (Knox et al., 2012).

Ghana ratified the United Nations Framework Convention on Climate Change in 1995 (EPA, 2011). The Kyoto Protocol[1] was adopted by Parliament in 2002 that eventually became the current National Climate Change Policy (NCCP). The policy clearly provides a defined pathway for dealing with the challenges of climate change (The Ministry of Environment, Science, Technology and Innovation [MESTI], 2015). Several initiatives and programs aimed at addressing the challenges of climate change are on-going. These include the Ghana Strategic Investment Framework (GSIF) for Sustainable Land Management 2011-2025, which seeks to adopt a programmatic to approach promote sustainable land management and address issues related to land degradation (EPA 2011). As part of efforts to meet the commitments of the Paris agreement, Ghana put forward some mitigation and adaptation actions in its "Intended Nationally Determined Contributions (INDC's); namely sustainable land use including food security, climate-proof infrastructure, equitable social development, sustainable mass transportation, sustainable energy security, sustainable forest management; and alternative urban waste management (Republic of Ghana 2015).

Reducing poverty and increasing food and nutrition security constitute a complex task that can be hard to accomplish through increased crop yields alone. In fact, after over three decades of agricultural-led development projects, the northern savannah zones of Ghana remain deprived (GSS 2015; UNDP-Ghana 2018). Consequently, sustainable improvements in agricultural productivity should be complemented with improvements in infrastructure, education, gender

[1] The Kyoto Protocol is an international treaty among developed countries that sets mandatory limits on greenhouse gas (GHG) emissions; targeting a reduction on GHG's by an average of 5.2% by 2012 based on 1990 levels. Although the agreement entered into force in 2005, the US failed to ratify it (UNDP 2016).

equality, land policy, market stability, financial services, technology access, environmental quality, and research and extension support, to ensure economic development (World Bank 2010; MoFA 2017). As recently noted by development economists, these issues interact considerably and their impacts are largely driven by policy decisions (Vale 2016; Tol 2018). Empirical analyses on adoption and impacts of climate-smart agricultural technologies, are therefore essential to provide stakeholders with up-to-date information for scaling up climate-smart agriculture to enhance sustainable rural development.

1.2 Climate-Smart Agriculture and Sustainable Land Management

The likelihood of current climate variability and future climate change having severe implications on all economies, is a generally accepted fact, although predictions differ among the scientific community (Barrios et al 2010; Elum 2017). A number of studies including the IPCC (2007; 2014) and World Bank (2010); identified three major physical impacts of climate change in African countries, namely temperature change, change in rainfall and sea level rise, all of which impact negatively[2] on agricultural productivity, farm income, food security and economic development (IPCC 2014; Abidoye and Odusola 2015).

In addition to unfavorable climatic conditions, low technology, weak infrastructure and institutional inefficiencies, continue to play a major role in farmers' exposure to production risks and low productivity (Yilma et al. 2008; Barrett et al. 2017; Di Falco and Veronesi 2014). These factors magnify the effects of climate change and increase the risks of crop failures, resulting in food insecurity. Despite the fact that SSA contributes less than 5% to global greenhouse gas (GHG) emissions, the region is the most vulnerable to the effects of climate change (IAASTD 2009). Proximity to the equator and low elevation also contributes to

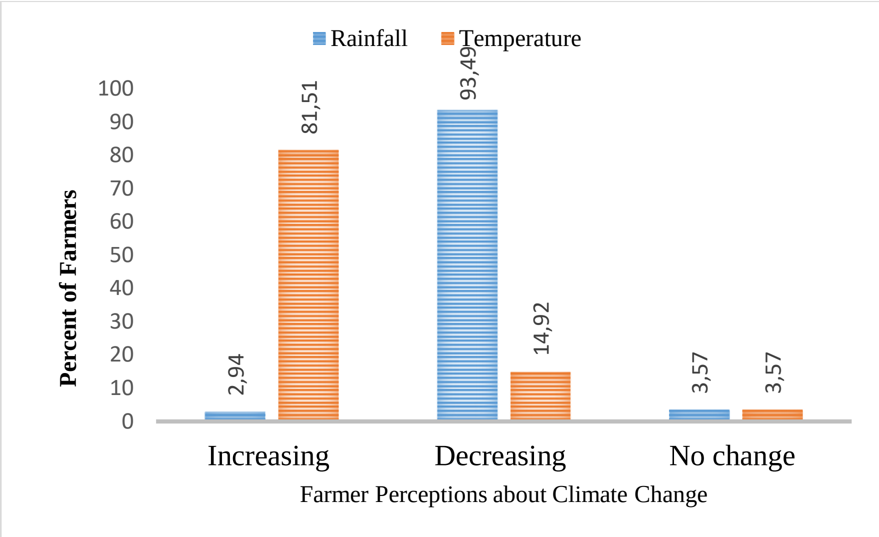
[2] Climate change may impact positively on agricultural production of some countries (especially the temperate regions), Cline (2009).

countries' vulnerability to the negative effects of climate change (Cline 2008; Barrios et al. 2010).

Apart from the direct physical effects on food production, climate influences the incidence and intensity of crop pest and pathogen infestations, post-harvest losses and food quality. Many pathogenic diseases affecting food and cash crops are associated with climate variables that result in yield losses (Anderson et al. 2004). Besides, current weather conditions affect food supply and quality, with some studies estimating that 30%–50% of total food production is lost globally, partly due extreme weather fluctuations (Gustavsson et al. 2011). Furthermore, in many SSA countries, technological limitations in processing, packaging, storage, transportation, as well as market inefficiencies in the food sector, are highly influenced by climatic factors, resulting in food waste, or preventing crops from being harvested on time to avoid spoilage (Godfray et al. 2010). In addition, flooding and temperature extremes can affect the stability of food availability by impeding the movement of food from production centers to consumers. This could result in altering of food prices in response to changes in the cost of transportation (access), and by increasing the likelihood of food contamination (utilization).

Two mechanisms have been identified globally as ways of dealing with the climate change and variability; adaptation and mitigation. According to the IPCC (2007, 2014), mitigation involves actions that result in reducing greenhouse gas (GHG) emissions mainly attributed to anthropogenic activities. Mitigation is considered as a long-term solution to on-going climate change and aims at minimizing the negative effects of climate change in the future (IPCC 2007; Elum et al. 2017). Adaptation on the other hand, involves adjustments in the natural, human and socio-economic systems in response to actual or anticipated climate change, as well as taking advantage of new opportunities (IPCC 2007). Thus, climate-smart agriculture seeks to enhance the resilience of agricultural systems and livelihoods and to reduce the risk of food and nutrition insecurity in the present, as well as the future (FAO 2013; Lipper et al. 2014).

Farmers' perceptions about climate change inform their decisions to adopt climate-smart technologies (Di Falco and Veronesi 2014). For instance in response to a question of how farmers perceived climate change in the last 20 years, it was observed that more than 80% of respondents indicated that there has been an increase in temperature trends, while about 93% reported a decrease in rainfall trends (see figure 1) confirming the scientific predictions in the literature on climate change in the area, the Sudan Savannah, Guinea Savannah and Transitional agro-ecological zones (Adiku et al. 2015; De Pinto et al 2012).



Source: Author's compilation from survey data

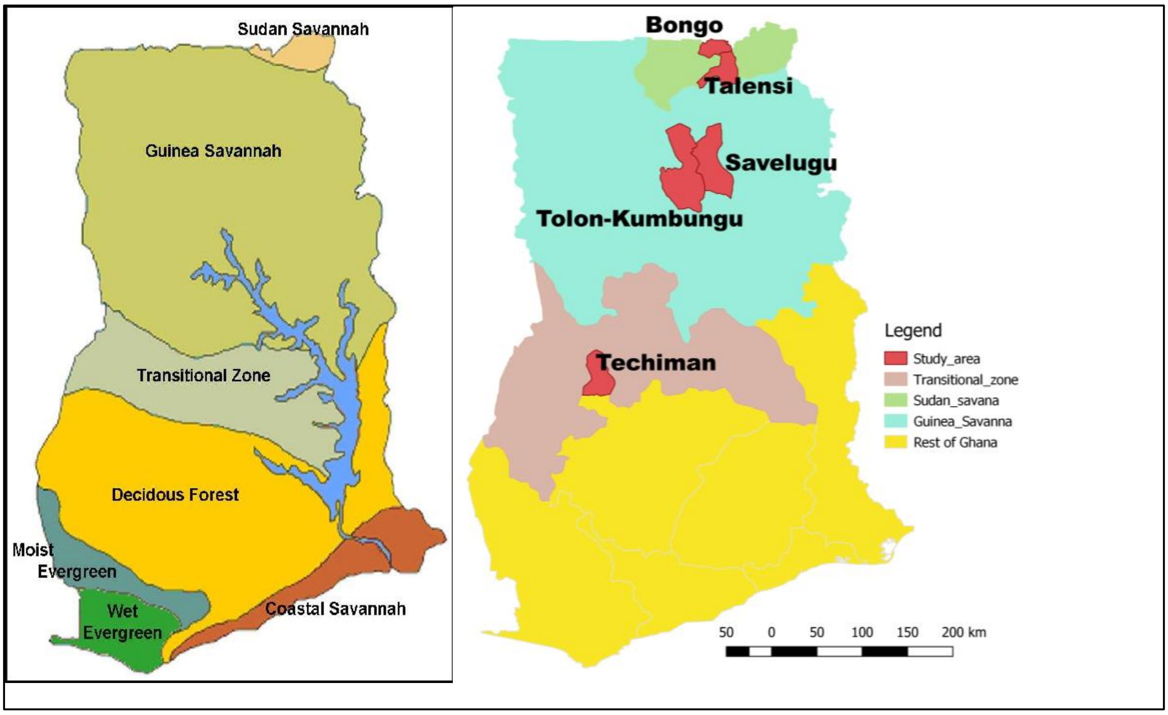
Figure 1.1: Households' perceptions on climate change over the past 20 years

The effects of climate change can be exacerbated by land degradation. The EPA (2011) identifies four major types of land degradation in Ghana, namely deforestation, soil erosion, declining soil fertility and deterioration of rangelands, which have been attributed to both bio-physical and anthropogenic factors. Meanwhile, 58% of the total land degradation occurs in the Sudan and Guinea savannah agro-ecological zones. The degradation of farm land on which the majority of the people depend for their livelihoods, therefore has serious consequences for sustainable agricultural growth and productivity. It is implicated in the poverty-degradation linkage and partly considered as the root cause of the vicious poverty cycle for many rural households in Ghana (EPA 2011; MoFA 2017). Sustainable management of land resources is therefore necessary for Ghana to fully develop its potential in agricultural sector for the achievement of its socio-economic development goal of poverty eradication and enhanced food and nutrition security (EPA 2011; MoFA 2016, 2017). This involves focusing on providing information and appropriate incentives to increase adoption and scale-up of SLM practices, and coordinate the activities of institutions and organizations involved in the promotion of SLM at the regional, district and local levels (MoFA 2016).

1.3 Study area, Agro-ecological zones and Poverty profile in Ghana

Ghana has been classified into six agro-ecological zones (Sudan savannah, Guinea savannah, Transition zone, Deciduous forest Rain forest and Coastal savannah zones). This study sampled food crop farmers from the Sudan savannah, Guinea savannah and the Transitional agro-ecological zones (see Figure 1.2). The savannah zones constitute the driest part of Ghana and most vulnerable to effects of climate variability. These areas are characterized with hot temperatures (30°C - 40°C) and long dry seasons from November to April, with average rainfall ranging from 800 mm to 1,200 mm per annum (Adiku et al. 2015). The Transitional zone experiences up to 1,300 mm of annual rainfall with two growing seasons, although the savannah conditions are gradually taking over the northern part of this zone.

The vegetation in the savannah zones consists of mainly grass with scattered drought resistant trees such as the shea, the baobab, dawadawa, and neem trees. The heterogeneous collection of trees provides much of domestic requirements for fuel wood and charcoal. Poverty levels are quite high. The Ghana Living Standards Survey round 6 (GLSS 6), as well as the 2010 Population and Housing Census (PHC) reported high levels of poverty in the northern savannah ecological zones comprising Upper East, Upper West and Northern regions (GSS 2015). Some studies have also shown the existence of close links between poverty, climate change and agroecology in Ghana (World Bank 2010; Wossen et al. 2014).



Source: Authors' compilation from EPA (2011) and the use of ArcGIS software

Figure 1.2: **Map showing the savannah and transitional agroecological zones and study area**

For instance, poverty incidence in the savannah zone is about 52-70% compared to the national average of 34% (GSS, 2015). In the Transitional and other agroecological zones, the reported poverty levels are relatively lower (Table 1.1).

Thus, harsh climate conditions resulting from climate change have the tendency to worsen the poverty levels of communities in the Savannah agroecological zones, especially households dependent on rain-fed crop production. The three northern regions in particular are also characterized by an unfavorable biophysical environment with frequent failure and uneven distribution of rainfall, poor soil quality and land degradation (UNDP-Ghana 2018). Thus, a more comprehensive approach, including identification of location specific adaptation practices that are consistent with the future climate trends, as well as practical adaptation planning process to guide selection and integration of recommendations into existing policies and programs are required through research (MoFA 2016).

Table 1.1: Poverty head count by region (poverty line = GH₵1,314)

Region	Census			GLSS 6			
	Poverty head count	Standard error	Absolute Difference (Census & GLSS 6)	Poverty head count	Standard error	95% confidence interval Lower limit	Upper limit
Western	19.2	0.0040	1.7	20.9	0.0252	15.94	25.82
Central	19.6	0.0072	0.8	18.8	0.0223	14.44	23.19
Greater Accra	6.6	0.0015	1.0	5.6	0.0151	2.65	8.57
Volta	33.3	0.0028	0.5	33.8	0.0343	27.12	40.57
Eastern	22.0	0.0097	0.3	21.7	0.0242	16.91	26.4
Ashanti	13.6	0.0035	1.2	14.8	0.0169	11.43	18.07
Brong Ahafo	28.6	0.0036	0.7	27.9	0.0215	23.64	32.09
Northern	**44.2**	**0.0062**	6.2	**50.4**	0.0318	44.12	56.59
Upper East	**45.9**	**0.0137**	1.5	**44.4**	0.0388	36.8	52.01
Upper West	**69.4**	**0.0102**	1.3	**70.7**	0.0275	65.29	76.07

Source: Authors' compilation from Ghana Statistical Service, 2015 Population and Housing Census data.

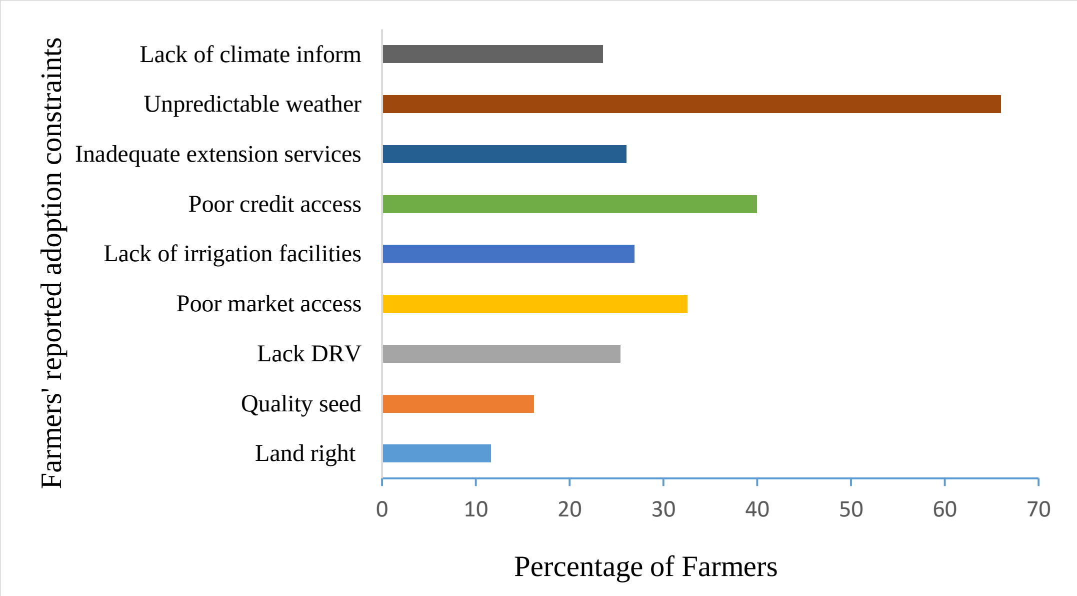
Besides these adverse biophysical conditions, institutional factors like lack of access to credit and insurance markets, high costs of inputs, and poor infrastructure are very prevalent (GSS 2015 UNDP-Ghana 2018).

1.4 Agricultural sector in Ghana

The agricultural sector is dominated by smallholders. Up to 95% of agricultural households in Ghana are engaged in crop farming (Kayode et al. 2014), with about 90% of farm holdings being less than 2 hectares (Ministry of Food and Agriculture (MoFA) 2016). The farm households produce a diversity of crops in mixed cropping systems mainly under rain-fed conditions. For instance, out of about 7.8 million hectares of agricultural land under cultivation, less than 1.0% is irrigated, while close to 99% of farm households depend on rainfall (MoFA, 2016). Commercial and large-scale farms are often plantation crops such as cocoa, oil-palm, rubber and coconut, and to a lesser extent, cereals (mainly rice and maize) and pineapples, usually in the forest agroecological zones. Many farm households also keep livestock such as sheep, goats, cattle, as well as poultry, mainly under extensive to semi-intensive production systems, with few commercial livestock farms.

In Ghana, climate change affects agricultural ecosystems, particularly in the northern savannah zones, through deviations over the long-term in key variables, mainly temperature and rainfall that affect plant growth and crop production in general. According to MoFA (2016), maize production recorded a reduction of 0.15% over the period 2008-2013, partly attributed to unfavorable climatic conditions (especially erratic rainfall) and declining soil fertility. Consequently, some farmers over time have employed various strategies including the use of drought tolerant crops that crops that do not dependent on fertilizer (millet, and sorghum) in the northern sector thereby causing the a decline in the cultivated areas of maize and other climate-sensitive (MoFA 2016).

In addition, farmers in Ghana face a number of challenges in their attempt to adopt technologies to ease production risks and to increase yields. These challenges, which haven mentioned earlier, range from institutional (extension services, credit market, climate information, land tenure) to infrastructural deficits (poor road network, inadequate irrigation facilities etc.). Figure 1.2 indicates some of the challenges reported by farmers in the study area. From the figure, lack of drought resistant varieties (DRV), climate information, poor credit and extension services are some policy issues, if addressed will enhance adoption of climate-smart technologies.



Source: Authors' compilation from field data

Figure 1.3: Farmers' Constraints to adoption of climate-smart & SLM technologies

1.5 Thesis structure

This study is a collection of research articles organized as follows. The article in Chapter 2 examines adoption of climate-smart practices and its effect on farm performance and risk exposure among smallholder farmers. Climate change continues to increase production risks especially among smallholder farmers. To the extent that farmers' risk exposure varies widely across agroecological zones in developing countries, it is important that in measuring farm performance, we employ techniques that account for heterogeneities in individual, as well as combination of different climate-smart practices, to ensure unbiased and consistent estimates. To ensure this, we employ a multinomial endogenous switching regression approach to enable us analyze individual and joint adoption of climate-smart practices and the impacts of adoption on crop yield and risk exposure. This approach allows us to account for selectivity bias caused by both observable and unobservable factors. The empirical results reveal that farmers' adoption of crop choice and soil and water conservation leads to higher crop yields and reduced exposure to down-side risks, with the largest impact on yields coming from joint adoption. The findings also show that education of the household head, extension access and weather information influence the likelihood of adopting these strategies. Thus, enhancing extension services and improved access to climate information and irrigation can reduce gaps in adoption of climate smart-practices that will eventually improve crop yields and reduce farmers' exposure to climate related production risks.

In Chapter 3, the study examines the role of climate-smart agriculture in improving household food and nutrition security. Particularly, the study examines the factors that influence farmers' decisions to adopt climate-smart practices and how adoption affects food and nutrition security among households, using an endogenous switching regression approach to account for selectivity bias. The study employed farm revenues, household dietary diversity scores and household food insecurity access scores as proxies for multi-dimensional outcomes of food and nutrition security. The results show that adoption positively and significantly influenced food and nutrition security. The impacts of adoption are greater in the lower quantiles of distributions of food and nutrition security, an indication of the potential role of climate-smart agriculture in reducing poverty among the poor. Adoption impacts also differed across agro-ecological zones.

Chapter 4 of this study explores the welfare implications of sustainable land management (SLM) practices among smallholder farmers in Ghana. Some concerns have been raised that adoption of sustainable land management practices and vulnerability to consumption poverty are insufficiently linked in SSA (Nkonya et al., 2016). In this study, we employed multivalued treatment effect model and dose-response functions to examine the impact of adoption intensity on poverty outcomes (poverty headcount ratio, poverty gap and poverty-gap squared) and to provide more information regarding the effectiveness of SLM practices. In particular, this allows the assessment of heterogeneous effects of adoption in a continuum context and provides information about the optimal level of adoption (Bia and Mattei, 2012; Esposti, 2017). The results showed that the average treatment effect of moving from low intensity to high intensity adoption levels differed across quantiles of per capita consumption. We also use a dose-response function to demonstrate that the treatment effect of adoption on per capita consumption and poverty outcomes is nonlinear, with optimal adoption level occurring between 60-70% of adoption intensity dose.

Given that farmer efficiency is necessary to the achievement of policy goals of the agricultural sector and for that matter the SDG's, Chapter 5 examines the role of adoption of SLM on technical efficiency and environmental inefficiency of farms. The study focuses on the relationship between SLM technology and technical efficiency on one hand, and SLM and excess herbicide use on the other. The study employs both selectivity bias-corrected stochastic production frontier (SPF) and data envelopment analysis (DEA) approaches. In the SPF approach, we accounted for technology differences by employing a meta-frontier framework. In the DEA, we obtained both TE score and slacks of environmental impact quotient (EIQ) of herbicide, which we used to as proxy for environmental inefficiency. The study then employed fractional regression models to examine the determinants of technical efficiency and environmental inefficiency among farmers. The results show that farmers adopting SLM technology exhibit higher levels of technical efficiency as compared to non-adopters. However, the results reveal that adoption is associated with excess EIQ which could have adverse environmental consequences. Chapter 6 presents conclusions and policy recommendations of the study.

References

Adiku, S. G. K., Dilys, S. M., Hathie, I., Diancoumba, M., et al. (2015). Climate Change Impacts on West African Agriculture: An Integrated Regional Assessment (CIWARA) in *Handbook of Climate Change and Agroecosystems: The Agricultural Model Inter-comparison and Improvement Project (AgMIP) Integrated Crop and Economic Assessments*, Imperial College Press, pp. 25-73.

Anderson, P.K., A. A. Cunningham, N. G. Patel, F. J. Morales, R. Paul, P. R. Epstein & P. Daszak. (2004). Emerging infectious diseases of plants: pathogen pollution, climate change and agro-technology drivers, *Trends in Ecology and Evolution* 19 (10): 535-544.

Barrett, C. B., Christiaensen, L., Sheahan, M. & Shimeles, A. (2017). On the Structural Transformation of Rural Africa, *Journal of African Economies* 26 (1): 11–35.

Barrios, S., Bertinelli, L. & Strobl, E. (2010). Trends in Rainfall and Economic Growth in Africa: A Neglected Cause of the African Growth Tragedy, *The Review of Economics and Statistics*, 92(2): 350–366.

Bia, M. & Mattei, A. (2012). Assessing the effect of the amount of financial aids to Piedmont firms using the generalized propensity score, *Statistical Methods Applications*, 21:485-516.

Castells-Quintana, D., Lopez-Uribe, M. del P., & McDermott, T. K. J. (2018). Adaptation to climate change: A review through a development economics lens. *World Development*, *104*, 183–196. https://doi.org/10.1016/j.worlddev.2017.11.016.

De Pinto, A., Demirag, U., Haruna, A., Koo, J., & Asamoah, M. 2012. *Climate change, agriculture, and food-crop production in Ghana. IFPRI Policy Note* No. 3. Washington, D.C., USA: International Food Policy Research Institute (IFPRI).

Di Falco, S. & Veronesi, M. (2014). Managing Environmental Risk in Presence of Climate Change: The Role of Adaptation in the Nile Basin of Ethiopia, *Environmental and Resource Economics*, 57(4): 553–577.

Elum, Z. A., M. D. Modise & A. Marr. (2017). Farmer's perception of climate change and responsive strategies in three selected provinces of South Africa, *Climate Risk Management 16:* 246-257.

Environmental Protection Agency EPA (2011). *Ghana's Second National Communication (GSNC) to the UNFCCC;* United Nations Development Programme: New York, NY, USA.

Esposti, R. (2017). The heterogeneous farm-level impact of the 2005 CAP-first pillar reform:

A multivalued treatment effect estimation, *Agricultural Economics* 48: 373–386.

Food and Agriculture Organization of the United Nations (FAO). 2013. Climate-Smart Agriculture Sourcebook. *Food and Agriculture Organization*, Rome.

Ghana Statistical Service (GSS) (2015). *Ghana Poverty Mapping Report*, Ghana Statistical Service, Accra, Ghana.

Godfray, H. C. J., J. R. Beddington, I. R. Crute, L. Haddad, D. Lawrence, J. F. Muir, et al. 2010. Food security: The challenge of feeding 9 billion people. *Science*, 327: 812–818.

Gustavsson, J., C. Cederberg, U. Sonesson, R. van Otterdijk, & A. Meybeck. 2011. *Global food losses and food waste: Extent, causes and prevention.* Rome, Italy: FAO. Retrieved from http://www.fao.org/docrep/014/mb060e/mb060e.pdf

International Assessment of Agricultural Knowledge, Science and Technology for Development (IAASTD). (2009). Agriculture at Crossroads. Ed. McIntyre, B. D., H. R. Herren, J. Wakhungu, R. T. Watson. Island Press, Washington, D. C.

IPCC (2007). *Climate Change 2007: Fourth Assessment Report of the Intergovernmental Panel on Climate Change*, Cambridge University Press, Cambridge.

IPCC, (Intergovernmental Panel on Climate Change). (2014). *Climate Change 2014 Synthesis Report. Summary for Policymakers. Ipcc*. https://doi.org/10.1017/CBO9781107415324

Kayode, G. A., Amoakoh-Coleman, M., Brown-Davies, C., Grobbee, D. E., Agyepong, I. A., Ansah, E., & Klipstein-Grobusch, K. (2014). Quantifying the validity of routine neonatal healthcare data in the Greater Accra Region, Ghana.

Knox, J., T. Hess, A. Daccache & T. Wheeler. 2012. Climate change impacts on crop productivity in Africa and South Asia, *Environmental Research Letters* 7: 034032 (8pp) .

Kunstmann H. & G. Jung (2005). Impact of Regional Climate Change on Water Availability in the Volta Basin of West Africa *IAHS Publication No. 295* Regional Hydrological Impact of Climate variability and Change, 75-85.

Lipper, L., Thornton, P., Campbell, B. M., Baedeker, T., Braimoh, A., Bwalya, M., … Torquebiau, E. F. (2014). Climate-smart agriculture for food security. *Nature Climate Change*, *4*(12), 1068–1072.

Ministry of Food and Agriculture (MoFA) (2016). Agricultural Sector Progress Report 2015. *Ministry of Food and Agriculture*, Accra, Ghana.

Ministry of Food and Agriculture (MoFA) (2017). Planting for Food and Jobs Strategic Plan For Implementation (2017-2020), *Ministry of Food and Agriculture*, Accra, Ghana.

Nkonya, E., Mirzabaev, A. & von Braun, J. (2016). Economics of Land Degradation and

Improvement: An Introduction and Overview, in Nkonya, E., Mirzabaev, A. & von Braun, J (Eds.), *Economics of Land Degradation and Improvement: A Global Assessment for Sustainable Development,* IFPRI, Washington, D.C.

Republic of Ghana (2015). Ghana's intended nationally determined contribution (INDC) and accompanying explanatory note, Republic of Ghana, online at: https://www4.unfccc.int/sites/ndcstaging/PublishedDocuments/Ghana%20First/GH_INDC_2392015.pdf.

Tol, R. S. J. (2018). The Economic Impacts of Climate Change. *Review of Environmental Economics and Polic*y, 12 (1): 4-25.

UNDP-Ghana. 2018. Northern Ghana Human Development Report 2018, *UNDP*, Ghana.

Vale, P. M. 2016. The changing climate of climate change economics, *Ecological Economics* 121: 12–19.

World Bank (2010). *Economics of Adaptation to Climate Change. Ghana Country Study*; World Bank: Washington, DC, USA.

Wossen, T., Berger, T., Swamikanu, N. & Ramilan, T. (2014).Climate variability, consumption risk and poverty in semi-arid Northern Ghana: Adaptation options for poor farm households**,** *Environmental Development* 12: 2-15.

Yilma, T., Berg, E., Berger, T., (2008). The agricultural technology-market linkage under liberalization in Ghana: Evidence from micro data. *Journal of African Economies* 17 (1): 62–84.

Chapter 2

Adoption of climate-smart practices and its impact on farm performance and risk exposure among smallholder farmers in Ghana

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Abstract

Increased climate variability during the last four decades has made the agricultural environment in many developing countries more uncertain, resulting in increasing risk exposure and crop failure. In this study, we use recent farm level data from Ghana to examine the drivers of individual and joint adoption of crop choice and soil and water conservation practices and how adoption of these practices impact on farm performance and exposure to risks. We employ a multinomial endogenous switching regression model to account for selectivity bias due to both observable and unobservable factors. The empirical results reveal that farmers' adoption of crop choice and soil and water conservation leads to higher crop revenues and reduced exposure to production risks, with the largest impact on crop revenues coming from joint adoption. The findings also show that education of the household head, extension access and weather information influence the likelihood of adopting these practices. Thus, enhancing extension services and access to climate information and irrigation can reduce gaps in adoption of climate smart-practices that will eventually improve crop revenues and reduce farmers' exposure to climate related production risks.

Keywords: Africa; Climate-smart practices; farm performance; impact assessment; Risk exposure.

JEL Codes: C34, D13, Q12

2.0 Introduction

Climate variability continues to be a major challenge to achieving food security in Sub-Saharan Africa (SSA) due to the incidence of high temperature, erratic rainfall regimes, coupled with low adoption of modern technologies (IPCC, 2007; World Bank, 2010). Although SSA contributes less than 5% of global greenhouse gas (GHG) emissions, it is the most vulnerable to the negative effects of climate change, as the region's development prospects are closely linked to climate because of heavy reliance on rainfall (IAASTD, 2009; Tol, 2018). The vulnerability has been attributed to structural, technological and institutional weaknesses, higher poverty, as well as relative proximity to the equator (IPCC, 2007). The impact of climate change on agricultural productivity especially in developing countries is well documented (IPCC, 2007; Di Falco and Veronesi, 2013; Gunathilaka et al., 2018). The key issue is therefore not whether climate change will have adverse impact on crop productivity, but the extent of productivity losses from climate variability or uncertainties and the prospect of mitigating the negative impacts through adoption of appropriate climate-smart practices.

The international community has recommended the incorporation of adaptation into national development plans (IPCC, 2007; World Bank, 2010). A better understanding of adaptation is critical, especially in developing countries and in the agricultural sector, because of their vulnerability to climate change (IPCC, 2007; Tibesigwa et al., 2014). As argued by Tol (2018), adaptation is increasingly being considered by economists more widely as part of important measures to complement climate mitigation. Various climate-smart practices including planting of new crop varieties, changing planting dates, growing drought resistant crops, use of crop insurance mechanisms, irrigation, and adoption of soil and water conservation measures, have been used by farmers in developing countries to cope with the negative effects of climate change and to ensure high yields (Di Falco and Veronesi, 2013; Adamson et al., 2017). Thus, a practice may be considered as "climate-smart", if it falls within the three main objectives of climate-smart agriculture, stated by the FAO (2013) as: (a) sustainably increasing agricultural productivity and incomes, (b) adapting and building resilience to climate change, and (c) reducing greenhouse gases emissions.

Although the promotion of climate-smart agriculture in SSA is ongoing as part of many developing countries' sustainable agricultural development policy (Lipper and Zilberman, 2018), empirical evidence shows that adoption rates among smallholder farmers are still low (Arslan et al. 2015; Barnard et al. 2015). For instance, in Zambia, Arslan et al. (2015) observe 6% and 37% adoption rates for minimum tillage and crop rotation, respectively. Promotion of climate-smart agriculture in Ghana gained momentum since the country ratified the United Nations Framework Convention on Climate Change in 1995 (Environmental Protection Agency [EPA], 2011). The Kyoto Protocol was adopted by Ghana's Parliament in 2002 and eventually led to the current National Climate Change Policy (NCCP) (Ministry of Environment, Science, Technology and Innovation [MESTI], 2015). Through various state and non-state agencies, Ghana has sought to make climate-smart agriculture part of its agricultural development policy (MSTTI, 2015; Ministry of Food and Agriculture [MoFA], 2018).

There exists extensive literature on adoption impacts of individual climate-smart practices, with divergent findings (e.g., Di Falco and Chavas, 2009; Abdulai and Huffman, 2014; Kato et al., 2011; Zougmore et al., 2014; Di Falco and Veronesi 2013; Ng'ombe et al. 2017). Among the frequently mentioned pathways include climate-smart agriculture's ability to increase crop yields, food and nutrition security, reduction in crop failure (e.g., Kato et al., 2011; Di Falco and Veronesi 2013; Abdulai and Huffman 2014). Other studies report lower farm returns from plots treated with certain soil conservations practices (e.g., stone bunds) in Bukina Faso (World Bank 2009), while Nkala et al. (2011) find no significant effect of minimum tillage on household incomes in Mozambique.

Furthermore, Di Falco and Chavas (2009) find positive effect of biodiversity on risk reduction among barley farms in Ethiopia. The study by Di Falco and Veronesi (2013) also indicate that adaptation to climate change led to increased yield among maize farmers in Ethiopia. Other studies have indicated that soil conservation, crop choice and other practices can increase technical efficiencies among farmers, as well as minimize on-farm environmental damage (Solis et al. 2007; Veettil et al. 2017; Sabiha et al. 2017). Although these studies contribute towards the understanding of the factors driving the adoption of climate-smart practice and impacts on productivity and risk exposure, there exist a gap in the literature about the potential complementarity or substitutability among individual and combined climate-smart practices. In addition, the mixed findings from these studies about adoption impacts on farm performance also provide motivation for further empirical investigation into the potential impacts of specific climate-smart agricultural practices on crop revenues and production risk exposure, with respect to agroecology.

Few studies have evaluated adoption and impacts of multiple climate-smart practices on smallholder farmers' productivity and risk exposure, usually from a monocropping perspective (e.g., maize, rice or wheat) (e.g., Di Falco and Veronesi, 2013; Kassie et al., 2014; Ng'ombe et al., 2017). However, this approach might under- or over-estimate the true impacts of adoption for a number of reasons. First, implementation of climate-smart practices, like soil and water conservation in a mixed cropping setting might offer benefits to other crops including maize or sorghum, which could not be captured if the analyst considered only maize yield and excluded other crops. Second, there may also be negative interaction among crops in mixed-crop setting, where only yield of one crop increases at the expense of others (e. g., Tessema et al., 2015).

In this study, we examine the adoption of a combination of climate-smart agricultural practices and their impacts on smallholder crop revenues and exposure to risk in Ghana. We define climate-smart practice more broadly to include crop choice and soil and water conservation measures (FAO, 2013). Crop choice as climate-smart agricultural practice is defined to include the use of modern varieties, drought resistant and early maturing varieties that enable crop farmers to cope with erratic rainfall or short rainfall season. It also captures changing crops in response to climate variability. A number of studies have linked adoption of crop choice/switching crops and planting dates to farmers' climate change adaptation behaviour (e.g., Deressa et al., 2009; Di Falco and Veronesi, 2013). It is common to intercrop cereals and other crops, especially in northern Ghana. Soil and water conservation also refers to the use of erosion control and other measures to prevent soil and nutrient loss and conserve soil moisture, such as minimum tillage, soil and stone bunds, and use of z*aï* techniques. The z*aï* technique is a soil conservation method that concentrates run-off water and organic manure in small round or square pits (Zougmore et al., 2014). In Ghana, it is mainly used in the dry Savannah zones particularly in Upper East region. Strategies that seek to minimize soil loss due to erosive rains, or reduce evaporation of water from the soil due to high temperatures, are expected to help improve crop performance (see Kato et al., 2011; Abdulai and Huffman, 2014).

We contribute to the literature in this regard by employing recent advancements in the impact assessment literature to identify location specific information on adoptable climate-smart practices, as well as implications of adoption on farm performance and risk exposure. To the best of our knowledge, this is the first of such study in Ghana and among a few of such studies in SSA. Specifically, we first examine the factors that affect farmers' decisions to adopt crop choice, and soil and water conservation measures, individually and jointly; secondly, we determine impacts of adoption on crop revenues and risk exposure among mixed crop plots. We employ recent survey data and use a multinomial endogenous switching regression approach (Bourguignon et al. 2007) to achieve our research objective. Given the fact that our sample is made up of mixed crop plots, we capture crop revenue as the value of all crops cultivated by the household on each plot (see Kato et al., 2011). The procedure by Antle (1983) is employed to estimate the crop revenue skewness, which is used as a proxy for downside risk or probability of crop failure. An increase in crop revenue skewness implies a decrease in downside risk, which indicates lower probability of crop failure (Di Falco and Chavas 2009).

Our study is relevant to the debate on whether farmers should adopt practices individually or as a package. This study will also contribute to efforts at identifying Ghana's Nationally Determined Contributions (NDCs), through which developing countries are expected to articulate their climate mitigation actions and commitment to implementation of the Paris Agreement (United Nations 2015; MoFA 2018). To the extent that climate-smart agriculture overlap with several development goals, such as poverty reduction and food security, the empirical findings from this study can have important implications for climate policy in SSA (Vale, 2016; Tol, 2018).

The rest of the paper is organized as follows. In the next section, we present the conceptual framework and econometric specification, as well as the estimation procedures. The description of the data, as well as variables employed in the empirical strategy is presented in section 3. In section 4, the empirical results are discussed, whilst the final section highlights the main conclusions and policy implications of the study.

2.1 Conceptual framework and econometric specification

We examine adoption and impacts of two climate-smart practices on farm performance. We follow previous studies (Di Falco and Chavas, 2009; Kassie *et al*., 2014) and calculated crop revenue skewness distribution that is approximated using the third central moment of crop revenue distributions. Crop revenue skewness is a good indicator of farm performance, especially under climate uncertainty because skewness captures the exposure to downside risk (Antle, 1983; Di Falco and Chavas, 2009). Thus, an increase in the crop revenue skewness implies a reduction in the probability of crop failure (Di Falco and Chavas, 2009). Estimating the moments of crop revenues follows a sequential estimation procedure by first regressing[3] crop revenue per acre on production inputs and other farm level variables, after which the residuals are retrieved. The third moments is calculated by raising the residual to the third power (Di Falco and Chavas, 2009). The estimated third moment of crop revenue is used as outcome variables in the MESR model to examine the impact of individual and joint adoption on risk exposure.

Modelling choice of climate-smart practice

Let's assume that farmers' decision to use a combination of climate-smart practices is to maximize expected benefits. The *i*th plot's expected benefit, V_{ij}^*, due to application of a combination of practices j, where $j(j = 1, \ldots, M)$, is a latent variable determined by observed characteristics (X_i), as well as unobserved factors (ε_{ij}), expressed as:

$$V_{ij}^* = X_{ij}\beta_j + \theta_j \bar{X}_{ij} + \varepsilon_{ij} \tag{1}$$

Let V_i denote an index that indicates the farmer's choice of a combination of practices, such that:

$$V_i = \begin{cases} 1 \text{ iff } & V_{i1}^* > \max_{k \neq 1}(V_{ik}^*) \text{ or } \varepsilon_{i1} < 0 \\ \vdots & \vdots \qquad\qquad \vdots \\ M \text{ iff } & V_{iM}^* > \max_{k \neq j}(V_{ik}^*) \text{ or } \varepsilon_{iM} < 0 \end{cases} \tag{2}$$

where $\max_{k \neq j}(V_{ik}^* - V_{ij}^*) < 0$. Equation (2) indicates that a farmer will apply climate-smart practice *j* on plot *i* to maximize expected benefit if the chosen practice provides greater expected benefit than any other alternative option $k \neq j$, that is if $\varepsilon_{ij} = \max_{k \neq j}(V_{ik}^* - V_{ij}^*) < 0, \forall\, j, k \in M$. In this study, the adoption of two climate-smart practices, crop choice and soil and water conservation, results in four possible combinations from which the farmer can choose (namely, crop choice only, soil and water conservation only, joint adoption and non-adoption).

[3] The OLS estimates of the crop revenue function are not reported in this paper to save space.

Assuming that ε_{ij} in Equation 1 is independently and identically Gumbel distributed, the probability that practice j will be chosen can be specified by a multinomial logit (MNL) model as (McFadden, 1973):

$$P_{ij} = P\left(\varepsilon_{ij} < 0 \middle| X_i\right) = \frac{\exp\left(X_{ij}\beta_j + \bar{X}_{ij}\delta_j\right)}{\sum_{k \neq 1}^{M} \exp\left(X_{ij}\beta_k + \bar{X}_{ij}\delta_k\right)} \tag{3}$$

where $\bar{X}_{ij}$ denotes a vector of average plot-specific variables and δ_j refers to the corresponding parameters to be estimated. The estimation of parameters of the latent model in equation 3 is done by maximum likelihood approach. We then model the chosen strategies within the multinomial endogenous switching regression framework (MESR) to link the climate smart practices to the outcomes of interest.

Multinomial endogenous switching regression model

The multinomial endogenous switching regression (MESR) model, was proposed by Bourguignon et al. (2007) and has been applied in recent empirical studies (e.g., Di Falco and Veronesi, 2013; Teklewold et al. 2013; Ng'ombe et al. 2017). We employ this approach in this study. The base category, non-adoption is indicated as $j = 1$. For the remaining practices ($j = 2$ crop choice, $= 3$ soil and water conservation only, and $j = 4$ joint adoption), at least one climate-smart practice combination is applied on a plot. The outcome equation for each potential regime j is given as:

$$\begin{cases} \text{Regime 1}: y_{i1} = Z_{i1}\alpha_1 + \bar{Z}_{i1}\theta_j + u_{i1} \; if \; V_i = 1 \\ \quad\quad\quad\quad \vdots \quad\quad\quad \vdots \quad\quad\quad \vdots \\ \text{Regime J}: y_{ij} = Z_{ij}\alpha_j + \bar{Z}_{ij}\theta_j + u_{ij} \; if \; V_i = \; j \end{cases} \tag{4}$$

where y_{ij} is the outcome variable (crop revenue or risk exposure) of the *ith* farm plot in regime j, Z_i represents a vector of farm and household characteristics, and the u's denote error terms with expected values of zero and constant variance , $Var\left(u_{ij} \middle| X_i, Z_i\right) = \sigma_j^2$, while α_j represents a vector of parameters to be estimated. The variable $\bar{Z}_i$ refers to mean-plot specific characteristics (e.g., soil fertility, plot slope and drainage level), and θ_j denotes the corresponding parameters to be estimated. This is essential in order to account for unobserved heterogeneity due to plot varying characteristics being correlated with household level variables when a household cultivates multiple plots (Mundlak 1978). A Wald test of the null hypothesis that the vector θ_j are jointly equal to zero is conducted to indicate the relevance of plot-specific heterogeneity (Teklewold et al. 2013).

To ensure that the estimates of α_j in Equation 4 are unbiased and consistent, inclusion of selection correction terms derived from the multinomial selection process, is required. We follow Bourguignon et al. (2007) and assume that the error terms (ε_{ij}) and u_{ij} are linearly correlated for every j option, such that the expected value of u_{ij} is stated as $E[u_1|\varepsilon_1, \dots \varepsilon_j] = \sigma \sum_{j=1 \dots M} \rho_j \varepsilon_j$, where ρ_j is the correlation between u_{ij} and ε_{ij}, while σ is the standard deviation of the error term u_{ij}.

Thus, the outcome equation (4), taking into consideration the choices made with bias correction, can be restated as in Teklewold et al. (2013):

Regime 1: $y_{i1} = Z_{i1}\alpha_1 + \sigma_1\hat{\lambda}_{i1} + \bar{Z}_i\theta_j + \omega_{i1} \quad if\ V_i = 1$

: : : (5)

Regime J: $y_{ij} = Z_{ij}\alpha_j + \sigma_j\hat{\lambda}_{ij} + \bar{Z}_i\theta_M + \omega_{ij} \quad if\ V_i = J$

where $\lambda_{ij} = \sum_{k \neq j}^{M} \rho_j \left[\frac{\hat{P}_{ik}\ln(\hat{P}_{ik})}{1-\hat{P}_{ik}} + ln\hat{P}_{ij}\right]$ refers to the inverse Mills ratios computed from the estimated probabilities in MNL model in Equation 3, ρ_j is the correlation coefficient between the error terms ε_{ij} and u_{ij}, with the error terms ω_{ij} assumed to have a zero mean and $\hat{P}_{ij}$ represents the estimated probability that plot i is treated with practice j.

Estimation of counterfactual and treatment effects

We estimate expected outcomes in the actual and counterfactual scenarios following Di Falco and Veronesi (2013) and Ng'ombe et al. (2017). Specifically, we first derive the expected outcomes of plots that were treated, which in our study means $j = 2, \dots$ M ($j = 1$ is the reference category; that is, non-adoption). From equation (5), the conditional expectations for each outcome variable based practice chosen as follows:

Adopters with adoption (actual adoption observed in the sample):

$$E(y_{i2}|\, V_i = 2) = \boldsymbol{Z_{i2}\alpha_2} + \sigma_2\hat{\lambda}_{i2} + \bar{Z}_i\theta_2$$
$$\vdots \qquad\qquad \vdots \qquad (6)$$
$$E(y_{iJ}|\, V_i = J) = \boldsymbol{Z_{ij}\alpha_j} + \sigma_j\hat{\lambda}_{ij} + \boldsymbol{\bar{Z}_i\theta_j}$$

The counterfactual case that adopters did not adopt is also stated as:

$$E(y_{i1}|\, V_i = 2) = \boldsymbol{Z_{i2}\alpha_1} + \sigma_1\hat{\lambda}_{i2} + \boldsymbol{\bar{Z}_i\theta_1}$$
$$\vdots \qquad\qquad \vdots \qquad (7)$$
$$E(y_{i1}|\, V_i = j) = \boldsymbol{Z_{ij}\alpha_1} + \sigma_1\hat{\lambda}_{ij} + \boldsymbol{\bar{Z}_i\theta_j}$$

The impact of adopting practice j is denoted as the average treatment effect on the treated (ATT), which is calculated by subtracting equation 6 from 7 as:

$$\text{ATT} = E(y_{2i}|\, V_i = 2) - E(y_{i1}|\, V_i = 2) = Z_{i2}(\alpha_2 - \alpha_1) + \boldsymbol{\bar{Z}_{i2}(\theta_2 - \theta_1)} + \hat{\lambda}_{i2}(\sigma_2 - \sigma_1) \qquad (8)$$

The term $\hat{\lambda}_{ij}(.)$, together with the Mundlak device ($\boldsymbol{\bar{Z}_{i2}}$), account for selection bias and endogeneity due to unobserved heterogeneity.

The MESR approach enables consistent and efficient estimation of $\boldsymbol{\alpha_j}$ and accounts for a reasonable correction of bias in the outcome equations, even when the independence of irrelevant alternatives (IIA) assumption is not met (Bourguignon et al., 2007). Another advantage of using this approach is the ability to evaluate impact of both individual and combination of climate-smart practices (Di Falco and Veronesi, 2013). In addition, it relaxes the restrictive assumptions of Lee's (1983)[4] selectivity model and provides a complete description of selectivity impacts on all options considered by farmers.

[4] In Lee's method, a single selectivity term is estimated for all choices (Lee 1983; Bourguignon et al. 2007).

For proper identification of the MESR model, including some variables in vector $\boldsymbol{X}_i$ that are not included in vector $\boldsymbol{Z}_i$ is recommended (Bourguignon et al., 2007). We use farmers' perception of drought, as well as access to climate information and association membership as identifying instruments (Di Falco and Veronesi, 2013). We confirmed the validity of these instruments by performing a falsification test, whereby a variable is considered as a valid instrument, if it affects farmers' decisions to adopt a practice, but not the outcome variables among non-adopters (Di Falco and Veronesi, 2013). We further performed a robust check of our results by employing an alternative approach using multivariate treatment effect, which also accounts for unobservable factors in a multinomial choice and impact analysis framework (Deb and Trivedi, 2006).

We control for potential endogeneity of some explanatory variables in our model, particularly off-farm work participation and extension visits. Off-farm work participation is potentially endogenous because adoption of some climate-smart practices is labour-intensive and households engaged in off-farm work may not be able to adopt such practices (labor-loss effect). On the other hand, income earned from off-farm work may be used to purchase inputs or invested in climate-smart practices (income-effect). In the case of extension visits, it is possible that farmers who are adopting may attract more visits by extension staff than non-adopters. Potential endogeneity of the variables was addressed using the control function approach (Wooldridge, 2015). The approach involves the specification of the potential endogenous variable (i.e. off-farm work participation or extension visit) as a function of explanatory variables influencing adoption of each practice, together with a set of instruments[5] in a first-stage Probit regression (in the case of extension visit, we employed Poisson specification in the first-stage). Instead of using the predicted values of off-farm participation or extension visit

[5] We used distance to capital district capital to instrument off-farm work participation. Also distance to nearest agricultural extension office was used to instrument extension visit variable.

variables, as in two-stage-least-squares, the observed values of the endogenous variables and the generalized residuals retrieved from a first-stage regression are included as covariates in the MESR model. Including the residuals serves as a control function, enabling the consistent estimation of the potentially endogenous variables in the MESR model (Wooldridge, 2010).

2.2 Data and descriptive statistics

The data used in this study were obtained from a survey during the 2015/2016 cropping season in 25 communities across five districts and three regions in Ghana. A multistage sampling procedure was employed to select and interview 476 households (cultivating 1,001 plots) in Upper East (UE), Northern (NR) and Brong-Ahafo (BA) regions. Based on agroecology, we selected five districts from the three regions (Bongo and Talinse in UE, Tolon and Kumbungu in NR, and Techiman-South in BA). Five communities were randomly selected from each district and 15-20 households from each community in proportion to the number of farmers in these communities. Finally, we obtained 203 households for NR cultivating 568 plots located in the Guinea Savannah, 147 households for UE in the Sudan Savannah, with 277 plots; and for BA in the Transitional zone, 126 households with 156 plots.

As indicated earlier, climate-smart practices include crop choice and soil and water conservation measures. Crop choice was practiced on about 18.58% of plots. Soil and water conservation in this study refers to plots that were treated with minimum tillage soil, or stone bunds and organic manure. Soil and water conservation was practiced on 35.26% of plots. In addition, 28.67% of plots were treated with both crop choice and soil and water conservation measures, while 17.5% of plots were considered as non-adopting plots. The descriptive statistics of all the variables are presented in Table 2.1. Since our sample is made up of farmers practicing mixed cropping, we constructed the crop revenue variable by summing up the value of all crops on a plot, following the example by Kato et al. (2011). The average reported crop revenue per plot is about 559 Ghana cedis (GHS). The crop revenue distributions by practice choice are presented in Figure 2.1. The distributions show indications of negative skewness, with greater variance, for non-adoption, compared with cases of adopted practices.

Table 2.1 Definition of variables and descriptive statistics

Variable	Variable description	Mean	SD
Crop revenue	Total crop revenue per acre (GHS) †	558.861	749.374
Fertilizer	Expenditure on fertilizer (organic and inorganic) GHS	225.197	429.479
Herbicide	Expenditure on herbicide used GHS	77.399	438.432
Hired labour	Expenditure on hired labour GHS	147.626	13.126
Farm size	Cultivated farm size in acre	7.157	5.829
Education	Years of formal education	5.49	5.020
Household size	Number of people in a household	5.95	3.080
Age	Age of farmer in years	39.64	13.83
Gender	Male=1, female=0	0.855	0.352
Off-farm	Farmer is engaged in off-farm activity=1, 0 otherwise	0.380	0.490
Livestock	Livestock ownership in tropical livestock units (TLU)‡	1.804	5.596
Extension visit	Number of extension visits	0.887	1.285
Distance-Capital	Distance to district capital	3.130	7.264
Distance-Ext	Distance to nearest extension office	1.390	4.220
Perception-drought	Perception of drought occurrence =1, 0 otherwise	0.751	0.433
FBO-mem	Farmer belongs to a group/association=1, 0 otherwise	0.302	0.459
Climate-info	Farmer receives current climate information = 1, 0 otherwise	0.570	0.490
Slope	Mean plot slope=1 if farm has portions of steep slopes, 0 otherwise	0.579	0.430
Erosion	Mean erosion level=1 if farm land has portions of moderate to severe erosion, 0 otherwise	0.895	0.528
Drainage	Mean plot drainage = 1 if farm land is well drained, 0 otherwise	0.461	0.419
Fertility	Mean fertility =1 if soil is considered fertile, 0 otherwise	0.141	0.231
Non-adoption	Percentage of plots without no adoption	17.48	-
Crop choice	Percentage of plots with crop choice practice	18.58	-
Soil &water cons	Percentage of plots with soil & water conservation practice	35.26	-
Joint adoption	Percentage of plots with joint adoption of crop choice and soil and water conservation	28.67	-
Number of plots		1001	
Number of HH		476	

† Exchange rate at the time of the survey was USD 1 = GHS 4.26 (source: Worldremit).

‡ TLU Conversion factors are: cattle = 0.7, sheep = 0.1, goats = 0.1, pigs = 0.2, chicken = 0.01.

SD refers to standard deviation.

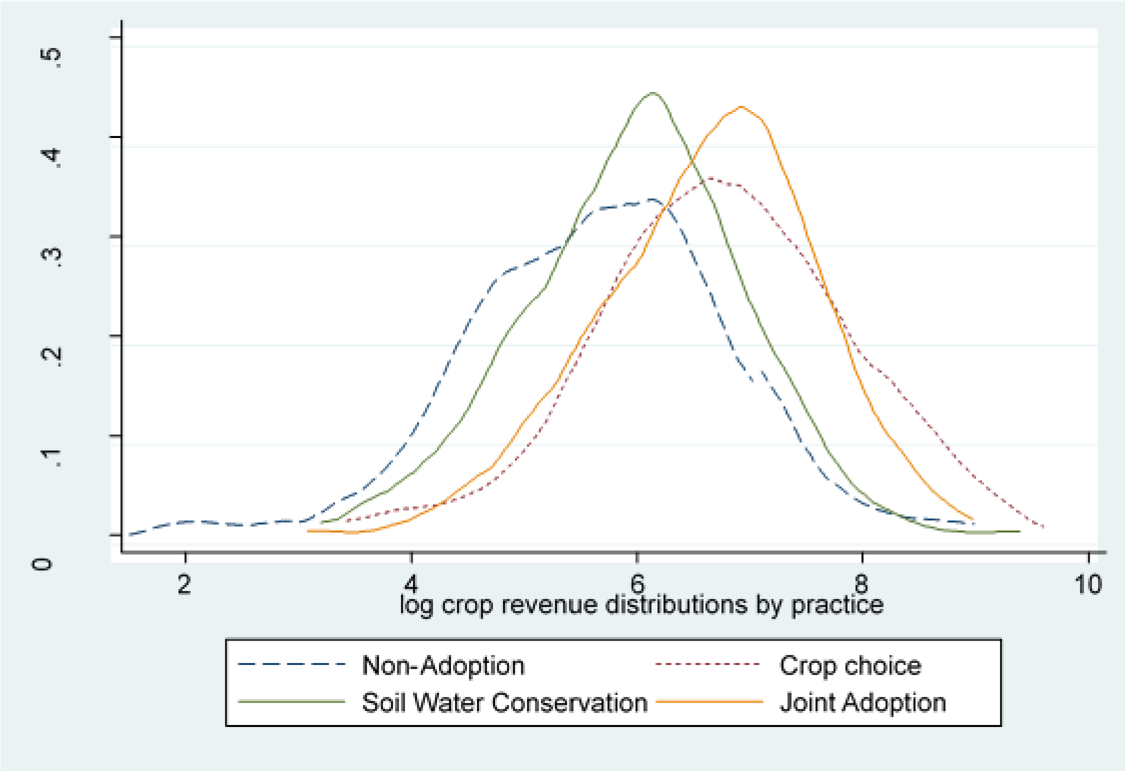

Figure 2.1: Kernel density distributions of crop revenue by adoption status

Information was also taken on general household characteristics, access to climate change information, the type of crops cultivated (see Table 2.A5) and various farming related activities, as well as perceptions on drought occurrence and access to weather or climate information and the practices being implemented to mitigate real or possible effects of drought and floods. We also capture farmers' reported plot characteristics, such as soil fertility, soil drainage level and slope of land.

We used rainfall and temperature data from the Global Weather Data of National Centers for Environmental Predictions (NCEP) climate data for the selected districts in Ghana, covering the period 1979-2014. Details of the climate data can be found at https://globalweather.tamu.edu/. The long-term averages of temperature and rainfall and their coefficients of variations were calculated and used as explanatory variables in the selection and outcome equations. The coefficient of variation of the climate variables are used as proxies for climatic shocks. We employed spatial interpolation techniques to determine household specific rainfall and temperature values, using the household location-specific coordinates (latitude, longitude and elevation) that was gathered through the survey (Wahba, 1990; Di Falco and Veronesi, 2013). These interpolated climate data were merged with survey data at the household level, using location/household identification variable that were generated during the field survey.

Furthermore, we include a number of control variables in our empirical specification. These include household characteristics (such as age of the head, education level of the head of the household, household size and gender); farm inputs (fertilizer, herbicides), ownership of resources (such as livestock ownership, farm size). These variables are included in line with the empirical literature on climate-smart agriculture, technology adoption and impact assessment (e. g., Di Falco et al., 2013; Kassie et al., 2014). The means of various variables related to the alternative choices are reported in Table 2.A2 in the Appendix. Although significant differences can be observed with respect to crop revenues among alternative practices, these differences do not account for selection bias arising from both observable and unobservable factors. These difference may also imply that these variables may influence farm performance differently, based on choice of climate-smart practice implemented. This further justifies our decision to employ the MESR in the analyses.

2.3 Empirical Results

Determinants of adoption of climate-smart strategies

The results of the determinants of adoption of climate-smart practices are presented in Table 2.2. The reference practice is non-adoption. The MNL model fits the data well, with the Wald test, $\chi^2 = 666.23, p > \chi^2 = 0.000$, rejecting the null hypothesis that all the regression coefficients are jointly equal to zero. The instruments (perception-drought, FBO-memb and

Climate-info) employed to identify the MESR are also jointly significant. A falsification test on the excluded instruments also showed that the instruments jointly influenced adoption at all levels, but not crop revenue or risk exposure of non-adopters (see Table 2.A3 in the Appendix).

The results show that characteristics of the household head, household endowments, inputs, climate and plot-specific variables, influence the adoption decisions of individual, crop choice only, soil and water conservation only, and joint adoption. Particularly, erosion and drainage levels (*Erosion, Drainage*) positively and significantly influence adoption of individual (crop choice only, soil and water conservation only), as well as joint adoption. Similar findings have been reported in Ethiopia by Di Falco and Veronesi (2013) and by Ng'ombe et al. (2017) in Zambia, underscoring the importance of capturing farm level characteristics in designing and implementing effective farm level climate-smart practices.

The results in Table 2.2 show that the coefficient of the age variable is negative and statistically significant in all practices signifying that younger farmers are more likely to adopt climate-smart practices. The results also reveal a positive and significant effect of household size on adoption of crop choice only, as well as soil and water conservation. The stronger effect of household size on adoption of soil and water conservation is consistent with expectations, considering the labour-demanding nature of this particular practice. The estimate for the education variable is positive and significant for individual and combined strategies, a finding that is consistent with previous studies (e.g., Abdulai et al., 2011; Di Falco and Veronesi, 2013).

Table 2.2: Parameter estimates of adoption of climate-smart practices: multinomial logit selection model†

	Crop choice (n=186)	Soil &Water cons(n=353)	Joint Adoption (n=287)
Variable	Estimate	Estimate	Estimate
Constant	-76.840 (135.36)	-61.625 (540.40)	-559.63 (577.73)
Age	-0. 724** (0. 306)	-0. 726** (0. 258)	- 1.134*** (0. 278)
Gender	19.226** (6.631)	41.455*** (6.317)	14.898** (5.685)
Household size	0.428** (0.176)	0.715*** (0.163)	0.184 (0.155)
Education	0.949** (0.388)	2.467*** (0.371)	0.841** (0.332)
Farm size	2.270** (0.985)	5.687*** (0.930)	1.412* (0.855)
Livestock	5.173** (1.961)	12.605*** (1.877	4.552** (1.686)
Off-farm	-8.439*** (2.713)	-17.658*** (2.600)	-7.088*** (2.334)
Fertilizer	1.864** (0.712)	4.526*** (0.682)	1.626** (0.612)
Herbicide	0.820*** (0.258)	1.870*** (0.248)	0.959*** (0.226)
Rainfall	-0.057 (0.050)	0.026 (0.045)	0.019 (0.046)
Temp	21.622 (13.508)	8.044 (12.327)	1.537 (12.341)
RFanom	11.665** (4.382)	6.880* (3.773)	0.129 (4.172)
Tem-anom	1.010* (0.530)	1.123** (0.305)	0.653*** (0.225)
Tem x RF-anom	0.274* (0.142)	0.052 (0.121)	0.520*** (0.127)
Extension	0.256** (0.102)	0.515** (0.210)	0.401* (0.221)
Slope	-7.559** (2.624)	-18.533*** (2.526)	-7.647** (2.296)
Erosion	18.812*** (7.186)	46.116*** (6.863)	15.116*** (6.154)
Drainage	10.183*** (3.163)	21.482*** (3.039)	8.390*** (2.739)
Fertility	1.131 (0.799)	4.497*** (0.771)	1.820** (0.743)
Perception-drought	1.719*** (0.308)	1.788*** (0.264)	0.391*** (0.124)
FBO_memb	0.963*** (0.303)	1.216*** (0.282)	0.515* (0.287)
Climate-info	0.367 (0.277)	0.440* (0.254)	1.082*** (0.262)
Resid-Off-farm	-1.552 (4.036)	8.478 (5.406)	5.280 (3.438)
Resid-Extension	0.284 (0.374)	0.086 (0.361)	0. 380 (0.347)
Joint sig Instruments (χ^2) in crop revenue equation	42.80***	65.64***	23.25***
Joint sig Instruments (χ^2) in Skewness equation	64.41***	41.33***	23.17***
Wald test, χ^2 (69)	666.23		
N	1001		

***, **, * represent 1%, 5%, and 10% significance level, respectively. Bootstrapped standard errors in parentheses

† Reference category is non-adoption.

Note: preliminary estimates with multivariate probit showed a positive significant correlation between crop choice and soil and water conservation with $a\ Rho = 0.327\ and\ Likehood\ Ratio\ LR = 27.38$.

The estimate for the coefficient of the livestock ownership variable (TLU) is positive and significant for all practice choices, indicating that livestock ownership could enhance adoption. Among the inputs, herbicides and fertilizer both positively and significantly influence the implementation of individual and joint adoption choices. The use of herbicide is becoming common among smallholders in Ghana due to the labour saving nature of this input, especially during land preparation and weed control. However, farmers' engagement in off-farm activity appears to negatively and significantly influence adoption of all climate-smart practices, suggesting that off-farm activity engagement and adoption of these practices may be competing for household labour resulting in the labour-loss effect (Taylor et al., 2003; Rakshandrah and Abdulai, 2015). As noted earlier, the potential endogeneity of off-farm work participation was addressed using the control function (CF) approach and the estimate of the residual term (*Resid-Off-farm*) from the first stage of CF regression[6] is not significant in all choices, signifying the exogeneity of off-farm participation in the model (Wooldridge, 2015). The results also show that extension visits (*Extension*) positively and significantly influence adoption of all climate-smart practices, a finding that is in line with that of Teklewold et al. (2013), who argue that adoption of climate-smart practices as package is knowledge-intensive and therefore requires skilled extension staff to facilitate the adoption process.

Interestingly, from the results, rainfall anomalies (*RFanom*) positively and statistically influence the adoption of crop choice only and weakly with soil and water conservation. Also, mean temperature (*Temp*) positively influences joint adoption, while temperature anomalies (*Tem-anom*) positively and significantly influence adoption of all strategies. We included an interaction term between temperature and rainfall variability (*Temp x RF-anom*). The results show that increasing variability in rainfall, combined with rising temperature would likely influence the adoption of crop choice only and joint adoption, but not necessarily soil and water conservation only, a finding that is consistent with the results reported by Moniruzzaman (2015).

[6] The first-stage estimates of the control function results are available but not reported here to save space.

Furthermore, the estimate for group membership variable (*FBO-memb*) is positive and significantly different from zero, suggesting that association membership increases the propensity to adopt crop choice, as well as soil and water conservation strategies. This finding supports the notion that farmers' association membership plays a significant role as source of information on input and innovations (Mutenje et al., 2016). The coefficient of the variable representing farmers' perception about drought occurrence (*Perception-drought*) is also positive and significantly associated with adoption of individual and combined choices, suggesting that upgrading farmers' climate change awareness enhances the adoption of climate-smart practices.

Determinants of crop revenue and skewness: Second stage MESR model

In Table 2.3, we present the determinants of crop revenues and skewness (downside risk exposure) by choice of climate-smart practices. The selectivity correction terms, denoted as m_1 *m2, m3* and *m4* capture selectivity effects arising from unobserved factors. The estimated variances are all bootstrapped with 100 replications to deal with heteroscedasticity as suggested by Bourguignon et al. (2007). The results show that the selectivity correction terms are significant in the revenue equations for *non-adoption*, *soil and water conservation only* and *joint adoption* options, indicating the presence of sample selectivity effects and using OLS would have produced biased and inconsistent estimates. Thus, accounting for selectivity effects is essential in obtaining consistent estimates in the MESR model.

Table 2.3: Impact of adoption choice on crop revenue: second-stage MESR estimation

Variable	Non-adoption (n=175)	Crop choice (n=186)	Soil &Water conservation (n=353)	Joint Adoption (n=287)
	Estimate	Estimate	Estimate	Estimate
Constant	3.259 (3.452)	-3.426(4.386)	-0.242 (1.133)	-0.535 (3.294)
Age	0.189* (0.095)	0.216 (0.167)	-0.067 (0.074)	0.102 (0.074)
Gender	-0.930* (0.500)	-1.140(9.213)	3.148(3.765)	-4.506 (4.171)
Household size	-0.052 (0.139)	-0.196 (0.241)	0.072(0.062)	-0.052 (0.112)
Education	0.629** (0.280)	0.703 (0.543)	1.214**(0.238)	0.328 (0.233)
Plot size	-2.152** (0.740)	-2.390* (1.283)	0.033(0.607)	-1.856** (0.643)
Livestock	3.304** (1.384)	3.557 (2.656)	1.955** (0.225)	1.544** (0.208)
Off-farm	4.219**(1.970)	4.354* (2.579)	1.179** (0.586)	3.296* (1.672)
Fertilizer	1.172** 0.511	1.323 (0.962)	1.315* (0.431)	0.693*** (0.225)
Weedicide	0.533** (0.225)	0.506 (0.340)	1.191** (0.134)	1.169** (0.144)
Rainfall	-0.045 (0.040)	0.035 (0.049)	0.007 (0.012)	0.001 (0.037)
Temp	-9.303 (10.747)	1.143 (1.359)	0.678 (3.621)	-2.159 (10.279)
RFanorm	-2.927 (3.706)	-1.272** (0.488)	-1.986 (0.512)	-4.360** (2.143)
Tem-anorm	-5.713* (2.975)	-2.982* (1.573)	-1.002 (1.131)	-0.582 (0.476)
Extension	1.722** (0.735)	1.847 (1.432)	5.710** (2.344)	8.775** (4.331)
Slope	-5.675*** (1.797)	4.140(3.335)	-1.163 (1.649)	1.958 (1.543)
Erosion-level	-1.193** (0.452)	-1.300 (1.019)	-4.155 (4.254)	-5.219** (2.687)
Drainage	-5.058** (2.234)	-5.380(4.358)	1.472 (1.887)	-2.794 (1.982)
Fertility	1.555** (0.527)	1.596 (1.059)	1.351** (0.479)	0.710** (0.328)
Selectivity terms				
m0 (C_0SW_0)	-0.159 (0.508)	-1.915 (1.307)	1.583* (0.892)	1.425* (0.846)
m1 (C_1SW_0)	1.677 (2.083)	0.340 (0.510)	-1.990** (0.748)	0.482 (0.502)
m2 (C_0SW_1)	-1.819* (0.953)	2.700 (1.660)	0.497 (0.489)	0.246 (0.858)
m3 (C_1SW_1)	-1.681 (1.116)	-1.269 (1.088)	-0.885 (1.053)	0.049 (0.379)

***, **, * represent 1%, 5%, and 10% significance level, respectively. Bootstrapped standard errors in parentheses

Turning to the effects of other variables, the results in Table 2.3 show that herbicide use significantly influences crop revenue among adopters of soil and water conservation only and joint adopters, but not crop choice only. This implies that application of herbicide could be a complementary input in effective adoption of soil and water conservation and result in high crop revenue. Rainfall anomaly (*RFanom*) has a negative and significant effect on crop revenue, with greater magnitude among non-adopters, suggesting that adoption of climate-smart practices might have played a role in minimizing the negative effect of rainfall anomaly on crop revenue among adopters. This finding is consistent with FAO's principle of climate-smart agricultural practices that seek to enhance farmers' resilience and ability to adapt to climate variability (FAO 2013). The coefficient of plot level fertility (*Fertility*) has the expected positive sign on crop revenue, particularly for adopters of soil and water conservation and joint adoption. Off-farm work participation (*Off-farm*) positively significantly influences crop revenue, implying possible income effect of off-farm work participation on farm output. The effect of other variables on the skewness or downside risk exposure by climate-smart practice are reported in Table 2.A1 in the appendix[7].

Impact of adoption of climate-smart agriculture strategies on crop revvunue and risk exposure

The impacts of adoption of individual and combined climate-smart practices on crop revenue and skewness (risk exposure) are presented in Table 2.4. Here, expected crop revenue (log) under the observed case that the farmer adopted the strategies, and the counterfactual situation that they did not adopt are indicated. The results show that the adoption of crop choice and soil and water conservation practices leads to significant improvement in crop revenues. The highest log revenue effect (1.149) is obtained from the joint adoption of crop choice and soil and water conservation strategies (about 20.6%), which is greater than the effect of each practice adopted

[7] For brevity, these estimates are not discussed in here.

independently, suggesting complementarity of the two climate-smart practices. In particular, the impacts of adoption of crop choice only, and soil and water conservation only are 13% and 12% increase in crop revenues, respectively. These findings are consistent with the results reported by Teklewold et al. (2013) for Ethiopia and Ng'ombe et al. (2017) for Zambia. The results also show that in all the counterfactual cases, adopters would have had lower crop revenues if they had not adopted.

Table 2. 4 Average treatment effects of adoption of individual and combined strategies on log crop revenue and downside risk

Outcome	Adoption decision		ATT	ATT by Agro-ecological zone			
	If adopters adopted	If adopters had not adopted		Change in outcome (%)	Sudan Savannah	Guinea Savannah	Transitional Zone
Log crop revenue							
Crop Choice	5.848	5.192	0.656*** (0.088)	12.63	0.262** (0.091)	0.252** (0.128)	0.519*** (0.160)
Soil and Water Conservation	5.978	5.356	0.622** (0.227)	11.62	0.884*** (0.075)	0.222*** (0.056)	0.235* (0.129)
Joint Adoption	6.714	5.565	1.149*** (0.100)	20.64	0.955*** (0.084)	0.126** (0.058)	0.115 (0.411)
Skewness (downside risk)							
Crop Choice	1.280	0.970	0.310*** (0.018)	32.0	0.202*** (0.001)	0.365*** (0.045)	0.388*** (0.054)
Soil and Water Conservation	-0.150	-0.231	0.081*** (0.005)	35.0	0.162*** (0.010)	0.193*** (0.010)	-0.067* (0.039)
Joint Adoption	0.734	0.523	0.211*** (0.007)	40.4	4.341*** (0.387)	4.293*** (1.101)	2.390*** (0.203)

***, **, * represent 1%, 5%, and 10% significance level, respectively. Figures in brackets refer to standard errors.

The results also reveal that the adoption of crop choice and soil and water conservation individually or jointly significantly increased crop revenue skewness, which indicates a reduction in the probability of crop failure or revenue loss. Specifically, adoption of individual options results in increased skewness by 32% and 35% for crop choice and soil and water conservation, respectively. The joint adoption of the two practices results in a 40% increase in skewness, indicating complementarity in lowering the probability of crop failure. These results confirm earlier findings by Kassie et al. (2014) for farms in Malawi, that adoption of on-farm climate-smart practices decreases farmers' exposure to downside risk and therefore reduces the risk of crop failure.

To provide further information about the impacts of individual and combination of climate-smart practices, we disaggregated the adoption impacts (ATT) by agro-ecological zones. The results show that joint adoption of the two practices has the highest positive and statistically significant impact on crop revenues for plots in the Sudan Savannah (ATT = 0.955). However, joint adoption has no significant impact on crop revenues in the Transitional zone. Interestingly, joint adoption reduces downside risk in all agro-ecological zones. This location-specific impact analysis provides important additional information that could be useful in promoting adoption of climate-smart agriculture in Ghana. A multivariate treatment effect regression (Deb and Trivedi, 2006) was estimated as a robustness check[8], and the results which are presented in Table A4 in the appendix show positive impact of individual and combined adoption of climate-smart practices. The results of the multivariate treatment effects regressions are generally consistent with that of the MESR, except in the case of impact of soil and water conservation only on crop revenue.

Overall, the findings emphasize the importance of adoption of crop choice and soil and water conservation among farmers as a means of managing ex-ante production risk, especially under climate uncertainty. The results also debunk the notion that farmers who adopt climate-smart practices to avoid crop failure end up obtaining lower yields (Adamson et al., 2017).

[8] Following an anonymous reviewer's comment, we decided to do this analysis to compare the estimates of the multivariate treatment effects approach to the MESR method adopted in this study.

2.4 Conclusions and policy implications

In this paper, we used farm level data from three agro-ecological regions in Ghana to examine the determinants and impacts of adoption of two climate-smart practices (crop choice and soil and water conservation) on crop revenues and risk exposure, measured as distribution of crop revenue skewness. We employed multinomial endogenous switching regression (MESR) model to account for selectivity bias due to observable and unobservable factors. The empirical results show that the highest crop revenue effect is obtained from the joint adoption of crop choice and soil and water conservation practices, suggesting complementarity in benefits. In addition, joint adoption of the two strategies significantly increased crop revenue skewness, implying that adoption decreases the exposure to expected downside risk, by lowering the probability of crop failure. A disaggregation of the adoption impacts on crop revenues and downside risk revealed that plots in the dry savannah agro-ecological zones experienced higher impacts of joint adoption, compared to plots in the transitional zone. The findings also revealed that extension access, farmer education, climate anomalies, as well as farmers' perception about drought and access to weather information are key determinants of adoption of crop choice and soil and water conservation measures.

Thus, policy interventions to increase agricultural productivity and reduce farmers' risk exposure should consider alleviating farmers' difficulties to adoption. For instance, government agencies (e.g., MoFA) in collaboration with private agri-input dealers associations, could facilitate the distribution of inputs, such as drought-tolerant seeds and herbicides, through certified agro-input outlets in farming communities, to enhance adoption. In addition, making quality climate information accessible to farmers will ease their adoption challenges including the right combination of practices to adopt. In view of the fact that effective adoption of climate-smart practices requires some knowledge and skills, enhancing farmer education and access to extension services should be among the policy measures that will facilitate adoption. This study particularly showed that package adoption of crop choice, and soil and water conservation practices will enable farmers to benefit from the positive synergistic effects of joint adoption on farm performance and reduction in risk exposure.

The findings of this study should be considered with some caveats since we relied mainly on cross-sectional survey data. First, analysis of panel data would have enabled us to capture the dynamic effects of climate-smart practices on crop revenues and risk exposure. For instance, some climate-smart agronomic measures such as soil and water conservation measures (e.g., stone bunds, minimum tillage, etc.) take time to produce effects, and the effects of climate-smart practices may last over several cropping seasons. Second, an experiment to determine farmers' risk preferences would have been a more appropriate proxy for measuring and estimating risk exposure; but we lack data on these measures. Despite these caveats, we do not expect systematic bias in our assessment. Thus, this study contributes to the growing body of literature on climate-smart agriculture and how the adoption of specific farm practices affects farm performance in an area where there is limited access to formal risk reduction measures, such as agricultural insurance.

References

Abdulai, A., Huffman, W., (2014). The Adoption and Impact of Soil and Water Conservation Technology: An Endogenous Switching Regression Application, *Land Economics*, 90 (1): 26–43.

Abdulai, A., Owusu, V. & Goetz, R. (2011). Land tenure arrangements and investment in land Improvement measures: theoretical and empirical analysis, *Journal of Development Economics*, 96 (1):66-78.

Adamson, D., Loch, A. & Schwabe, K. (2017). Adaptation responses to increasing drought frequency, *Australian Journal of Agricultural and Resource Economics*, 61:385-403.

Adiku, S. G. K., Dilys, S. M., Hathie, I., Diancoumba, M., et al. (2015). Climate Change Impacts on West African Agriculture: An Integrated Regional Assessment (CIWARA) in *Handbook of Climate Change and Agroecosystems: The Agricultural Model Inter-comparison and Improvement Project (AgMIP) Integrated Crop and Economic Assessments*, Imperial College Press, pp. 25-73.

Antle, J. M. (1983). Testing the Stochastic Structure of Production: A Flexible Moment-Based Approach, *Journal of Business and Economic Statistics*, 1:192-201.

Barrett, C. B., Christiaensen, L., Sheahan, M. & Shimeles, A. (2017). On the Structural Transformation of Rural Africa, *Journal of African Economies*, 26, AERC Supplement 1: 11–35.

Bourguignon, F., Fournier, M. & Gurgand, M. (2007). Selection Bias Corrections Based on the Multinomial Logit Model: Monte Carlo Comparisons, *Journal of Economic Surveys*, 21(1): 174-205.

Claessens, L., Antle, J. M., Stoorvogel, J.J., Valdivia, R., Thornton, P. K., Herrero, M. (2011). A method for evaluating climate change adaptation strategies for small-scale farmers using survey, experimental and modeled data, *Agricultural Systems*, 111: 85-95.

Deressa, T. T., Hassan, R. M., Ringler, C., Alemu, T., &Yesuf, M. (2009). Analysis of the Determinants of Farmers' choice of Adaptation Methods and Perceptions of Climate Change in the Nile Basin of Ethiopia, *International Food Policy Research Institute.* Washington, DC.

Di Falco, S. & Veronesi, M. (2013). How can African Agriculture Adapt to Climate Change? A Counterfactual Analysis from Ethiopia, *Land Economics*, 89(4):743-766.

Di Falco, S., Chavas, J.P., (2009). On crop biodiversity, risk exposure and food security in the highlands of Ethiopia. *American Journal of Agricultural Economics*, 91 (3):599–611.

Dimova, R. & Gang, I. N. (2007). Self-selection and wages during volatile transition, *Journal* *of Comparative Economics*, 35: 612–629.

Food and Agriculture Organization of the United Nations (FAO) (2013). Climate-smart agriculture source book, *FAO*, Rome.

Ghana Statistical Service (GSS) (2015).Ghana Poverty Mapping report, *Ghana statistical service*, May, 2015, Accra, Ghana.

Hausman, J. & McFadden, D. (1984). Specification Tests for the Multinomial Logit Model, *Econometrica*, 52 (5): 1219-1240.

Huang, J., Wang, Y. & Wang, J. (2015). Farmers' adaptation to extreme weather events through Farm management and its Impacts on the Mean and Risk of rice yield in China. *American Journal of Agricultural Economics*, 97(2): 602-617.

IFAD (International Fund for Agricultural Development) (2012). Republic of Ghana: Country programme evaluation. IFAD Report No. 2433-GH, May 2012, online at https://www.ifad.org/documents/38714182/39712661/ghana2012.pdf.

International Assessment of Agricultural Knowledge, Science and Technology for Development (IAASTD) (2009). Agriculture at a Crossroads, *IAASTD Global Report*, Island Press, Washington, DC.

IPCC (2007), *Climate Change 2007: Fourth Assessment Report of the Intergovernmental Panel on Climate Change*, Cambridge University Press, Cambridge.

Jones, P. G. & Thornton, P. K., (2003). The potential impacts of climate change on maize production in Africa and Latin America in 2055, *Global Environmental Change*, 13 (1): 51-59.

Kassie, G. T., Abdulai, A., Green, W. H., Shiferaw, B., Abate, T., Tarekegne, A. & Sutcliffe, C. (2017). Modeling Preference and Willingness to Pay for Drought Tolerance (DT) in Maize in Rural Zimbabwe, *World Development,* 94: 465–477.

Kassie, M., Teklewold, H., Marenya, P., Jaleta, M. & Erenstein, O. (2014). Production Risk And food security under Alternative Technology Choices in Malawi: Application of Multinomial Endogenous Switching Regression, *Journal of Agricultural Economics*, 66 (3):640-659.

Kato, E. Ringler, C. Yesuf, M. & Bryan. E. (2011). Soil and Water Conservation Technologies: A Buffer against production risk in the face of climate change? Insights from the Nile basin in Ethiopia, *Agricultural Economics,* (42): 593-604.
in Ethiopia, *Agricultural Economics,* 42, 593-604.

Rakshandrah, K., R., and Abdulai, A. (2015). Off-farm work, land tenancy contracts and

Investment in soil conservation measures in rural Pakistan, *Australian Journal of Agricultural and Resource Economics*, 59, 1–19.

Koundouri, P., Nauges, C. & Tzouvelekas, V. (2006). Technology Adoption under Production Uncertainty: Theory and Application to Irrigation Technology, *American Journal of Agricultural Economics,* 88 (3): 657–70.

Lee, L. F. (1983). Notes and Comments Generalized Econometric Models with Selectivity, *Econometrica*, 51(2) 507-515.

McFadden, D. (1973). Conditional logit analysis of qualitative choice behavior, in: Zarembka, P. (ed.), *Frontiers in Econometrics*, Academic Press, New York.

Ministry of Environment, Science, Technology and Innovation (MESTI) (2015). *Ghana National Climate Change Master Plan Action Programmes for Implementation: 2015–2020,* MESTI, Accra, Ghana.

Moniruzzaman, S. (2015). Crop choice as climate change adaptation: Evidence from Bangladesh, *Ecological Economics*, 118: 90–98.

Mundlak, Y. (1978). On pooling of time series and cross section data, *Econometrica*, 64: 69–85.

Mutenje, M., Kankwamba, H., Mangisonib, J. & Kassie, M. (2016). Agricultural innovations And food security in Malawi: Gender dynamics, institutions and market implications, *Technological Forecasting and Social Change*, 103: 240–248.

Nelson, W., Naambuyi, D., Owusu, A. et. al. (2010). Guidebook on Integrating Climate Change and Disaster Risk Reduction into National Development, Policies and Planning in Ghana, *Environmental Protection Agency*, Ghana.

Nkonya, E., Mirzabaev, A. & von Braun, J. (2016). Economics of Land Degradation and Improvement: An Introduction and Overview, in Nkonya, E., Mirzabaev, A. & von Braun, J (Eds.), *Economics of Land Degradation and Improvement: A Global Assessment for Sustainable Development*, IFPRI, Washington, D.C.

Sabiha, N. E., Salim, R. & Rahman, S. (2017). Eco-efficiency of high-yielding variety rice cultivation after accounting for on-farm environmental damage as an undesirable output: an empirical analysis from Bangladesh, *Australian Journal of Agricultural and Resource Economics*, 61:247-264.

Taylor, J. D., De Braw, A. & Rozelle, S. (2003). Migration and Source Communities: A New Economics of Perspective from China, *Economic Development and Cultural Change*, (52): 75-101.

Tibesigwa, B., Visser, M. & Turpie, J. (2014). The impact of climate change on net revenue and food adequacy of subsistence farming households in South Africa, *Environment and Development Economics*, 20: 327–353.

Tol, R. S. J. (2018). The Economic Impacts of Climate Change, *Review of Environmental Economics and Polic*y, 12 (1): 4-25.

Vale, P. M. (2016). The changing climate of climate change economics, *Ecological Economics*, 121: 12–19.

Veettil, P. C., Krishna, V. V. & Qaim, M. (2016). Ecosystem impacts of pesticide reductions through Bt cotton adoption, *Australian Journal of Agricultural and Resource Economics*, 61: 115–134

Wahba, G. (1990), *Spline Models for Observational Data*, Philadelphia: Society for Industrial and Applied Mathematics.

Wooldridge, J. M. (2015). Control Function Methods in Applied Econometrics, *Journal of Human Resources*, 50 (2):420-445.

World Bank (2010). The Costs to Developing Countries of Adapting to Climate Change: New Methods and Estimates. Available online: http://www.worldbank.org/eacc. (accessed on 7th January 2016).

Wossen, T., Berger, T., Swamikanu, N. & Ramilan, T. (2014). Climate Variability, Consumption Risk and Poverty in Semi-Arid Northern Ghana: Adaptation Options for Poor Farm Households, *Environmental Development*, 12:2–15.

Zougmore, R., Jalloh, A. & Tioro, A. (2014). Climate-smart soil water and nutrient management options in semi-arid West Africa: a review of evidence and analysis of stone bunds and Zai techniques, *Agriculture and Food Security*, 3 (16):1-8.

Table 2. A1: Determinants of downside risk by climate-smart practices: second-stage MESR estimation (dep. variable: revenue skewness)

Variable	Non-adoption (n=175	Crop choice (n=186)	Soil &Water cons (n=353)	Joint Adoption (n=287)
Constant	0.887 (2.085)	-2.408(1.521)	0.982 (1.108)	0.624(0.816)
Gender	-0.414* (0.230)	-0.717** (0.333)	0.218 (0.168)	-0.202 (0.141)
HH_size	-0.437 (0.579)	-1.272* (0.714)	0.418 (0.359)	-0.136 (0.254)
Education	2.823* (1.506)	4.408** (1.966)	-1.378 (1.018)	1.507 (0.931)
Plot size	-6.730* (2.781)	-1.285** (0.520)	2.322 (2.628)	-5.531** (2.704)
Livestock	1.474 (0.821)	2.213** (0.991)	6.489*** (2.138)	0.844* (0.475)
Off-farm	-2.056* (1.124)	-2.769** (1.367)	0.902** (0.311)	0.915** (0.452)
Fertilizer	4.959* (2.700)	8.112** (3.680)	-2.427 (1.900)	2.798 (1.714)
Weedicide	-2.296 (1.117)	-3.087** (1.369)	1.067 (0.705)	-1.094 (0.729)
Rainfall	-0.144 (0.255)	0.228 (0.164)	-0.102 (0.128)	-0.105 (0.105)
Temp	-0.248 (0.643)	0.773 (0.482)	-0.312 (0.344)	-0.176 (0.247)
RFanorm	-0.066 (0.109)	-0.555** (0.210)	0.157(0.149)	0.601 (0.974)
Tem-anorm	-0.386 (0.326)	-0.503 (0.489)	0.239(0.449)	0.981 (0.758)
Extension	0.716 (0.390)	1.117** (0.533)	-0.354(0.278)	0.408 (0.251)
slope	0.240 (0.152)	0.268** (0.123)	-0.079(0.713)	0.103 (0.715)
Erosion-level	-0.458 (0.249)	-0.838** (0.374)	0.258(0.194)	-0.248 (0.161)
Drainage	-0.227 (0.118)	-0.347** (0.161)	0.110(0.864)	-0.115 (0.740)
Fertility	0.656 (0.438)	0.844** (0.382)	-0.148(0.205)	0.345 (0.201)
Selectivity terms				
m0 (C_0SW_0)	-0.307 (0.221)	-1.083** (0.488)	-0.816(0.666)	-1.045(0.825)
m1 (C_1SW_0)	0.293 (1.021)	0.196 (0.221)	0.005(0.608)	0.648(0.587)
m2 (C_0SW_1)	-0.628 (0.653)	-1.621*** (0.219)	0.009(0.404)	-0.972(0.819)
m3 (C_1SW_1)	-1.473** (0.585)	-0.337 (0.454)	0.682(0.502)	0.185(0.344)

***, **, * represent 1%, 5%, and 10% significance level, respectively. Bootstrapped standard errors in parentheses

Table 2.A2: Means of variables by choice of climate-smart practices and pooled sample

Variable	Non-adoption	Crops choice only	soil & water cons only	Joint adoption	Pooled sample	SD
Crop revenue	473.77	606.74*	625.42**	665.02***	562.791	24.52
Off-farm	0.314	0.543	0.376	0.292	0.356	0.015
Age	38.103	40.398	40.042	36.267	38.907	0.421
Gender	0.754	0.833**	0.882***	0.928***	0.855	0.011
HH_size	6.171	5.957	6.585	7.723***	6.575	0.109
Education	4.177	5.995***	3.927	4.067	4.468	0.167
Plot size	5.994	7.179**	6.345***	8.628**	7.157	0.184
Fertilizer	254.280	236.914	249.973	337.174**	259.664	18.759
Hiredlabour	173.897	97.228*	125.463	190.723	147.626	13.126
Weedicide	131.711	38.134**	40.099**	130.303	77.399	13.858
Livestock	1.041	2.060**	1.774*	1.096**	1.804	5.596
Extension	0.514	1.011**	0.934***	1.195***	0.887	0.041
Per_Drought	0.589	0.855***	0.655**	0.872***	0.751	0.014
weatherinfo	0.440	0.349*	0.220***	0.210***	0.293	0.255
FBO-mem	0.120	0.459***	0.450*	0.429**	0.302	0.459
Slope	0.579	0.430	0.695*	0.528	0.579	0.430
Erosion-level	0.815	0.528*	0.461	0.417	0.544	0.419
Drainage	0.561	0.319	0.895**	0.528	0.461	0.419
Fertility-level	0.241	0.331	0.461	0.416	0.141	0.231
N	175	186	353	287	1001	

*, **, *** denotes significance level at 10%, 5% and 1%, respectively, based on t-tests of mean differences of variables. The base-category is non-adoption.

Table 2.A3: Test of validity of instruments used to identify the MESR model

Variable	Crop revenue of non-adopters	Revenue skewness of non-adopters
Perception-drought	-0.149 (0.237)	0.273 (0.901)
Climate-info	-0.112 (.170)	-1.020 (0.646)
FBO-memb	0.004 (0.172)	0.577 (0.654)
Constant	6.259*** (0.642)	1.198 (2.438)
F-tests on instruments	1.202 [p = 0.234]	1.160 [p = 0.327]

Standard errors in parentheses. The values in the square bracket indicate the p-values of the F-test indicating the validity of the instruments used to identify the MESR model.

Table 2.A4: Treatment effects of adoption on log crop revenues and downside risk: Multivariate treatment effects regression (Robustness check) †

Practice	Estimate	Standard Errors
Log Crop revenues		
Crop choice only	0.433**	0.222
Soil and water conservation only	0.151	0.171
Joint adoption	0.520**	0.204
Skewness (downside risk)		
Crop choice only	0.917***	0.254
Soil and water conservation only	0.327**	0.121
Joint adoption	0.963**	0.367

, * significant at 5% and 1% respectively. Reference category is non-adoption
†The entire results of the multivariate treatment effects regression are available on request.

Table 2.A5: The distribution of crops on plot of respondent farmers

Crop	% of Plots
Maize	28.57
Rice†	14.38
Millet	11.24
Sorghum	7.37
Groundnut	14.19
Yam	2.94
Cassava	4.33
Vegetables	15.85
Number of plots	1,001

† Apart from rice, the rest of the crops were mostly intercropped.

Chapter 3

Can farm households improve food and nutrition security through adoption of climate-smart practices? Empirical evidence from northern Ghana

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Abstract

In this study, we examine the factors that influence farmers' decisions to adopt climate-smart practices and how adoption affects food and nutrition security in Ghana, using an endogenous switching regression approach to account for selectivity bias. The empirical results show that adoption positively and significantly impacts food and nutrition security. The impacts of adoption are greater in the lower quantiles of distributions of food and nutrition security, an indication of the potential role of adoption in reducing poverty among the poor. Policy efforts that seek to improve farmers' access to machinery and extension services may enhance adoption of climate-smart practices.

Keywords: Climate-smart practices, food security, nutrition security, endogenous switching regression, quantile treatment effects.

JEL: Q01, Q12, C31

3.0 Introduction

In recent times, the goals of poverty alleviation and food and nutrition security enhancement in sub-Saharan Africa (SSA) have been at the forefront of national and international policy agendas. In particular, the Sustainable Development Goals (SDG's), which are the blueprint to achieve a better and more sustainable future for all, emphasize the need to significantly reduce poverty and ensure food and nutrition security, as well as sustainable agriculture by the year 2030 (United Nations 2015). The agricultural sector remains a major contributor to food and nutrition security, as well as economic growth in many developing countries, accounting for about 65% of the labor force and 32% of GDP in SSA (World Bank 2010; Fuglie 2018). In Ghana, the sector employs about 75% of the rural active population, who cultivate less than two hectares on average and produce mainly food crops with low technical and operational efficiencies (Ghana Ministry of Food and Agriculture (MoFA) 2017).

However, land degradation, inadequate infrastructure and institutional bottlenecks, as well as climate variability and change are among the challenges that have contributed to food shortages in many parts of Ghana, particularly in the northern Savannah zones (World Bank 2010; Abdulai and Huffman 2014; MoFA 2017). Using different climate scenarios, Ghana's Environmental Protection Agency [EPA] (2011)[9] projected that cassava yields are expected to decline by 3%, 13.5% and 53% in the years 2020, 2050 and 2080, respectively as a result of the rise in mean temperature and reduction in duration of cropping season. In the same study, rice yields on the average will decrease by 8% due to climate change. These projections, together with a number of studies (e.g., Kurukulasuriya and Mendelsohn 2008; IPCC 2014; Asfaw, Battista, and Lipper 2016; Brown et al. 2017) indicate that SSA's crop and livestock yields will

[9] The study constructed three climate change scenarios for the main climatic variables; mean monthly rainfall, maximum, minimum and mean daily temperatures; to cover the whole country.

decline unless farmers adopt climate-smart technologies. The Food and Agriculture Organization (FAO) at the Hague Conference on Agriculture, Food Security and Climate Change in 2010 also identified climate-smart agriculture as one of the surest ways to achieve sustainable agricultural development for food security under climate change (FAO 2013; Global Nutrition Report 2015).

Meanwhile, available evidence shows that autonomous adoption of certain practices among farmers is occurring in response to climate variability to ensure food availability (Kurukulasuriya and Mendelsohn 2008; Di Falco, Veronesi, and Yesuf. 2011). In particular, studies have shown that farm households in SSA have adopted a mix of different climate-smart practices, including the use of high-yielding crop varieties, changing planting dates, growing drought-tolerant crops, use of crop insurance mechanisms, irrigation, and soil and water conservation measures (Di Falco et al. 2011; Abdulai and Huffman 2014). These practices and other measures that enable farmers to produce food sustainably under unfavorable climatic conditions and declining soil fertility are referred to as climate-smart agricultural practices (FAO 2013). Although some of these practices have been employed by farmers in isolation or in combination for yield enhancement, some studies (e.g., Di Falco et al. 2011; Deressa et al. 2009) refer to them as adaptation strategies or climate-smart practices (Asfaw et al. 2016). The FAO (2013) indicates that farmers' implementation of these practices in response to long-term changes in climate variables is referred to as adaptation and the practices are referred to as climate-smart practices. As argued by Vale (2016), defining climate-smart agriculture (adaptation) often overlaps with the rural development agendas of many SSA countries, which suggests the capacity of socioeconomic systems (farming systems) to respond to extreme climate events.

Several studies have analyzed the determinants of adoption and diffusion of various climate-smart practices and to some extent the impact of adoption on farm productivity and net returns in SSA countries (e. g., Kurukulasuriya and Mendelsohn 2008; Di Falco et al. 2011; Kassie et al. 2015; Asfaw et al. 2016). However, the literature on impact of adoption of these practices, particularly on food and nutrition security, from the Ghanaian perspective remains scant, as adaptation impacts have been observed to be location specific (Di Falco et al. 2011; Vale 2016). The study by Kurukulasuriya and Mendelsohn modeled the sensitivity of agriculture to climate change and farmers' choice of irrigation and its impact on net revenues. Their study found that African agriculture is sensitive to rainfall reduction, and they recommended irrigation as an effective adaptation strategy for coping with climate change. The study by Kassie et al. (2015) also identified climate shocks (particularly rainfall and temperature), as well as plot and household characteristics as factors that significantly influence farmers' decisions to adopt sustainable intensification practices in Tanzania.

In the Ghanaian context, few studies have examined the adoption and impacts of climate-smart practices (Abdulai and Huffman 2014; Nkegbe and Shankar 2014). However, these studies have been limited to impacts on farm performance and did not include climate variables to account for shocks. For example, the study by Nkegbe and Shankar (2014) examined the intensity of adoption without any consideration of impact of adoption. The study by Abdulai and Huffman (2014) analyzed the adoption of soil and water conservation measures and the impacts of adoption on yields and net-farm revenues, without considering climate variables or dietary diversity as an outcome. Although these studies contribute towards the understanding of the factors driving the adoption and impacts of climate-smart practices among farmers, the impact of adoption on food and nutrition security are not considered. Meanwhile, recent studies have shown that smallholder farmers are among the world's most undernourished people (Frelat et al. 2016). As argued by Brown et al. (2017), adoption of climate-smart practices can minimize the adverse impacts of climate change and affect the four components of food and nutrition security, which include food availability, food access, food utilization and stability for the poorest people across the world.

Food availability refers to the existence of adequate quantities of food in the right quality that may be supplied through domestic production or import or storage (FAO 2009). At the household level, climate change has the potential to shift farmland suitability for crop production[10], unless farmers adopt climate-smart practices to sustain food availability. Access to food on the other hand, refers to the ability of the individual, household or community to purchase food in sufficient quantity and quality; while food utilization describes how food is used to ensure that individuals or households benefit from the nutrients contained in it (FAO 2009). Since most poor households obtain their micronutrients from plant sources (Global Nutrition Report 2015), climate change may influence the quality of nutrients in some plants and therefore affect food utilization. Finally, the stability of these components also determines food and nutrition security outcomes. Thus, food and nutrition security stability refers to the situation where food availability, access, and utilization do not vary to a level that negatively affects food and nutrition security status of an individual, household or community, due to unpredictable events such as climate change (FAO 2009).

To the extent that rainfall variability and declining soil fertility due to land degradation negatively impact on crop yields and food availability, studies that address these issues would significantly contribute to the literature on the impact of adoption of climate-smart practices, as well as the design of agriculture and climate adaptation policies. The present study aims at identifying the factors that influence farmers' decisions to adopt climate-smart agronomic practices, and how the adoption of these practices impact on food and nutrition security of rural households in Ghana. We employ recent survey data of 476 households from three agro-

[10] Climate change could lead to increase in suitable farm lands in higher latitudes and a decline in farm lands in low latitudes (IPCC 2014).

climatic zones to analyze the differential impacts of adoption across these agro-ecological zones. We use an endogenous switching regression (ESR)[11] approach to account for selectivity bias that arise from observed and unobserved factors. This approach allows us to examine the determinants of smallholder adoption decisions and their related household food and nutrition security implications, measured in terms of farm revenues, household dietary diversity scores (HDDS) and household food insecurity access scores (HFIAS). The HDDS is a count of all food groups consumed by the members of the household, while HFIAS is a scale that is constructed based on the idea that the experience of food insecurity (access) causes predictable reactions and behavioral responses (Weismann et al. 2006; Coates et al. 2007). A high HDDS is correlated with improved food and nutrition security, while a high HFIAS signals food insecurity. The two concepts are explained in detail in the data and descriptive statistics section.

This study contributes to the literature in two ways. First, our study is the first to explicitly relate adoption of climate-smart agricultural practices to HDDS and HFIAS. This is essential for climate-smart agriculture policy mainstreaming (FAO 2013). Second, our multi-level analyses using ESR and quantile treatment effects approaches also enable us to identify the most vulnerable group among smallholders for targeting of nutrition policies. In addition, since food insecurity and malnutrition are still widespread problems in many developing countries, particularly, the northern savannah zones, the question of how to make adoption of climate-smart practices and food systems more nutrition-sensitive is of high relevance for research and policy.

The rest of the paper is organized as follows: the next section briefly explains the concept of climate-smart agriculture and food and nutrition security. This is followed by a discussion of the data. We then present the conceptual framework and estimation techniques used in the

[11] For robustness checks, we use treatment effects Poisson regression to estimate adoption impacts on HDDS and HFIAS due to the count nature of these variables, comparing the estimates to that of the ATT from the ESR estimates.

study. The presentation and discussion of the empirical results then follow, while the final section highlights the main conclusions and policy implications of the study.

3.1 Climate-smart agriculture and food and nutrition security

Farmers in highly vulnerable agro-climatic zones are constantly employing and reorienting agricultural systems to support food and nutrition security under the new realities of climate change. Climate-smart agriculture seeks to enhance the resilience of agricultural systems and livelihoods and to reduce the risk of food and nutrition insecurity in the present, as well as the future (FAO 2013; Lipper et al. 2014). These practices include conservation tillage (minimum or zero-tillage), use of improved and drought tolerant varieties, crop rotation and mixed-cropping, etc., which enable farmers to produce food sustainably. The potential to improve food availability through increased productivity via adoption of climate-smart agricultural technologies has been reported in a number of studies (e.g. Jones et al. 2014; Asfaw et al. 2016).

According to the accepted definition, food and nutrition security "exists when all people, at all times, have physical and economic access to sufficient, safe, and nutritious food that meets their dietary needs and food preferences for an active and healthy life" (FAO 2009 p.1). Different indices have been used to capture food and nutrition security, given the multidimensional nature of the concept (Maxwell, Vaitla, and Coates 2014). For smallholder farmers, farm income or its proxy can be used to examine the relationship between food and nutrition security and climate-smart agriculture. We employ the HDDS and HFIAS to relate the psychological dimensions of food and nutrition security to adoption of climate-smart practices.

Thus, improving the understanding of the nexus between climate-smart agriculture and food and nutrition security, through research, could be useful to the implementation of domestic agricultural and rural development policies. For instance, recent government policy initiatives, such as the “One-Village-One-Dam” and “Planting for Food and Jobs” (MoFA 2017)[12], have also acknowledged climate-smart agriculture as an important pathway to achieving higher youth employment and sustainable food and nutrition security. In particular, the UNDP-Ghana (2018) report[13] on northern Ghana observes that the high dependence of the population in the Savanna zones on unimodal rainfall for farming as the source of livelihoods, makes it imperative to promote adoption of climate-smart technologies to ensure farming systems sustainability amidst climate change.

3.2 Data and Descriptive Statistics

The data used in this study were obtained from a survey during the 2015/2016 cropping season in 25 communities across five districts in Ghana. A multistage random sampling procedure was employed to select and interview (in-person) 476 households (cultivating 1,001 plots) across three regions; Upper East (UE), Northern Region (NR) and Brong-Ahafo (BA) regions. Based on agroecology, we selected five districts (Bongo and Talinse in UE, Tolon and Kumbungu in NR, and Techiman-South in BA). The GSS (2012) report[14] indicated that the total number of households in northern savannah ecological zones and BA was 923,049 with the NR taking the greatest share (more than 34%), while about 74% of the active population was engaged in agriculture. We took into account the land size and population of farmers in the Guinea Savannah and put greater weight on the sub-sample from the NR. Finally, we obtained 203 households for NR cultivating 568 plots; 147 households in the UE with 277 plots; and for BA,

[12] The “Planting for Food and Jobs” is a Ghana government’s flagship policy initiative that seeks to enhance agricultural modernization to achieve greater employment opportunities, poverty reduction and household food and nutrition security (MoFA 2017).

[13] The report, the second of regional human development reports in Ghana by the UNDP, focuses on human development outcomes in the context of socio-economic disparities in what has generally been the most marginalized region (Northern Region, Upper East and Upper West) in Ghana.

[14] The report GSS report includes UW and VR, which are not considered in the current study. However, even without these regions the Guinea Savanah zone still contains the highest population of farm households, given that more than 95% of farm households in these zones cultivate crops (GSS 2012).

126 households with 156 plots. Information was taken on general household characteristics, land holding, the type of crops cultivated, irrigation access and various farming related activities, as well as perceptions on local climate and the agronomic practices being implemented to mitigate real or potential effects of climate change. In line with the existing literature on agricultural technology adoption analysis, we also captured farmer reported plot characteristics, such as soil erosion, drainage level and slope of land (see Di Falco et al. 2011; Kassie et al. 2015). Information on household food and nutrition security was also collected from the survey.

Given that food and nutrition security is multi-dimensional, we captured it with three measures. First, we use farm revenues under the assumption that increased farm revenues tend to enhance food and nutrition security (Di Falco et al. 2011), since it ensures the ability of households to access food for consumption. As argued by Sen (1981), the ability of an individual to access food at the household level depends on both the level of production and market access of food through purchase. Some studies have presumed that smallholder farmers often achieve food security by consuming their own produce (Hawkes and Ruel 2008). However, Brown et al. (2017) observed that purchasing food from the markets plays an important role in enhancing the dietary diversity of smallholder farmers. Thus, farm revenue can be a strong indicator of food access, especially if farmers can generate adequate income and purchase from markets to enhance their dietary diversity.

Our second metric of food security is the household food insecurity access score (HFIAS). The HFIAS is an index that captures different behavioral and psychological dimensions of food insecurity (access), quantified and summarized into a scale (Coates et al. 2007; Maxwell et al. 2014.). The minimum score is 0 for a household with no reported food insecurity (better food access). The maximum score for a household is 27 for a food insecure household with high frequency of occurrence of consuming less preferred food to skipping meals as a result of inadequate access to food (Coates et al. 2007). The third measure is the household dietary diversity score (HDDS) based on the procedure described by Swindale and Bilinsky (2006).

Table 3.1 Definition of variables and descriptive statistics

Variable	Variable Description	Mean	Std. Dev.
Farm revenue	Monetary value of farm produce (GHS)	1857.70	2708.38
HDDS	HH dietary diversity score, measured by the consumptions of 12 categories of foods in the past 7 days, (0-12).	8.22	2.73
HFIAS	HH food insecurity access score. A food secure HH has a score of 0, absolutely food insecure HH has a score of 27.	4.30	4.82
Adoption	Farmer adopts climate-smart practice=1, 0 otherwise	0.66	0.47
Fertilizer	Fertilizer (org. and inorganic) GHS	208.32	625.39
Herbicide	Cost of herbicide used GHS	58.17	204.49
Hired labor	Hired labor GHS	182.73	530.66
Farm size	Total Farm size of HH in acres	1.96	1.49
Education	Years of formal education	5.49	5.02
Household size	Number of people in a household	5.95	3.08
Age	Age of farmer in years	39.64	13.83
Gender	Male=1, female=0	0.84	0.36
Off-farm	Farmer is engaged in off-farm activity=1, 0 otherwise	0.38	0.49
Livestock	Livestock ownership in tropical livestock units	1.84	4.78
Machinery	Farmer owns motokia or tractor =1, 0 otherwise	0.17	0.38
CVRF[b]	Mean Coefficient of variation of rainfall for all agroecological zones	0.41	0.14
Credit constraint	Credit constrained=1, 0 otherwise	0.39	0.49
Extension	Number of extension visits	0.91	1.29
weather information	Received information on climate =1, 0 otherwise	0.57	0.49
Drought perception	Farmer perceived probability of drought	0.76	0.44
Crop choice	Farmer adopts drought resist/early maturing-varieties varieties=1, 0 otherwise	0.75	0.43
Soil and water conservation	Farmer adopt soil and water conservation measures=1, 0 otherwise	0.52	0.50
Slope	Plot is moderate to steep slope =1, 0 otherwise.	0.58	0.43
Soil drainage	Plot is well drained =1, 0 otherwise	0.46	0.42
Erosion level	Plot is moderately to severely eroded=1, 0 otherwise	0.14	0.23

[a]Exchange rate is US dollar 1 = GHS 4.26 at the time of the survey
[b]mean coefficient of variation of rainfall from all agro-ecological zones (see table A5 in the Appendix)

The food consumed by a household within a seven-day period were put into twelve[15] food groups, namely, cereals, tubers and roots, vegetables, fruits, meat and poultry, eggs, fish, pulses and nuts, legumes, milk and milk products, oils and fats, sugar and honey and miscellaneous (spices and condiments) (Swindale and Bilinsky 2006). This was used to calculate the HDDS that has been found to be a good predictor of child nutritional status (Maxwell et al. 2014; Gebreyesus et al. 2015) and will therefore be useful as a measure of dietary quality at the household level.

The HDDS is determined from the household's consumption of different food groups over a given reference period (Swindale and Bilinsky 2006)[16]. While calorie consumption and food purchases have been considered as more objective indicators of food and nutrition security (Weismann et al. 2006; Maxwell et al. 2014), subjective food security measures (including HDDS and HFIAS) are by no means nontrivial measures of food and nutrition security. These measures have been employed with other metrics by international agencies including the World Food Program (WFP), FAO and USAID in assessing food security situation in many developing country surveys (Maxwell et al. 2014).

While our approach of using HDDS and HFIAS data to measure food and nutrition security is useful, it is important to acknowledge a few limitations of this approach (Maxwell et al 2014). In the first place, by using a single seven-day recall, we are unable to account for seasonal variation in food and nutrition security. Second, it is impossible to account for intra-household food distribution. Third, the single seven-day recall data on HDDS and HFIAS are only a proxy of actual food access and nutrition quality (Maxwell et al. 2014). While we keep these limitations in mind, we do not anticipate a systematic bias in our assessment, because the same

[15] There is still no strict consensus on the right number of groups to use (Maxwell et al. 2014).
[16] We used a 7-days recall period as a reference for both HDDS and HFIAS determination, for ease of recall (Swindale and Bilinsky, 2006).

issues hold for both adopters and non-adopters of climate-smart agricultural practices among farmers in the study area.

Climate-smart agronomic practices and other variables

The survey showed that up to 316 respondents or 66% of farm households (Table 3.1) across the study area had implemented one or more of the climate-smart agronomic practices (soil and water conservation and crop choices) in the past five years. Soil and water conservation refers to the use of erosion control and other measures to prevent soil and nutrient loss and conserve soil moisture, including minimum tillage, soil and stone bunds. Strategies which seek to minimize soil loss due to erosive rains or evaporation of water from the soil due to high temperatures are expected to help improve crop performance (see Kato et al. 2011). Crop choice as a climate-smart strategy is defined to include the use of modern varieties, drought resistant and early maturing varieties. It also captures changing crops in response to climate variability (particularly erratic rainfall). Some studies have reported that farmers who adopt crop choice/switching crops and planting dates in response to climate change have improved farm yields or reduced their risk exposure (Di Falco and Veronesi 2014; Kassie et al. 2017). A number of studies have examined the adoption and impacts of these climate-smart practices on farm performance and food security in different contexts (e.g., Asfaw et al. 2016; Kathage et al. 2016).

From Table 3.1, the average age of farmers in our sample is 40 years, an indication of the youthful nature of Ghana's population and great potential for agricultural development in the area. A recent UNDP report shows that a greater proportion of the population in the northern savannah zone is below 40 years (UNDP-Ghana 2018). The sample average household size is 6 persons, with a household cultivating an average 2 hectares or less, reflecting the general smallholder nature of agriculture in the study area (GSS 2012). The mean years of schooling

(5.5) is slightly lower than the national average[17], indicating the generally low level of education among farmers in our sample.

The reported HDDS of 8.2 (minimum (0) to maximum (12)) and HFIAS of 4.3 (ranging from 0-21) in the past seven days, suggests the existence of some level of food and nutrition insecurity among the sampled households. In general, an increase in HDDS reflects an improvement in the household's dietary quality and nutrition security, while a decrease in HFIAS implies an improvement in household access to food (Swindale and Bilinsky 2006). The mean differences of key variables between adopters and non-adopters are presented in table A1 in the appendix.

To capture agro-ecological zone effect, we calculated the coefficient of variation of rainfall (*CVRF*)[18] for the three agro-climatic zones considered (Sudan Savanna, Guinea Savanna and Transitional zone). Variation in climate variables particularly rainfall is an indicator of climate shock and farmers are expected to respond to these shocks by adopting climate-smart practices (Di Falco et al. 2011). Farmer reported plot level characteristics (plot slope, drainage and erosion level) were also captured as these have been reported to influence farmers' adoption decisions (see Kassie et al. 2015).

Conceptual framework and estimation techniques

In this study, we examine the impact of adoption of climate-smart agricultural practices on household food and nutrition security. As noted by Alderman et al. (1995), such an assessment can be done within the context of intra-household decision-making framework, using the collective model approach, where the assessment of welfare of individuals in a household can be considered. However, given the cross-sectional data available for this study, without detailed

[17] According to the GSS (2012), the average level of schooling is about 7 years.
[18] Summary of the statistics of the coefficient of variation of rainfall for the three agro-ecological zones considered in this study are reported in the table A3 in the appendix.

information on consumption of individual household members, we are not able to examine the impact within the concept of intra-household resource allocation. We therefore use the unitary approach that views the household as a collection of individuals that maximize a common utility or welfare function (Haddad et al. 1997). This implies that household resource allocation including on-farm adoption of climate-smart agricultural practices is determined simultaneously, making the unitary or non-separable framework more appropriate in this context.

Thus, we model the household's decision to adopt climate-smart agricultural practices under the assumption that farmers are risk-neutral and choose between adoption and non-adoption to maximize expected net benefits. Thus, climate-smart agriculture practice is adopted when the net benefits associated with adoption is greater than the benefits from non-adoption. The adoption of climate-smart agricultural practice is expected to influence farm output (food supply), household dietary diversity and for that matter food and nutrition security. If we consider food and nutrition security (farm revenues, HDDS and HFIAS) to be a linear function of adoption of climate-smart practices, along with other observed variables, the linear regression equation can be specified as:

$$Q_i = \mathbf{K}_{\boldsymbol{i}}\boldsymbol{\gamma} + \delta Adopt_i + \mu_i \qquad (1)$$

where Q_i refers to food and nutrition security outcomes such as farm revenues, HDDS and HFIAS of household i; $Adopt_i$ is a dummy variable denoting the adoption decision, $\mathbf{K}_i$ is vector of explanatory variables that include farm and household level characteristics, such as age, household size, gender, access to extension services, participation in off-farm work, as well as climate variables, $\boldsymbol{\gamma}$ is a vector of parameters to be estimated; δ is also a parameter capturing the effect of adoption on outcome Q_i, and μ_i is the error term.

Estimating the impact of adoption using equation 1 might yield biased and inconsistent estimates, because it assumes that a farmer's decision to adopt is exogenous. However, as widely documented in the empirical literature, given that farmers self-select into adoption, this decision may be endogenous (Heckman 1979). Moreover, farmers that decide to adopt may also be systematically different from those that do not adopt. In addition, unobserved factors influencing the adoption decision – such as innate managerial skills of farmers – may also affect the food and nutrition security outcomes, resulting in biased and inconsistent estimates of $\boldsymbol{\gamma}$ and δ. To account for selectivity bias due to observed and unobserved factors, we employ an endogenous switching regression (ESR)[19] approach, where the adoption decision ($Adopt =$ 1 or 0) is considered as a switch or adoption status indicator, with two outcome regimes. The specification used in estimating the ESR model is presented as follows:

$$Adopt_i = \boldsymbol{X}_i\boldsymbol{\alpha} + \varepsilon_i \qquad (2)$$

Adopters Regime: $Q_{i1} = \mathbf{K}_{\boldsymbol{i}}\boldsymbol{\gamma}_{\mathbf{1}} + \mu_{i1}$, if $Adopt = 1$ (3a)

Non-adopters Regime: $Q_{i0} = \mathbf{K}_{\boldsymbol{i}}\boldsymbol{\gamma}_{\mathbf{0}} + \mu_{i0}$, if $Adopt = 0$ (3b)

where Q_{i1} and Q_{i0} represent the food and nutrition outcomes for adopters and non-adopters, respectively, $\boldsymbol{X}_i$ is a vector of variables that include farm and household characteristics, $\boldsymbol{\alpha}$ is a vector of parameters to be estimated, while ε_i is an error term. Although the variables in the vectors $\mathbf{X}_{\boldsymbol{i}}$ in equation 2 and $\mathbf{K}_{\boldsymbol{i}}$ in equations 3a and 3b are similar, it is important to note that for proper identification, at least one variable (instrument) in vector $\mathbf{X}_{\boldsymbol{i}}$ is excluded from $\mathbf{K}_{\boldsymbol{i}}$. In our case, we employed variables related to farmers' drought perception and access to weather information. Intuitively, these variables may affect farmers' decisions to adopt climate-smart agricultural practices, but not necessarily the food and nutrition security outcomes among adopters. In the joint estimation, these variables were excluded[20] from the outcome equations.

[19] Among studies that have employed this framework include Di Falco, Veronesi, and Yesuf (2011); and Abdulai and Huffman (2014). Also see Lokshin and Sajaia (2004), for detailed implementation in Stata.
[20] Estimates about the test of validity of the excluded instruments are available on request.

Equations 2, 3a and 3b are estimated simultaneously for each of the food and nutrition security outcomes.

Using the ESR approach enables us to account for both observed and unobserved heterogeneity between adopters and non-adopters of climate-smart agricultural practices in the two regimes. This approach also enables us to construct counterfactual outcomes for the two regimes, which allows comparisons of the expected food and nutrition security outcomes (farm revenues, HDDS and HFIAS) of true adopters and their counterfactual, and to calculate the average treatment effect on the treated (ATT), stated as follows:

ATT = $E(Q_{1i}|\ Adopt_i = 1) - E(Q_{0i}|\ Adopt_i = 1)$ (4).

Equation 4 mimics an experimental situation, where $E(Q_{1i}|\ Adopt_i = 1)$, captures the expected outcome given that a farmer truly adopts, while $E(Q_{0i}|\ Adopt_i = 1)$ depicts the expected outcome of counterfactual situation, if an adopter had not adopted (i.e. hypothetical non-adopter). Another advantage of the ESR approach is that it employs full information maximum likelihood (FIML) estimation, which is more efficient, compared to approaches that use two-stage estimators (Lokshin and Sajaia 2004).

Potential plot-level unobserved heterogeneity problem that may arise with households cultivating multiple plots was addressed by Mundlak's approach (Mundlak 1978)[21]. In addition, the variable, participation in off-farm work may also be endogenous because income earned from off-farm work can be invested in climate-smart technologies or yield enhancing inputs (income effect). On the other hand, engaging in off-farm work may lead to reduced time allocation to on-farm practices (labor-loss effect).The potential endogeneity of the variable (off-farm work) was addressed using the control function approach proposed by Wooldridge (2015). The approach involves the specification of the potential endogenous variable (i.e. off-farm work

[21] See Di Falco et al. 2011 and Kassie et al. 2015 for the application of this approach in multiple plot framework.

participation) as a function of explanatory variables influencing adoption, together with a set of instruments in a first-stage probit regression. Instead of using the predicted values of off-farm participation variable as in two-stage-least-squares, the observed values of off-farm work participation variable and the generalized residuals from a first-stage regression are included as covariates in the ESR model. Including the residuals serves as a control function, enabling the consistent estimation of the off-farm work participation variable in the ESR model.

Since the ESR does not allow quantile estimations, we estimated a set of quantile treatment effects regressions using equation 1 to see how adoption influences different parts of the distribution of food and nutrition security outcomes and to account for heterogeneity at different distributions of these outcomes (see Froelich and Melly 2010). In addition, given the fact that household dietary diversity scores (HDDS) and food insecurity access scores (HFIAS) are count variables, we estimated a treatment effects Poisson model while accounting for selectivity bias, as a robustness check.

3.3 Empirical results and discussions

This section presents the results from the empirical analysis. First, we discuss the factors that influence the adoption of climate-smart practices. As noted earlier, the ESR approach estimates two separate but related outcome equations, one for each group (adopters and non-adopters), in combination with a selection equation (adoption). Second, the estimates for the determinants of food and nutrition security outcomes (farm revenues, HDDS and HFIAS) are presented. Thirdly, the treatment effects of adoption on the farm revenues, HDDS and HFIAS (ATT) are discussed.

Drivers of adoption of climate-smart practices

The results of the determinants of adoption are reported in column two of Table 3.2. The results generally indicate that the adoption of climate-smart agronomic practices is significantly influenced by household characteristics (education, household size, and gender), resource constraints (farm size, machinery, off-farm participation), plot level characteristics (slope, drainage and erosion level), as well as climate perception and information related variables. The estimated coefficient of rainfall variability (CVRF) is positive and significantly different from zero, suggesting that farmers are adopting climate-smart practices in response to climate shock.

Table 3.2 ESR results for determinants of adoption of climate-smart practices and log farm revenues of adopters and non-adopters

	Adoption	Adopters Log-farm revenue	Non-adopters Log-farm revenues
Constant	-1.388 (1.093)	6.606*** (0.681)	6.575***(1.439)
Herbicide (log)	0.092** (0.041)	0.041* (0.024)	0.103* (0.061)
Hired labor (log)	-0.021 (0.028)	0.007 (0.016)	0.090** (0.034)
Farm size (log)	0.252 (0.177)	-1.127*** (0.127)	-1.847*** (0.227)
Education	0.075*** (0.016)	0.002 (0.010)	0.0211 (0.033)
Household size	0.322*** (0.057)	0.035** (0.013)	0.014(0.033)
Age	0.006 (0.005)	-0.002 (0.003)	0.004(0.006)
Gender	-1.223*** (0.193)	0.156 (0.165)	0.305(0.255)
Off-farm	-0.324*** (0.140)	-0.114 (0.098)	0.343 (0.218)
Credit constraint	-0.057 (0.136)	0.173* (0.092)	0.076 (0.172)
Machinery	0.411** (0.208)	0.168 (0.114)	0.230 (0.292)
CVRF	0.002** (0.001)	-0.042** (0.016)	-0.057*** (0.021)
Extension contact	0.204*** (0.049)	0.039 (0.030)	0.033 (0.120)
Mean_slope	0.902**(0.471)	-0.619** (0.255)	0.445 (0.711)
Mean _drainage	1.199***(0.475)	0.523* (0.304)	0.4661(0.6271)
Mean_soil erosion	-3.745**(1.395)	0.711 (0.742)	-0.637 (1.950)
Joint sig plot variables $\chi^2(3)$	17.78*** [0.001]	15.69** [0.003]	3.03 [0.550]
Weather information	0.496** (0.201)		
Drought perception	0.395*** (0.108)		
Off-farm-resid	-0.003 (0.022)		
$ln\sigma_1/ln\sigma_0$		-0.266*** (0.056)	-0.061 (0.182)
ρ_1/ρ_0		0.004 (0.138)	-0.419 (0.621)
Sample size	476		
Wald test (ρ =0)	0.35 [0.554]		
Log pseudolikelihood = -821.741			

***, **, * represent 1%, 5%, and 10% significance level, respectively. Values in parentheses are standard errors. Values in square brackets are p-values.

The estimate of the household size variable is positive and significantly different from zero, indicating that larger households, with potentially higher labor force, are more likely to adopt climate-smart practices. The estimate for the education variable is also positive and significantly different from zero, indicating that farmers with higher education are more likely to adopt climate-smart practices. Female farmers are also more likely to adopt, as indicated by the negative and significant coefficient of the gender variable, a finding that is consistent with that of Malapit and Quisumbing (2015).

The estimate of machinery is positive and statistically significant, indicating that ownership of farm machinery including motorcycles and "motor-kia[22]" increases the likelihood of adoption. Participation in off-farm work negatively influences the likelihood of adoption, a finding that is in line with the labor-loss effect of the new economics of labor migration hypothesis (Taylor, De Braw, and Rozelle 2003), which states that participation in off-farm work may divert labor from intensive on-farm activities, thus negatively influencing farmers' adoption decisions. The insignificance of the estimates of the residual *Off-resid*, indicates absence of simultaneity bias, and consistent estimation of the off-farm work variable (Wooldridge 2015).

Another interesting observation is the estimate for the coefficient of access to extension variable. We find that farmers' extension contacts increase their probability of adoption. Extension contacts are means by which farmers obtain relevant information about climate-smart practices. In addition, farmers' perception about drought occurrence in the near future increases their likelihood of adoption, a finding that is consistent with the results reported by Kassie et al. (2017) about farmers' increased preference for drought tolerant maize in Zimbabwe. Mean-plot level characteristics also tend to influence the probability of adoption by households as shown by the Wald test for joint significance of plot level variables. In particular, the variable

[22] The "motor-kia" is an important transport machine especially in the rural areas and for carting farm produce. It is a motorized three-wheel light-freight vehicle, with open or fully closed small truck/cabin. It has helped to relieve transport difficulties, including that of agriculture, especially in northern Ghana.

for plot drainage positively influence adoption, suggesting that well drained soils which are more likely to be fertile, need to be conserved to maintain their productivity. Erosion level however, significantly reduces the probability of adoption. These findings suggest that farmers consider factors related to land quality in their decisions to adopt climate-smart agronomic measures. Farmers' perceptions about drought and access to weather information also significantly influence their probability of adoption of climate-smart practices, a finding that is consistent with many previous studies in SSA (see Di Falco et al. 2011; Asfaw et al. 2016).

Determinants of farm revenues among adopters and non-adopters

The results on the determinants of farm revenues among adopters and non-adopters are presented in Table 3.2. Columns three and four indicate the results of the farm revenue equations for adopters and non-adopters, respectively. The results indicate that hired labor positively and statistically influence farm revenues of non-adopters, while household size, which indicates labor potential of the household, positively and significantly influences farm revenues of adopters. Farm size is negatively associated with farm revenues among both adopters and non-adopters, a finding that is consistent with the inverse farm size productivity relationship in literature, with higher farm productivity being associated with smaller farm sizes (e. g. Assuncao and Braido 2007). The coefficient of variation of rainfall (CVRF) is also negatively associated with farm revenues, although the effect is higher (in magnitude and statistical power) among non-adopters than adopters, suggesting that adoption climate-smart agricultural practices could be playing positive role in reducing the effect of rainfall variability as observed in previous studies (Di Falco et al. 2011; Adiku et al. 2015). The household characteristics including age, gender, and participation in off-farm work are not significantly associated with farm revenues of adopters and non-adopters. Furthermore, plot quality variables jointly influenced farm revenues of adopters, but not that of non-adopters. The likelihood ratio tests for joint independence of the three equations (adoption and farm revenue functions for adopters and non-adopters) show that the equations are not dependent, as illustrated by the error correlation terms, ρ_1/ρ_0, suggesting that selection bias arising from unobserved factors are undetectable due to low statistical power. In other words, there is no evidence to confirm that unobserved characteristics influence both farmer's decision to adopt climate-smart practices and farm revenues at the same time in this study. However, since the ESR approach also accounts for selection bias from observed factors, its use in this study is still relevant.

Determinants of HDDS and HFIAS among adopters and non-adopters

The results in Table 3.3 show the determinants[23] of HDDS and HFIAS of adopters and non-adopters. Unlike in the farm revenue functions, some key household characteristics (household size, gender, off-farm) are significant, especially in the HDDS functions. For instance, the coefficient for household size is negative and statistically significant for the HDDS suggesting that larger family size, all things being equal, is associated with low dietary quality. The positive and significant coefficient of the variable representing education suggests that higher educational attainment may be correlated with greater dietary quality in terms of increased HDDS. This is consistent with findings of earlier studies that observed positive and significant correlation between education and dietary quality of the household (Jones et al. 2014). This could be due to the fact that education enhances farmers' knowledge on food and nutrition security.

The estimate of the gender variable is negative and statistically significant, indicating that female headed households are associated with increased dietary diversity (HDDS) among adopters, an observation that is consistent with earlier findings that linked empowered female household heads to increased dietary diversity in Ghana (Malapit and Quisumbing 2015). It is

[23] The *movestay* command in STATA jointly estimates the selection (adoption) and the outcome equations for adopters and non-adopters (Lokshin and Sajaia 2004). The determinants of adoption results of the ESR estimation for HDDS and HFIAS are not reported here since the estimates are not different from those presented in table 2, but these estimates are available on request.

significant to mention that women are generally in charge of food preparations in many parts of Africa, and therefore tend to influence the dietary quality. This finding reiterates the significant role gender could play in food and nutrition security as indicated in the recent Ghana National Nutrition Policy 2014-2017.

Table 3.3 ESR results for determinants of HDDS and HFIAS of adopters and non-adopters

	HDDS[a]		HFIAS[b]	
	Adopters	Non-adopters	Adopters	Non-adopters
Constant	4.181** (2.065)	3.515**(1.380)	3.930 (4.286)	5.651 (6.167)
Herbicide	-0.043 (0.075)	-0.104 (0.139)	-0.219** (0.126)	-0.499* (0.274)
Hired-labor	0.021 (0.051)	-0.220** (0.096)	-0.058 (0.102)	0.157 (0.193)
Farm size	1.202*** (0.362)	0.053 (0.676)	-0.544 (0.716)	-0.289 (1.286)
Education	0.080*** (0.031)	0.003 (0.053)	-0.068 (0.058)	-0.122 (0.095)
Household size	-0.107** (0.040)	0.077(0.095)	-0.094 (0.076)	-0.183 (0.187)
Age	-0.018** (0.010)	-0.006 (0.016)	-0.032 (0.020)	-0.040 (0.030)
Gender	-0.449 (0.472)	-1.389** (0.513)	-0.615 (0.750)	0.938 (1.208)
Off-farm	0.643** (0.324)	0.335* (0.196)	-1.571** (0.563)	-0.755** (0.253)
Credit constraint	0.003 (0.002)	0.142 (0.463)	0.028 (0.083)	0.068 (0.136)
CVRF	-0.148*** (0.037)	-0.213*** (0.051)	0.187** (0.068)	0.063*** (0.011)
Extension contact	0.181* (0.101)	0.105 (0.281)	-0.282* (0.145)	-0.196 (0.575)
Joint sig plot variables χ^2 *(3)*	8.34* [$p = 0.080$]	21.73*** [$p = 0.001$]	22.15*** [$p = 0.001$]	23.21*** [$p = 0.001$]
$ln\sigma_1/ln\sigma_0$	0.780*** (0.023)	0.898*** (0.020)	1.434*** (0.011)	1.553*** (0.022)
ρ_1/ρ_0	0.250 (0.258)	-0.061 (0.283)	-0.023 (0.153)	0.168 (0.287)
Sample size	476		476	
Wald test ($\rho = 0$)	0.88 [$p = 0.347$]		0.340 [$p = 0.558$]	

***, **, * represent 1%, 5%, and 10% significance level, respectively. Values in parentheses are standard errors. Values in square brackets are p-values.
[a]HDDS: Household dietary diversity score. [b]HFIAS: Household food insecurity access score

The estimate of the gender variable is negative and statistically significant, indicating that female headed households are associated with increased dietary diversity among adopters (Table 3.3), an observation that is consistent with the findings by Malapit and Quisumbing (2015) that linked empowered female household heads to increased dietary diversity in Ghana. It is significant to mention that women are generally in charge of food preparations in Africa, and therefore tend to influence the dietary quality. This finding reiterates the significant role gender could play in food and nutrition security as indicated in the recent Ghana National Nutrition Policy 2014-2017.

The coefficient of off-farm work is positive (in the case of HDDS), but negative (for HFIAS) and statistically different from zero, suggesting that engaging in off-farm work may lead to an increase in dietary diversity/dietary quality (HDDS) and improvement in food access (HFIAS). The result here is probably due to the income effect of off-farm work participation, with households using earnings from off-farm work to improve their food and nutrition security. However, access to credit (captured as credit constrained) does not significantly influence HDDS or HFIAS. Interestingly, rainfall variability (*CVRF*) appears to negatively influence food and nutrition security outcomes (i.e. negatively influencing HDDS and positively increasing HFIAS). Interestingly, plot level characteristics also jointly determine the food and nutrition security outcomes of households as indicated by the Wald test of joint significance, suggesting that improving soil fertility/plot quality of farm households could indirectly enhance food and nutrition security outcomes. Extension contact has the expected signs in both HDDS and HFIAS, but only marginally significant (at 10% level) for adopters, indicating the important role extension service could play in enhancing food and nutrition security.

Effect of adoption on food and nutrition security outcomes (farm revenues, HDDS and HFIAS

An important objective of this study is to determine the effect of adoption of climate-smart practices on food and nutrition security outcomes. The use of the ESR approach enables us to obtain the expected outcomes of food and nutrition security, conditional on adoption. The difference between expected outcomes of adopters who actually adopted and the expected outcomes if they (adopters) had not adopted, is called average treatment effect on the treated (ATT) (equation 4). The results of the estimated ATT are presented in Table 3.4.

Table 3.4 Impact of adoption of on food and nutrition outcomes (ATT) based on total sample and Agro-ecological zones

Variable		Adopters	Non-adopters	ATT-ESR [t-value]	% change in outcome
Treatment effects (based on total sample)					
Farm revenue (log)		7.08	6.30	0.78*** [14.65]	12.40
Household dietary diversity scores (HDDS)		8.60	7.47	1.13*** [10.00]	15.20
Household food insecurity access score (HFIAS)		3.86	5.95	-2.09*** [-21.75]	-35.10
Treatment effects based on Agro-ecological zone (AEZ)[a]					
Guinea Savannah	Farm Rev. (log)	6.96	6.14	0.82*** [12.12]	13.40
	HDDS	7.79	6.66	1.13*** [10.01]	16.90
	HFIAS	4.70	6.98	-2.28*** [-19.51]	-32.60
Sudan Savannah	Farm Rev. (log)	7.07	6.34	0.72*** [8.79]	11.40
	HDDS	8.62	7.28	1.34*** [8.57]	18.40
	HFIAS	2.06	3.07	-1.01*** [-5.54]	-32.80
Transitional zone	Farm Rev. (log)	7.34	6.78	0.56*** [5.78]	8.30
	HDDS	10.11	9.58	0.53*** [14.36]	5.50
	HFIAS	2.59	3.46	-0.87*** [-5.85]	-25.20

***, ** represent 1% and 5% significance level, respectively. Values in square brackets are t-values
[a]The predicted outcome variables (farm revenues, HDDS and HFIAS) were sorted based on agro-ecological zones and t-tests were conducted to determine differences between adopters and counterfactuals with respect to these outcomes.

The results indicate that adoption significantly increased farm revenues of adopters. Specifically, the expected log farm revenues of adopters is 7.08 compared to 6.30, if they were not to adopt (Non-adopters), representing an increase in farm revenues (ATT=0.78) of about 12.4%. The results also show that expected HDDS, given adoption of climate-smart practices, changed by 1.13, representing 15.2% increase in HDDS. In addition, the impact of adoption on household food insecurity access scores (HFIAS) is -2.09, which represents a 35% decrease in food and nutrition insecurity.

Based on agro-ecological zones, the results in Table 3.4 also indicate that the effects of adoption of climate-smart practices are higher in the Sudan Savannah agro-ecological zone than in the transitional zone. It can be seen that on average, households in the Transitional zone generally obtained higher HDDS. This can partly be attributed to the diversity of natural edible plants and other non-timber forest food related products that can be found in this area, as compared to the Savannah zones. However, the net effect of adoption indicates that greater percentage change[24] in expected HDDS is noticed among households in the Sudan Savannah zones (18%), compared to those in the Transitional zone (8%). The effect of adoption in respect of HFIAS is much larger in percentage terms in the two Savannah zones, implying that adoption led to greater improvement in HDDS in Savannah agro-ecological zones than in the Transitional zone.

The effect of adoption on food and nutrition security outcomes based on quantile treatment effects regression are presented in Table 3.5. The results suggest that the magnitude of the changes in farm revenues, HDDS and HFIAS vary across quantiles of these outcomes. With respect to farm revenues, the effect of adoption is significant in all quantiles except the 0.75 quantile. In the case of dietary diversity, adoption has a significant impact in the lower quantiles (0.1 and 0.25), with no statistically significant effect of adoption in the median and upper quantiles of dietary diversity (HDDS), suggesting that households with lower dietary diversity tend to benefit more from adoption in terms of food and nutrition security.

[24] For robustness check we performed treatment effects Poisson analyses for HDDS and HFIAS, as the two measures can be considered as count variables. The results are presented in table A2 in the appendix. The values for percentage change in HDDS given adoption (ATT-Poisson) in treatment effects Poisson model are similar to those reported in table 4.

Table 3.5 Treatment effect of adoption at different quantiles of on farm revenues, HDDS and HFIAS based on quantile treatment effect (QTE) regressions

Quantile	Log farm revenue		HDDS		HHFIAS	
	Coefficient	% Impact[a]	Coefficient	% Impact	Coef	% impact
0.1	0.316***	37.20	0.252***	28.70	0.000	0.00
	(0.130)		(0.074)		(0.021)	
0.25	0.324**	38.30	0.157**	17.00	0.001	0.00
	(0.146)		(059)		(0.110)	
0.5	0.242*	27.40	0.027	2.70	-0.510**	-39.95
	(0.133)		(0.042)		(0.208)	
0.75	0.138	14.80	0.010	1.00	-0.223**	-20.00
	(0.137)		(0.038)		(0.112)	
0.9	0.197*	21.80	0.009	0.90	-0.241***	-21.40
	(0.117)		(0.322)		(0.079)	

***, **, * represent 1%, 5%, and 10% significance level, respectively. Values in parentheses are standard errors.

The treatment effects of adoption on HFIAS are however more greatly felt among farm households in the median (0.5) and higher quantiles of HFIAS, indicating that even households with reported higher levels of HFIAS, tend benefit if they adopt climate-smart agricultural practices.

3.4 Conclusions and policy implications

This study examined the factors that affect farmers' decisions to adopt climate-smart agronomic practices in Ghana, and how adoption influences food and nutrition security, measured in terms of farm revenues, household dietary diversity and household food insecurity access scores. We used data from a recent survey of farmers in the Northern, Upper East and Brong-Ahafo regions, representing three agro-ecological zones in Ghana, to estimate the determinants of adoption and impacts of adoption on food and nutrition security. We employed an endogenous switching regression model that accounts for potential selection bias that arises from both observed and unobserved factors. In addition, we estimated the effects of adoption across different quantiles of food and nutrition security outcomes to assess the distributional effects of adoption impacts.

The empirical results revealed that several household and farm-level variables significantly influence farmers' decisions to adopt climate-smart agronomic practices. In particular, the results showed that long-term rainfall variability exhibit a positive effect on adoption decisions of farmers, signifying farmers' response to erratic rainfall patterns. Thus, policy measures aimed at increasing farmers' resilience to weather variability could include the promotion of drought tolerant and early maturing varieties, increased access to irrigation facilities and improved climate information delivery. The recent Ghana government policy initiative of "One-Village-One-Dam", which aims at constructing many dams across the country, particularly in the northern savannah zone, may be useful in minimizing the risks associated with climate change, especially the erratic rainfall patterns.

The findings also revealed that adoption of climate-smart practices had positive and significant impact on food and nutrition security. We also found that the impact of adoption differed across quantiles and agro-ecological zones. The general pattern from the quantile analysis indicated that the effects of adoption on food and nutrition security improvement are generally higher for the poorer farm households, whose dietary diversity scores fall within lower quantiles. Thus, if the notion that food crop farmers are mostly smallholders is considered, then this analysis provides evidence that adoption of climate-smart practices tend to benefit poor farmers through higher relative food and nutrition outcomes and reduction in food and nutrition insecurity.

Another policy implication of this study is that understanding the determinants of adoption of climate-smart practices could facilitate the design and dissemination of strategies to enhance farmers' resilience at community, district and regional levels. Strengthening of extension services and the incorporation of climate change sensitization into extension delivery could enhance adoption of climate-smart practices to improve farmers' resilience. These findings may be beneficial to the implementation of the government flagship program of "Planting for Food and Jobs" that aims to promote food security and youth employment through agriculture

(MoFA, 2017). Our results also provide support for the National Nutrition Policy for Ghana (NNP) (2014-2017). The goal of the NNP is to 'ensure optimal nutrition and health of all people living in Ghana, to enhance capacity for sustainable economic growth and development' (NNP, 2013, p. 23). In addition, the findings suggest that promotion of climate-smart agriculture can be employed as part of domestic efforts to achieve the United Nations Sustainable Development Goals; to end hunger, achieve food and nutrition security, as well as promote sustainable agriculture.

The results of this study should be interpreted with caution. As noted earlier, by using a single seven-day recall, we are unable to account for seasonal variation in food and nutrition security. In addition, it will be impossible for the current analyses to report on intra-household food distribution, as we did not capture data on these issues. Finally, the recall data on HDDS or HFIAS are only proxies of actual food access and nutrition quality. In spite of these caveats, we are not expecting a systematic bias in our assessment. Thus, this assessment is useful in deepening the understanding of the links between adoption of climate-smart agricultural practices and food and nutrition security.

References

Abdulai, A., and W. Huffman. 2014. The Adoption and Impact of Soil and Water Conservation Technology: An Endogenous Switching Regression Application. *Land Economics* 90 (1): 26–43.

Alderman, H., P. A. Chiappori, L. Haddad, J., Hoddinott, and R. Kanbur. 1995. Unitary versus Collective Models of the Household: Time to Shift the Burden of Proof? *World Bank Research Observer* 10: 1-19.

Asfaw, S., F. D. Battista, and L. Lipper. 2016. Agricultural Technology Adoption in the Sahel: Micro-evidence from Niger, *Journal of African Economies* 25 (5): 637-669.

Assuncao, J. J., & Braido, L. H. B. 2007. Testing household-specific explanations for the inverse productivity relationship, *American Journal of Agricultural Economics* 89(4): 980-990.

Brown, M. E., E. R. Carr, K. L., Grace, K. Wiebe, C. C. Funk, W. Attavanich, P. Backlund, and L. Buja. 2017. Do markets and trade help or hurt the global food system adapt to climate change? *Food Policy* 68: 154–159.

Coates, J., B. L. Rogers, P. Webb, D. Maxwell, R. Houser, and C. McDonald. 2007. Diet Diversity Study: Final Report to the World Food Program. *Friedman School of Nutrition Science and Policy*, Tufts University, Medford, MA.

Di Falco, S., M. Veronesi, and M. Yesuf. 2011. Does adaptation to climate change provide food security? A micro-perspective from Ethiopia. *American Journal of Agricultural Economics* 93(3): 829–846.

Di Falco, S., and M. Veronesi. *2014*. Managing Environmental Risk in Presence of Climate Change: The Role of Adaptation in the Nile Basin of Ethiopia. *Environmental and Resource Economics* 57(4): 553–577.

Food and Agriculture Organization of the United Nations (FAO). 2013. Climate-Smart Agriculture Sourcebook. *Food and Agriculture Organization*, Rome.

FAO. 2009. Draft declaration of the World Summit on Food Security. *Food and Agriculture Organization* 16–18 November 2009. Rome.

Frelat, R., S. Lopez-Ridaura, K. E. Giller, M. Herrero, S. Douxchamps, A. A. Djurfeldt, O. Erenstein, B. Henderson, M. Kassie, B. K. Paul, C. Rigolot, R. S. Ritzema, D. Rodriguez, P. J. A. van Asten, and M. T. van Wijk. 2016. Drivers of household food availability in sub-Saharan Africa based on big data from small farms. *Proceedings of the National Academy of Sciences* USA, 113, 458-463.

Froelich, M., and B. Melly. 2010. Estimation of quantile treatment effects with Stata. *Stata Journal* 10 (3): 423–457.

Fuglie, K. 2018. R&D Capital, R&D Spillovers, and Productivity Growth in World Agriculture. *Applied Economic Perspectives and Policy 40* (3): 421-444.

Gebreyesus, S. H., T. Lunde, D. H. Mariam, T. Woldehanna, and B. Lindtjørn. 2015. Is the adapted Household Food Insecurity Access Scale (HFIAS) developed internationally to measure food insecurity valid in urban and rural households of Ethiopia? *BMC Nutrition*, 1:2-10.

Global Nutrition Report. 2015. Climate Change and Nutrition. *Global Nutrition Report* 2015: 76-84.

Ghana Statistical Service [GSS] 2012. “2010 Population and Housing Census, Summary Report of Final Results” *Ghana Statistical Service*: Accra.

Haddad, L., J. Hoddinott, and H. Alderman. (Eds.). (1997). *Intra-household Resource*

Allocation in Developing Countries: Models, Methods, and Policy. Baltimore: Johns Hopkins University Press.

Hawkes, C., and M. T. Ruel. 2008. From Agriculture to Nutrition: Pathways, Synergies and Outcomes. *Agriculture and Rural Development* No. 53340, The World Bank.

Heckman, J. 1979. Sample Selection Bias as a Specification Error. *Econometrica* 47 (1): 153-161.

IPCC. 2014. *Climate change 2014: Impacts, adaptation, and vulnerability. Part A: Global And sectoral aspects. Contribution of working group II to the fifth assessment report of the Intergovernmental Panel on Climate Change.* Cambridge, United Kingdom: Cambridge University Press.

Jones, A. D., A. Shrinivas, and R. Bezner-Kerr. 2014. Farm production diversity is associated with greater household dietary diversity in Malawi: Findings from nationally representative data. *Food Policy* 46:1-12.

Kassie, M., H. Teklewold, M. Jaleta, P. Marenya, and O. Erenstein. 2015. Understanding the Adoption of a Portfolio of Sustainable Intensification Practices in Eastern and Southern Africa. *Land Use Policy* 42: 400–411.

Kassie, G. T., A. Abdulai, W. H. Green, B. Shiferaw, T. Abate, A. Tarekegne, and C. Sutcliffe. 2017. Modeling Preference and Willingness to Pay for Drought Tolerance (DT) in Maize in Rural Zimbabwe. *World Development* 94: 465–477.

Kathage, J., M. Kassie, B. Shiferaw, and M. Qaim. 2016. Big Constraints or Small Returns? Explaining Nonadoption of Hybrid Maize in Tanzania, *Applied Economic Perspectives and Policy* 38 (1):113-131.

Kato, E., C. Ringler, M. Yesuf, and E. Bryan. 2011. Soil and water conservation technologies: a buffer against production risk in the face of climate change? Insights from the Nile basin in Ethiopia. *Agricultural Economics* 42*:* 593–604.

Kurukulasuriya, P., and R. Mendelsohn. 2008. A Ricardian analysis of the impact of climate change on African cropland. *African Journal of Agricultural and Resource Economics* 2 (1): 1-23.

Lipper, L. P. Thornton, B. M. Campbell, T. Baedeker, A. Braimoh, M. Bwalya, P. Caron, A. Cattaneo, D. Garrity, K. Henry, R. Hottle, L. Jackson, A. Jarvis, F. Kossam, W. Mann, N. McCarthy, A. Meybeck, H. Neufeldt, T. Remington, P. T. Sen, R. Sessa, R. Shula, A. Tibu, and E. F. Torquebiau. 2014. Climate-Smart Agriculture for Food Security. *Nature Climate Change* 4: 1038-2437.

Lokshin, M., and Z. Sajaia. 2004. Maximum Likelihood Estimation of Endogenous Switching

Regression Models. *Stata Journal* 4(3): 282–89.

Malapit, H. J. L., and A. R. Quisumbing. 2015. What dimensions of women's empowerment In agriculture matter for nutrition in Ghana? *Food Policy* 52: 54–63.

Maxwell, D., Vaitla, B., and J. Coates. 2014. How do indicators of household food insecurity measure up? An empirical comparison from Ethiopia. *Food Policy* 47**:** 107-116.

Ministry of Food and Agriculture (MoFA). 2017. Planting for Food and Jobs Strategic Plan For Implementation (2017-2020), *Ministry of Food and Agriculture*, Accra, Ghana.

Mundlak, Y. 1978. On pooling of time series and cross section data. *Econometrica* 64: 69–85.

National Nutrition Policy (NNP). 2013. National Nutrition Policy 2014-2017. Government of Ghana. https://extranet.who.int/nutrition/gina/sites/default/files/GHA%202013%20National%20Nutrition%20Policy.

Nkegbe, P. K., and B. Shankar. 2014. Adoption intensity of soil and water conservation practices by smallholders: evidence from northern Ghana. *Bio-based and Applied Economics* 3(2): 159-174.

Sen, A. 1981. Ingredients of Famine Analysis: Availability and Entitlements. *Quarterly Journal of Economics* 96 (3): 433-464.

Swindale, A., and P. Bilisnky. 2006. Household Dietary Diversity Score (HDDS) for Measurement of household food access. *Indicator Guide Version 2, Food and Nutrition Technical Assistance (FANTA)*, USAID.

Taylor, J. D., A. De Braw, and S. Rozelle. 2003. Migration and Source Communities: A New Economics of Perspective from China. *Economic Development and Cultural Change* 52: 75-101.

UNDP-Ghana. 2018. Northern Ghana Human Development Report 2018, *UNDP*, Ghana.

United Nations. 2015. Transforming Our World: The 2030 Agenda for Sustainable Development. Doc. A/RES/70/1. https://sustainabledevelopment.un.org/content/documents/21252030%20Agenda%20for%20Sustainable%20Development%20web.pdf.

Vale, P. M. 2016. The changing climate of climate change economics, *Ecological Economics* 121: 12–19.

Weismann, D., J. Hoddinott, N. L. Aberman, and M. T. Ruel. 2006. Review and Validation of Dietary Diversity, Food Frequency and Other Proxy Indicators of Household Food Security. *International Food Policy Research Institute*, Washington, D.C.

Wooldridge, J. M. 2015. Control Function Methods in Applied Econometrics. *Journal of*

Human Resources 50 (2): 420-445.

World Bank 2010. *Economics of Adaptation to Climate Change. Ghana Country Study*. World Bank: Washington, D.C.

Appendix

Table A1: Differences in means of the characteristics of adopters and non-adopters

Variable	Adopters	Non-adopters	Diff
	Mean	Mean	(t-value)
Farm revenue (log)	7.08	6.84	0.24**[2.41]
HFIAS	3.86	5.17	-1.31** [-2.81]
HDDS	8.03	7.77	0.26 [0.96]
Fertilizer	250.53	121.98	128.56** [2.26]
Herbicide	68.66	37.46	31.20 [1.58]
Hired labor	219.62	109.88	109.74* [2.14]
Farm size	2.10	1.69	0.41** [2.87]
Education	5.37	5.72	-0.35 (-0.72)
Household size	6.15	5.55	0.60* [2.00]
Age	39.49	39.92	0.42 [0.32]
Gender	0.85	0.82	0.03 [1.00]
Off-farm	0.35	0.44	0.090* [-1.9]
Credit constraint	0.42	0.36	0.07 [1.36]
Livestock	1.89	1.74	0.15 [0.32]
Machinery	0.21	0.10	0.11*** [3.00]
Extension	1.044	0.64	0.41*** [3.28]
Weather information	0.61	0.50	0.11**[2.45]
Drought perception	0.77	0.68	0.09** [2.08]

***, **, * represent 1%, 5%, and 10% significance level, respectively. Values in square brackets are t-ratios
Sub-samples consist of 360 adopters and 160 non-adopters

Table A2: Treatment effects Poisson model (ATT-Poisson)

Variable		Adoption decision		ATT-Poisson [t-value]	% Change in Outcome
		Adopters	Non-adopters		
Full sample					
Dietary diversity scores (HDDS)		8.59	7.51	1.07** [8.79]	14.30
Food insecurity access score (HFIAS)		5.48	7.97	-2.49** [-6.84]	-31.20
Based on Agro-ecological zone (AEZ)					
Guinea Savannah	HDDS	7.53	6.46	1.08*** [13.82]	16.70
	HFIAS	7.66	13.45	-5.78*** [-10.52]	-43.00
Sudan Savannah	HDDS	8.71	7.34	1.37*** [13.35]	18.70
	HFIAS	3.66	5.63	-1.96*** [-5.92]	-34.90
Transitional zone	HDDS	10.44	8.92	1.52*** [12.74]	17.00
	HFIAS	3.22	4.46	-1.24*** [-7.85]	-27.80

***, ** represent 1% and 5% significance level, respectively. Values in square brackets are t-values

Table A3. Rainfall (RF) means and coefficient of variation (CV)

Agro-ecological zone		Mean	Std	Coefficient of variation of rainfall *(CVRF)*
Guinea Savannah	Long-term mean RF for Guinea Savannah (mm)	926	337.80	0.56
Sudan Savannah	Long-term mean RF for Sudan Savannah (mm)	674	374.32	0.36
Transitional Zone	Long-term mean RF for Transitional zone (mm)	1267	379.71	0.30

Source: Own calculations from The National Centers for Environmental Prediction (NCEP) Climate Forecast System Reanalysis (CFSR) climate data from 1979 to 2014 on the website: https://globalweather.tamu.edu/

Methodological Appendix

The ESR model

The ESR model is based on the random utility framework. The selection equation in our case is a binary adoption model, where farmers decide between adoption and non-adoption of climate-smart agricultural practices[25] based on farm and household characteristics. The adoption model is specified as:

$$Adopt_i = \boldsymbol{X}_i\boldsymbol{\alpha} + \varepsilon_i \qquad (1)$$

where *Adopt* is a dummy variable for climate-smart agricultural practices adoption by household i, $\boldsymbol{X}_i$ is a vector of explanatory variables, $\boldsymbol{\alpha}$ is a vector of parameters to be estimated, and ε is an error term with mean zero and variance σ_ε^2. The two-regime outcome equations (for adopters and non-adopters) are food and nutrition security production functions, stated as:

Adopters Regime: $Q_{i1} = \mathbf{K}_{\boldsymbol{i}}\boldsymbol{\gamma}_1 + \mu_{i1}, \quad \text{if } Adopt = 1$ (2a)

Non-adopters Regime: $Q_{i0} = \mathbf{K}_{\boldsymbol{i}}\boldsymbol{\gamma}_0 + \mu_{i0}, \quad \text{if } Adopt = 0$ (2b)

where Q_{i1} and Q_{i0} represent food and nutrition security outcomes for adopters and non-adopters, respectively. $\mathbf{K}_{\boldsymbol{i}}$ is a vector of explanatory variables, and $\boldsymbol{\gamma}_1$ and $\boldsymbol{\gamma}_0$ are vectors of parameters to be estimated for the adopter and non-adopter regimes, while μ_1 and μ_0 are the respective error terms.

Using OLS to estimate $\boldsymbol{\gamma}_1$ and $\boldsymbol{\gamma}_0$ would produce inconsistent estimates, because the expected values of the error terms, conditional on the sample selection, are non-zero (Heckman 1979; Lokshin and Sajaia 2004). Selection bias occurs if $\text{corr}(\varepsilon, \mu_1)$ or $\text{corr}(\varepsilon, \mu_0) = \rho \neq 0$. The error terms ε, μ_1 and μ_0 are assumed to have a trivariate normal distribution with zero mean and variance and covariance matrix specified as:

$$\text{Cov}(\mu_1, \mu_0, \varepsilon_i) = \begin{bmatrix} \sigma_1^2 & \sigma_{10} & \sigma_{1\varepsilon} \\ \sigma_{10} & \sigma_0^2 & \sigma_{0\varepsilon} \\ \sigma_{1\varepsilon} & \sigma_{0\varepsilon} & \sigma_\varepsilon^2 \end{bmatrix} \qquad (3)$$

where $\sigma_\varepsilon^2 = var(\varepsilon)$, is variance of the error term in the adoption equation, and $\sigma_1^2 = \text{var}(\mu_1)$ and $\sigma_0^2 = \text{var}(\mu_0)$, $\sigma_{1\varepsilon} = \text{cov}(\mu_1, \varepsilon)$, $\sigma_{0\varepsilon} = \text{cov}(\mu_0, \varepsilon)$ and $\sigma_{10} = cov(u_1, u_0)$. It is assumed

[25] The practices considered in this study include adoption of crop choice, and soil and water conservation practices (soil and stone bunds, minimum tillage).

that the variance of the error term in the selection equation is one; ie., $\sigma_{\varepsilon}^{2} = 1$, since $\boldsymbol{\alpha}$ is estimable only up to a scale factor (Maddala, 1983). The expected values of the error terms given adoption and non-adoption are $E(\mu_1|Adopt = 1) = \sigma_{1\varepsilon}\lambda_1$ and $E(\mu_0|Adopt = 0) = \sigma_{0\varepsilon}\lambda_0$, in equations 2a and 2b, respectively, where λ_1 and λ_0 refer to the inverse Mills ratios. Thus, the expectations of the selectivity corrected outcome equation for adopters (equation 2a) and can be specified as:

$$E(Q_{i1}|Adopt_i = 1) = \mathbf{K}_{\boldsymbol{i}}\boldsymbol{\gamma}_1 + \sigma_{1\varepsilon}\lambda_1 \quad \text{(4a),}$$

while the expectation of adopters, if they had not adopted (counterfactual or hypothetical non-adopters) can be stated as:

$$E(Q_{i0}|Adopt = 1) = \mathbf{K}_{\boldsymbol{i}}\boldsymbol{\gamma}_0 + \sigma_{0\varepsilon}\lambda_1 \quad \text{(4b),}$$

The difference between 4a and 4b gives the average treatment effect on the treated (ATT) (Lokshin and Sajaia 2004)[26], stated as:

$$\text{ATT} = E(Q_{1i}|\ Adopt_i = 1) - E(Q_{0i}|\ Adopt_i = 1) = \mathbf{K}_{\boldsymbol{i}}(\boldsymbol{\gamma}_1 - \boldsymbol{\gamma}_0) + \lambda_{1i}(\sigma_{1_\varepsilon} - \sigma_{0_\varepsilon}) \quad \text{(5).}$$

Apart from estimates for $\boldsymbol{\gamma}_1$ and $\boldsymbol{\gamma}_0$, full information maximum likelihood (FIML) also generates $\rho_{1\varepsilon}$ and $\rho_{0\varepsilon}$, which are estimates of the correlation coefficients between the error terms in the outcome and selection equations. The signs and statistical significance levels of these estimated correlation coefficients have economic interpretations (see Abdulai and Huffman 2014).

Estimating adoption effects on food and nutrition security outcomes

Using the ESR model enables us to estimate the effects of household, farm level and other explanatory variables on food and nutrition security outcomes in the adopters and non-adopters regimes, as well as estimate the net effect of adoption on food and nutrition security outcomes.

[26] Taking the differences in effects, $\sigma_{1_\varepsilon} - \sigma_{0_\varepsilon}$, while holding λ_{1i} constant ensures the elimination of the effects of unobserved factors, and ensuring that the food and nutrition outcome differences would be mainly attributed to adoption impacts, without any unobserved factors.

Essentially, this is achieved by comparing the expected outcomes of adopters with and without adoption (hypothetical non-adopters) to derive the average treatment effect on the treated (ATT).

Quantile treatment effects regressions (QTE)

Since the ESR does not allow quantile estimations, we estimated a set of quantile treatment effects regressions to examine how adoption differentially affects different parts of the distribution of farm revenues, household dietary diversity scores (HDDS) and household food insecurity access scores (HFIAS). Thus, the outcome equation in the context of quantile regression is expressed as:

$$Q_i = \mathbf{K}_{\boldsymbol{i}}\boldsymbol{\gamma}_\tau + \delta Adopt_i + \mu_{i\tau} \text{ with } P_\tau(Q_i|Adopt_i, \boldsymbol{K}_i) = \mathbf{K}_{\boldsymbol{i}}\boldsymbol{\gamma}_\tau + \delta Adopt_i,\ \tau \in (0,1) \qquad (6)$$

where $Adopt_i$ and $\mathbf{K}_i$, are as defined earlier, $\boldsymbol{\gamma}_\tau$ a vector of parameters to be estimated in each quantile (τ); $\mu_{i\tau}$ is a vector of residuals. $P_\tau(Q_i|Adopt_i, \boldsymbol{K}_i)$ indicates the τ^{th} conditional quantile of Q_i, given adoption and other covariates, such that $0 < \tau < 1$. From the estimated coefficient δ, the percentage change in food and nutrition security outcome when farmers switch from non-adoption to adoption can be expressed as:

$$\%\nabla_Q = 100(e^\delta - 1). \qquad (7)$$

where δ is the coefficient of adoption variable, $Adopt$ in each quantile e^δ is the exponential value of coefficient δ, while $\%\nabla_Q$ refers to percentage change in the food and nutrition security outcomes, as farmers switch from non-adoption to adoption.

Poisson treatment effects regression

Another robustness check was a Poisson regression, which we ran on the dietary diversity scores (HDDS) and household food insecurity access scores (HFIAS). This was based on the fact that the two outcomes are basically count variables.

Chapter 4

Household welfare implications of sustainable land management practices among smallholder farmers in Ghana

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Abstract

This study employs farm household data to examine the impact of adoption of sustainable land management (SLM) practices on consumption and poverty outcomes using multivalued treatment effects approaches. The generalized propensity score approach was employed to account for selectivity bias due to observed characteristics among households. Using a doubly robust treatment effects estimator, we found that increasing intensity of adoption of SLM resulted in improved per capita consumption expenditure, reduced poverty headcount and poverty gap among farm households. The results of the multivalued treatment effects approach revealed significant differences between adopters of different adoption intensities, a finding that is not possible with binary treatment effect approaches. The findings also revealed that the average treatment effect of moving from low intensity to high intensity adoption levels differed across quantiles of per capita consumption. We also used a dose-response function to demonstrate that the treatment effect of intensity of adoption on per capita consumption and poverty outcomes is nonlinear, with optimal adoption level occurring between 60-70% of adoption intensity dose.

Keywords: Sustainable land management, household welfare, multivalued treatment effect, generalized propensity scores, dose-response functions.

JEL Codes: C31, D13, Q12, Q15

4.0 Introduction

Agriculture in Sub-Saharan Africa (SSA), especially crop production, is highly dependent on the sustainability of farm lands and other natural resources. Recent evidence of increased global climate change events (rising temperatures, erratic rainfall patterns etc.) are likely to expose degraded lands to further low productivity (IPCC, 2014). Addressing both poverty and vulnerability to climate change are two of the major challenges to food production and sustainable development in the 21st century (Tol, 2018). Vulnerability to climate change can also lead to outcomes that perpetuate poverty (Barbier and Hochard, 2018). A study by the World Bank in the Sahel region of West Africa mentioned land degradation as an important factor contributing to low agricultural productivity, poverty and environmental problems (World Bank, 2009). This is important amid recent findings that more than 60% of the rural population in developing countries depend on marginal and less fertile lands (Barbier and Hochard, 2018).

Despite severe impact of land degradation on the livelihoods of farm households and the significant role that land plays in human welfare and development, investments in sustainable land management (SLM) are low, especially in developing countries (Nkonya et al., 2016). Recent studies have shown that SSA accounts for about 22% of the total global cost of land degradation that is estimated at 300 billion USD (Nkonya et al., 2016). Meanwhile, significant benefits associated with investment in restoration of degraded lands, as well as land improvement measures have been reported in a number of studies (Shiferaw, and Holden, 1998; Arslan et al., 2015; Nkonya et al., 2016; Barbier and Hochard 2018). For instance, on average, investment benefits accruing from restoration of degraded lands can be up to five times the cost of investment (Nkonya et al., 2016). However, state financing of sustainable land management projects is low in SSA, with concerns that the large share of donor contribution to SLM expenditure poses a threat to sustainability of investment in SLM practices (Gondo, 2010).

As part of the measures to improve farm output of smallholder farmers, some emphasis is being placed on intensification of smallholder agriculture through the use of new technologies (the use of improved and drought tolerant varieties), as well as adoption of sustainable land management practices. However, some concerns have been raised that adoption of sustainable land management practices and vulnerability to consumption poverty are insufficiently linked in SSA (Chomitz et al. 2007; Nkonya et al., 2016). Even though several studies have been conducted on adoption of SLM practices in SSA (e.g., Zougmore et al., 2014; Adnan et al., 2017), few studies address the link between adoption intensity of sustainable land management practices and household poverty (e.g. Shiferaw and Holden, 2007; Babatunde and Qaim, 2010). Most studies on analyses of impact of adoption on welfare outcomes focus on causal effects of binary treatment of technology using propensity score matching (PSM) or endogenous switching regression (ESR), and whether the household has positively benefited from the technology (e.g. Di Falco et al. 2011; Amare et al. 2012, Abdulai and Huffman, 2014).

While acknowledging the advantage of the endogenous switching regression (ESR) approach in accounting for unobservable attributes in impact assessment, this approach is not able to handle multivalued or continuous treatment variables. As in PSM, the ESR approach classifies all adopting farmers (adopters) in the same manner, irrespective of the intensity of adoption (Bia et al., 2014). This may lead to significant loss of information in situations where the treatment variable is multivalued. For this reason, it is important to go beyond discrete binary causal effect of SLM practice analysis on welfare outcomes. Estimating multivalued treatment effect at different levels of adoption intensity, or dose-response and treatment effect functions may provide more information regarding the effectiveness of SLM practices. In particular, this allows the assessment of heterogeneous effects of adoption in a continuous context and provides information about the optimal level of adoption (Bia and Mattei, 2012; Esposti, 2017).

In addition, the link between adoption intensity of SLM practices and poverty is an issue of empirical interest that has not received much attention. This is even more important in areas facing threats of land degradation and climate risks. A number of studies (e.g. Zougmore et al., 2014; Tesfaye, et al. 2016) have linked adoption of stone and soil bunds and organic manure to improved farm productivity and household welfare, especially in SSA. Experimental evidence in Burkina Faso shows that during dry periods, crops on plots with stone bunds and Zai[27] techniques could produce yields that are two to three times higher than those on control plots (Zougmore et al., 2014). Despite these observed benefits of SLM practices, there are instances where adoption of SLM practices result in exposing farm households to poverty (World Bank, 2009). The contrasting evidence on the impact of SLM practices adoption provides more room for further empirical investigation on the subject.

The objective of this study is to examine the impact of adoption intensity of sustainable land management practices on household welfare and to analyze the heterogeneity effects of adoption intensity. We also estimate dose-response functions to assess the optimal level of adoption intensity of SLM practices that has the desired impact on farm household welfare. We capture welfare by the following outcomes: consumption per capita and poverty status (poverty headcount, poverty gap and poverty gap-squared). Adoption intensity is measured as reported expenditures on common sustainable land management practices in the study area, which are identified in the literature to significantly influence land quality and productivity (Zougmore et al. 2014).

We employ recent advancements in the impact assessment literature to analyse adoption intensity impact on these outcomes in multivalued treatment effect (mTE) framework, as well as a dose-response (DRF) context (Cattaneo et al, 2013; Bia et al 2014). We use survey data

[27] It is a soil conservation technique especially on degraded lands, where small pits (Zai holes) are made just before the season starts to enable the soil concentrate enough water (and organic manure)

from five districts in three agro-ecological zones of Ghana. The study area (Sudan Savannah, Guinea Savannah and TZ agro-ecological zones) is characterized by an unfavorable biophysical environment, with frequent failure and uneven distribution of rainfall, poor soil quality and land degradation (Wossen et al., 2014), and high poverty incidence (44-70%) (GSS, 2015; Zereyesus et al., 2017). To the extent that sustainable land management is an integral part of the needed structural change in agriculture to end extreme poverty in rural African economies (Nkonya et al., 2016), the findings of this study would be useful for policy that seeks to address land degradation, climate change and poverty in Ghana.

The rest of the study is organized in the following manner. In section 4.1, we develop and discuss the conceptual framework and estimation strategy used in the analysis. Data and descriptive statistics are presented in section 4.2, while the econometric results are presented in section 4.3. Section 4.4 concludes with the key findings and policy implications of the study.

4.1 Conceptual framework

In this section, we present the conceptual framework and empirical specification to guide the analysis.

Conceptual model

We employ a simple model that captures the potential gains from adoption of sustainable land management (SLM) practices as benefits (or losses) in the utility function of farm household members. Basically, we assume that farmers make the decision on the extent to which they adopt SLM practices in farming or not all. In this regard, we consider a risk-neutral farm household that maximizes utility dependent on net returns, π, subject to input and output markets and a farm-output technology set that is quasi-concave in the vector of variable inputs K and environmental factors, X. This may be expressed as:

$$\max_{K} U(\pi) = \max_{K} U(PQ(K, X) - w'K) \tag{1}$$

where U denotes utility, P represents a vector of farm produce prices and Q is output , which depends on the vector of input quantities K and environmental and household characteristics X, while w is a vector of input prices. Let's assume that $K_{SLM} \in w'K$, such that adoption of SLM improves the quality of land, farm's output level, net returns and ultimately household welfare.

In deciding whether or not to adopt SLM practices, the household weighs up the expected net benefits from adoption, represented as $U_a^*(\pi)$ and the expected net benefits from non-adoption represented as $U_n^*(\pi)$. Adoption then occurs if the net benefits from adoption is positive i.e. if $U_a^*(\pi) > U_n^*(\pi)$. Remember that the parameters of net benefits are not observable, but may be represented by a latent variable, such that the observed decision $U(\pi) = 1$, if $U_a^*(\pi) > U_n^*(\pi)$ and $U(\pi) = 0$, if $U_a^*(\pi) \leq U_n^*(\pi)$. The utility of adoption can be related to vectors of farm and household characteristics, X_i and inputs K_{iSLM} as follows:

$$U(\pi_i) = \partial' K_{iSLM} + \alpha' X_i + \tau_i \ , \tag{2}$$

where α and ∂ are vectors of parameters, i is an index for household, and τ is an error term with zero mean and a variance of σ_τ^2.

Given that adoption of SLM practices has a positive impact on utility, the farmer will intensify adoption to improve land sustainability and quality until the expected marginal returns from adoption equals the expected marginal returns from non-adoption of these measures; i.e. $\frac{\partial E(\pi)_a}{\partial K_{iSLM}} = \frac{\partial E(\pi)_n}{\partial K_{iSLM}}$, where the indices a and n refer to adopters and non-adopters respectively.

A number of constraints such as labor requirements, liquidity constraints and various forms of incomplete climate or weather information may however hinder farmers from attaining optimum levels of adoption of SLM practices (Zougmore et al., 2014). Thus, the farmers' chosen level of adoption intensity may differ from their potential optimum. Other factors such as access to extension services, land tenure or usufruct rights may be contributing to lower than optimal adoption intensities. The conceptual framework developed in this section is employed below to analyze the impact of sustainable land management adoption intensity on farm household welfare; specifically, per capita consumption expenditure (PCE) poverty headcount, poverty gap and poverty gap-squared.

Welfare impacts of adoption of sustainable land management practices

Analyzing the impact of adoption intensity of SLM practice can be quite problematic in the presence of non-randomness of adoption decisions. The non-randomness of adoption intensity decisions raises issues of sample selection bias. A common solution to this problem is the use of matching approaches, in which individuals of the treatment group (adopters) are paired with individuals of the control group (non-adopters) that are similar in their observable characteristics.

Given that selection into treatment is based on observable characteristics, Rosenbaum and Rubin (1983) and later several authors (e.g. Imbens, 2000 and Cattaneo 2010) have shown that individuals of different treatment groups but with similar characteristics (X_i) can be compared as if treatment assignment was random. Their approach involves estimating the propensity score $p(X_i)$, which is defined as the conditional probability of being selected into the treatment group, given pre-treatment characteristics X_i. An underlying assumption of the propensity score-matching approach is the unconfoundedness, or conditional independence assumption (CIA)[28] (Imbens and Wooldridge, 2009). With this assumption, the average treatment effect on the treated (ATT) can then be estimated as follows:

$$ATT = \mathrm{E}[Y_i^a - Y_i^n | a = 1, p(X_i)] = \mathrm{E}\{\mathrm{E}[Y_i^a | a = 1, p(X_i)] - \mathrm{E}[Y_i^n | a = 0, p(X_i)] | a = 1\} \quad (4)$$

[28] This condition simply states that common characteristics that affect treatment assignment and treatment-specific outcomes must be observable, such that once these observable characteristics are controlled, then the dependence between treatment assignment and treatment-specific outcomes is completely removed (Imbens, 2000).

Analyzing treatment effect of adoption using equation 4 is only applicable to situations where the treatment variable is dichotomous/binary in nature. Apart from PSM, the endogenous switching regression (ESR) is also popular in the impact assessment literature, particularly in the past decade. Despite the popularity of the ESR approach (Lokshin and Sajaia 2004) in impact assessment due to its ability to account for both observable and unobservable factors influencing both treatment assignment and outcomes, the approach cannot be applied to multivalued treatment situations. Even though the multinomial ESR (BFG) approach (Bourguinon et al. 2007) can be used to identify and determine farmers' decisions to adopt different categories of SLM practices and analyze the impacts on outcomes of interest, the approach is unable to estimate average treatment effects of moving from one treatment level to another. To the extent that the treatment variable considered in this study is non-binary, but multivalued in nature, the multivalued treatment effect (mTE) model proposed by Cattaneo (2010) is used in this study.

Multivalued treatment effects of adoption

In this study, we follow the framework presented by Linden et al. (2016) to specify the impact of adoption intensity on per capita consumption expenditure (PCE) and poverty outcomes. In the multivalued treatment effect framework, for each individual i, $\{i = 1, \dots N\}$, the variables Y_i, T_i and X_i are observed. Y_i is a vector of outcomes, T_i is a multivalued treatment variable (expenditures on SLM), which takes integer values between 0 and φ and X_i represents the vector of household and farm characteristics. The variable $D_{it}(T_i)$ which denotes the indicator of receiving treatment t for farmer i can be expressed as:

$$D_{it}(T_i) = \begin{cases} 1, & if \ T_i = t \\ 0, & otherwise \end{cases} \qquad (5)$$

For each farmer, $Y_{i0}, \dots, Y_{i\varphi}$ indicate the potential outcomes for each farmer i where $T = t$ and $t \in \Lambda = \{0, \dots \varphi\}$. Note that only one of the potential outcomes Y_{it} is observed, depending on the treatment status. Following the framework of Cattaneo (2010), the observed outcome Y_i can be expressed as a function of the treatment indicator D_{it} and potential outcome Y_{it} as:

$$Y_i = \sum_{t=0}^{\varphi} D_{it}(T_i)Y_{it}. \tag{6}$$

Let m and l denote the distinct treatment levels, such that the treatment effect (δ) of treatment level m versus l can be expressed as the difference between potential outcomes associated with these levels:

$$\delta = E[Y_{im} - Y_{il}], \forall m, l \in \Lambda \tag{7}$$

It will be difficult to objectively identify treatment effect from equation 7 without further assumptions, due to the non-randomness of treatment assignment in observational data as in this study. To create the semblance of randomness, the multivalued TE approach employs two assumptions, namely, the conditional independence assumption (CIA) and the overlap assumption (Imbens and Wooldridge 2009; Cattaneo 2010; Esposti 2017). The CIA assumption implies that once we control for observable pre-treatment characteristics (X_i), the choice of SLM adoption level is as good as random assignment and therefore uncorrelated with potential household welfare outcomes; i.e.

$$Y_{it} \perp D_{it} | X_i, \forall t \in \Lambda = \{0, \dots \varphi\} \tag{8}$$

where the potential outcome Y_{it} and treatment D_{it} are independent ($\perp$), given the covariates X_i. In the impact evaluation literature, the CIA is considered a strong assumption as it requires that no unobservable confounders such as farmers' risk preferences or unpredictable climate variability that influence farmers' adoption intensity of SLM practices and also affect potential welfare outcomes (e.g. per capita expenditure) are present. A violation of this assumption results in biased estimation of treatment effect of adoption. However, in the presence of adequate data set with sufficiently good predictors of the treatment indicator (D_{it}), it is possible to obtain valid estimates of average treatment effects of adoption intensity on welfare outcomes (Hirano and Imbens 2004; Cattaneo 2010; Yang et al. 2016).

The overlap assumption is stated as; $0 < \Pr[T_i = t|X_i = x], \forall t \in \Lambda$. This assumption ensures that for every covariate X_i, there should be a positive probability that an individual with similar characteristic could be assigned to each treatment level. These two assumptions, CIA and overlap are jointly referred to as ignorability[29] assumption (Rosenbaum and Rubin, 1983; Cattaneo, 2010). A third assumption, the stable unit-treatment value assumption (SUTVA)[30] is also of essence in identifying average treatment effects, although this cannot be verified from the data. Given these assumptions, it is possible to use propensity score regression adjustment or more robust approaches to estimate conditional mean functions (at different treatment levels, φ) by parametric regressions to determine treatment effects (Cattaneo 2010; Yang et al. 2016; Esposti 2017).

The generalized propensity score (GPS) serves as a practical alternative, instead of directly conditioning on X_i in a multivalued treatment situation. The GPS is defined as the conditional probability of a farmer belonging to a particular adoption intensity level of SLM given the pretreatment covariates X_i (Imbens and Wooldridge, 2009); i.e.

$$r(t, x) \equiv \Pr[T_i = t|X_i = x] = E[D_{it}(T_i)|X_i = x], \forall t \in \Lambda \qquad (9)$$

where $r(t, x)$ (GPS) can be estimated by multinomial logit model, given the characteristic values of the treatment. The GPS can be employed to weigh observations and estimate the potential outcome means (POM) and average treatment effects (ATE) for SLM intensity levels

[29] Ignorability implies that treatment assignment is assumed to be random conditional on a set of observable factors and a common support condition (Cattaneo, 2010; Linden et al. 2016).

[30] The SUTVA requires that, there are no spillover effects from adoption of SLM practices (Cattaneo, 2010; Imbens and Wooldridge, 2009). This implies that the welfare outcome from own adoption of a farmer should be attributed to his participation only and not due to adoption effect of the other farmers (i.e. No-interference component). The second component of SUTVA is that each potential outcome must be well-defined (single version of each treatment level). SUTVA excludes the possibilities of units interfering with each other and multiple versions of a treatment (Merz, 2016).

among farmers with $T_i = t$ in the sample. For example, using the efficiency influence function (EIF) estimator (Cattaneo et al. 2013), POM can be stated as:

$$\hat{\mu}_t^{EIF} = \frac{1}{N}\sum_{i=1}^{N}[\frac{Y_i D_{it}(T_i)}{\hat{r}(t, X_i)} - (\frac{D_{il}(T_i)-\hat{r}(t, X_i)}{\hat{r}(t, X_i)})\hat{Y}_i(t)] \quad (10)$$

$$\text{ATE} = (\hat{\mu}_{EIF,m} - \hat{\mu}_{EIF,l}) \quad (11)$$

where $\hat{r}(t, X_i)$ is the estimated GPS and $m, l = t, \forall t \in \Lambda$, N refers to the total number of observations belonging to the treatment level, with $T_i = m$ and $T_i = l$; m, $l \in \Lambda$={0,1, 2}. In our data, Λ = 1 denotes the low intensity SLM adoption, Λ = 2 denotes the high intensity SLM adoption, and Λ = 0 denotes the minimal or non-adoption of SLM; $\hat{Y}(t)$ refers to the estimated conditional mean functions for each treatment level.

The quantile multivalued TE (QTE), are also estimated to determine the heterogeneity in treatment effects at the lower (0.25), middle (0.5) and upper (0.75) quantiles of the distribution of welfare outcomes. The efficiency influence estimator (EIE) proposed by Cattaneo (2010) was employed to estimate both ATE and quantile treatment effects (QTE) as this estimator is doubly robust compared to only inverse probability weighted treatment (IPW) or regression adjustment (RA) estimators (Cattaneo et al. 2013; Linden et al. 2016).

To implement the multivalued treatment effect, the GPS was estimated using multinomial logistic regression with the three-level treatment variable as the outcome, expressed as $\hat{r}(x, t) = \frac{\exp(X_i\hat{\beta}_t)}{1+\sum_{t=0}^{T}\exp(X_i\hat{\beta}_t)}$; where $\hat{r}(x, t)$ refers to the estimated GPS. The choice of right-side variables (X_i) was determined using *bfit* command in Stata[31]. For each treatment level, potential outcome means were estimated. Additionally, pairwise contrasts were estimated between all adoption

[31] ***bfit*** sub-command is used to sort a set of fitted candidate regression models by an information criterion, (BIC or AIC). It then puts the best-fitting model in **ereturn**, and displays a table showing the ranking of the models fitted (Catteneo et al. 2013).

intensity levels to obtain the ATE, and across all quantiles (QTE), using the *pwcompare*[32] command in Stata 13.

Dose-response functions (DRF)

We employ the generalized propensity score (GPS) for continuous treatment case suggested by Hirano and Imbens (2004) to capture the impact of adoption on household welfare in a continuum instead of the different discrete analyses discussed above. The analysis here is in respect of only the sub-sample of adopters. Our interest is the average dose-response function (DRF), which relates the potential welfare outcome $Y_i(t)$ of farm household i to each possible adoption intensity level t. This is formally expressed as:

$$\theta(t) = \mathrm{E}[Y_i(t)]\,, \forall t \in \Lambda' \qquad (12)$$

where θ represents the DRF, and t is the treatment level, which is measured as the expenditure on SLM practices in the season. In line with Hirano and Imbens (2004), we presume weak unconfoundedness. Under this assumption, it is possible to estimate the average DRF by using the GPS to remove the selection bias (Hirano and Imbens 2004; Bia et al. 2014). Although the assumption of unconfoundedness is strong and usually untestable, it does not need to be generally applicable, as its plausibility depends on richness of information, especially on covariates that predict selection into treatment (Hirano and Imbens 2004; Bia and Mattei 2012). In our study, we assume that all variables listed in Table 4.A1 are good predictors of treatment assignment (sustainable land management adoption intensity) (Testfaye et al. 2016), and that the unconfoundedness assumption holds. Table 4.A3 also shows that the common support condition is achieved as the mean differences of covariates in all strata of the treatment variable balance out except the altitude variable.

[32] The *pwcompare* performs Wald tests using linear combinations of marginal linear predictions and uses the delta method to estimate the variance (Stata 2013; Cattaneo et al. 2013).

After estimating the GPS ($\hat{R}_i$), the conditional expectation of each outcome is modeled as a function of two scalar variables the treatment (T_i) and the GPS ($\hat{R}_i$): i.e. $\theta(t, r) = \mathrm{E}\left[Y_i | T_i = t, \hat{R}_i = r\right]$. This is done using a quadratic approximation (Bia and Mattei 2012) as:

$$\mathrm{E}\left[Y_i | T_i = t, \hat{R}_i = r\right] = \partial_0 + \partial_1 T_i + \partial_2 T_i^2 + \partial_3 \hat{R}_i + \partial_4 \hat{R}_i^2 + \partial_5 T_i \hat{R}_i \quad (13)$$

The last stage involves the estimation of dose-response function at each level of the treatment t, and averaged over the GPS at that particular level of treatment; that is

$$\mu(t) = \mathrm{E}[\theta\{t, r(t, X_i)\}] \quad (14)$$

The DRF specification is estimated using least-squares regression for continuous welfare outcomes (PCE, poverty gap and poverty-gap squared), and a Logit regression for poverty headcount. Confidence bounds at 95% level are estimated using the bootstrapping procedure (Hirano and Imbens 2004).

4.2 Data and descriptive statistics

The data used in this study were obtained from a survey conducted during the 2015/2016 cropping season in 25 communities across five districts in Ghana. A multistage random sampling procedure was employed to select and interview 476 households across three regions; Upper East (UE), Northern Region (NR) and Brong-Ahafo (BA) regions. Based on agroecology, we selected five districts (Bongo and Talinse in UE, Tolon and Kumbungu in NR, and Techiman-South in BA). We took into account the land size and farmer population of the Guinea Savannah and put greater weight on the sub-sample from the NR. Finally, we obtained 203 households for NR, 147 households for the UE and 126 households for the BA.

Dependent variables

Descriptive statistics and explanations of the variables employed in the subsequent sections are provided in Table 4.1. Four outcome measures are included in the analysis. The households' per capita consumption calculated from total household consumption expenditures[33] related to adult equivalents. We made this conversions based on suggested approach employed by the Ghana Statistical Service (GSS).

Table 4.1: Definition of variables and descriptive statistics

Variable	Variable Description	Mean	Std. Dev.
Consumption/1000 [34]	Per capita household consumption expenditure (GHS)	1.295	2.017
Poverty	Headcount index used to estimate poverty= 1 if household is poor, 0 otherwise	0.689	0.463
Fertilizer	Farmer applied chemical fertilizer=1, 0 otherwise	0.29	0.45
Off-farm	Farmer is engaged in off-farm activity=1, 0 otherwise	0.38	0.49
Adoption	Farmer adopts sustainable land management=1 practice, 0 otherwise	0.388	0.48
Adoption intensity	Reported expenses on stone/soil bunds construction and purchase of organic manures	292.0	447.0
Farm size	Total Farm size of HH in ha	1.96	1.49
Education	years of formal education of HH-head	5.49	5.02
Hh_size	Number of people in a household	5.95	3.08
Age	age of farmer in years	39.64	13.83
Gender	Male=1, female=0	0.84	0.36
Livestock	Livestock ownership in tropical livestock units	1.84	4.78
Machinery	Farmers owns farm machinery =1, 0 otherwise	0.17	0.38
Credit access	Applied for credit and received part or none =1, 0 otherwise	0.39	0.49
Tenure_sec	Farmer has long-term (>5 years) usufruct right=1, 0 otherwise	0.716	0.451
Proximity_city	Distance to nearest district capital (km)	5.57	5.07
Group-memb	Farmer belongs to a farmer group=1, 0 otherwise	0.31	0.46
Extension	Number of extension visits	1.13	1.49
Rfcondition	Farmer prediction of RF condition in the next 5 years (0-1)	0.64	0.48
LocAltit/1000	Household specific location altitude (m), from digital device: to capture location fixed effects	0.234	0.129

[a]Exchange rate is US dollar 1 = GHS 4.26 at the time of the survey

[33] It is significant to mention that while household income indicates the ability of the household to obtain its basic needs, *per capita* expenditure reflects the effective consumption of households and for that matter provides more information about welfare and poverty status (Becerril and Abdulai, 2010).

[34] This computed using total HH expenditure (excluding expenses on SLM) and household size

The Ghana Statistical Service (2015) also reported an upper poverty line of 1,314 GH cedis per adult equivalent per year (295.35 US Dollar) as at 2013, indicating the minimum requirement to cover an individual's dietary needs. Based on this poverty line and the actual household consumption expenditures, we constructed the poverty status, poverty gap and poverty gap-squared variables. The poverty status is a dummy variable showing whether or not a household falls below the poverty line, while the poverty gap indicates the intensity of poverty in terms of how much a household is below the poverty line. The poverty-gap squared on the other hand shows the level of inequality among the poor by attaching greater weight to poorer households (Foster, Greer and Thorbecke 1984)[35]. From Table 4.2, the average poverty headcount index among the sampled farmers is about 69%. The estimated poverty gap and poverty gap-squared indices are 37% and 24%, respectively.

Table 4.2: Summary of outcome variables

Variable	No. observations	Mean	Standard Deviation
PCE/1000 GHS	476	1.295	2.017
Poverty Headcount	476	0.689	0.463
Poverty gap	476	0.367	0.323
Poverty gap-squared	476	0.238	0.270
Adoption Intensity (Expenditure on SLM)	207	292.00	447.00

Adoption intensity variable

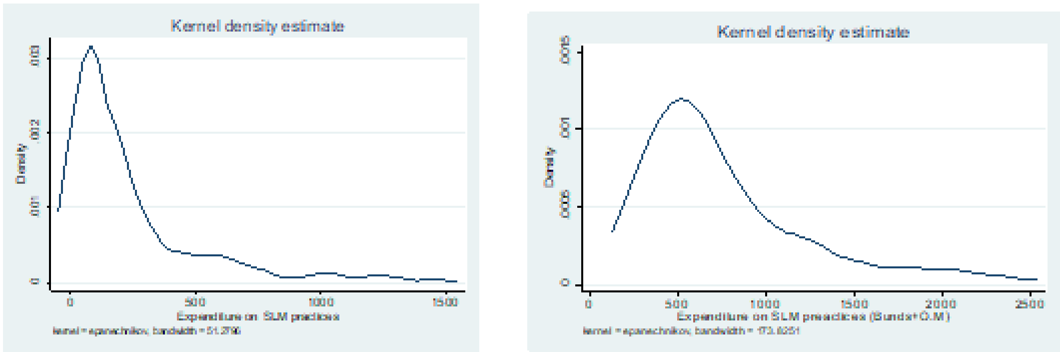
Our next important variable is the intensity of adoption, which is the treatment variable. In the present analysis, the intensity of adoption of sustainable land management practices is measured by the expenditure on two important categories of SLM practices in the Savannah and transitional agro-ecological zones, namely bunds (soil and stone) and organic manures. For the

[35] The Foster–Greer–Thorbecke (FGT) (1984) indices are commonly used means to estimate poverty in a population. The FGT class of poverty measure is written generally as: $P_\tau = \frac{1}{N}\sum_{i=1}^{M}\left[\frac{z-c_i}{z}\right]^\tau$, where N is the number of people in the sample population, z is the poverty line, c_i is *per capita* consumption for the i[th] person, and τ represents poverty aversion parameter. When $\tau = 0$, P_τ is simply the headcount index or the proportion of people that is poor. When $\tau = 1$, P_τ is the poverty gap index, which reflects the depth of poverty defined by the mean distance to the poverty line, where the mean is formed over the whole sample population with a zero poverty gap for the non-poor in the population. P_τ represents severity of poverty and reflect the extent of inequality among the poor when $\tau = 2$.

purposes of this study, farmers who spent on only organic manures (farm yard manure, compost) were classified as *low intensity adopter*s. *High intensity adopters* refer to those using bunds (stone/rock bunds) which effectively goes with the application of organic manures (Zougmore et al. 2014). The reported average expenditure on these sustainable land management practices was GHS 292.0 (Table 4.2). Adoption of these measure have been reported to reduce the challenges associated with land degradation, depletion of soil fertility and water stress, especially in dry agro-ecological zones (Shiferaw and Holden 1998; Abdulai and Huffman, 2014; Zougmore et al. 2014; Wossen et al. 2014). In particular, the adoption of soil and water conservation measures in SSA has resulted in improved yields, farm incomes and reduction in poverty (Wossen et al. 2014).

As evident in Table 4.1, about 39% farmers were classified as adopters (using stone/soil bunds and or organic manure). As indicated previously, adopters of bunds (soil/stone) often do so together with the use of organic manure. These are referred to as high intensity adopters. Those spending only on organic manures are referred to as low intensity adopters. Even though SLM practices adoption is reported to improve farm outcomes, adoption challenges including liquidity constraints, incomplete information about the impact of these practices, can lead to dis-adoption/non-adoption which may result in low farm productivity and farm incomes, as well as reduction in per capita consumption at the household level (World Bank 2009). Thus, we used the intensity of adoption to assess the impact of adoption on *per capita* consumption and poverty outcomes. We consolidated the expenses on bunds and organic manures into one variable referred to as the adoption intensity.

Figures 4.1 (**a**) and (**b**) present the kernel density estimates of intensity of adoption of SLM practices by farmers. It is clear from the figures that majority of adopters are within the low intensity level, with few farmers at the high intensity levels. This distribution further indicates the importance of the use of multivalued treatment effects approach in identifying the impact of adoption intensity on the expected welfare outcomes.



(a) O.M (b) Bunds+ O.M

Figure 4.1: **Distribution of expenditure on sustainable land management practices**

The household and farm characteristics employed in the analysis include variables that represent attributes of the household head (age, education), household composition, land tenure (usufruct right), liquidity constraints, access to climate information, as well as farmers' perception about rainfall variability. The rationale for the inclusion of these variables is explained briefly below.

Particularly, household characteristics (size and head's education) have been reported to significantly influence the labor supply and human capital capacity which together impact adoption of agricultural technologies (Di Falco et al. 2011). In addition the household endowments (livestock ownership, off-farm income) have been found to influence farmers' soil investment decisions, while tenure security also plays a vital role in determining the extent of soil conservation investment among farmers (Abdulai et al. 2011). The variable *Location_Alt* captures location specific environmental confounders (including soil characteristics and micro-climate of the farm). Figure 4.A2 also presents the reported constraints to adoption of SLM practices. Among high intensity adopters, unpredictable climate in the area was indicated as the greatest constraint. Tenure security (51%) and access to credit (52%) were also identified as constraints especially among low intensity adopters and non-adopters (Abdulai et al. 2011).

4.3 Empirical Results and discussion

Multivalued TE estimates

The estimation of multivalued TE using Cattaneo et al. (2013) approach involves three stages. The first stage involves estimation of the GPS using a multinomial logit (ML) model. It is important to note that, the parameters in the ML-model in Table 4.A1 in the Appendix refer to different intensity (treatment) levels and as such these estimates cannot be interpreted as marginal effects (Cattaneo et al. 2013). It is however significant to note that most of the estimated parameters in Table A1 are significantly different from zero at the different intensity (T_i) levels. The balancing tests on the overlap or common support are shown by the density plots of the predicted probabilities (GPS)[36] in Figure 4.A1 in the appendix. It is important to indicate that none of the graphs show a mass at zero or one[37]. This indicates that overlap or common support condition has been met. From Table 4.A1 also, the potential complementarity of chemical fertilizer and sustainable land management is obvious, a finding that is in line with the findings of Holden and Lunduka (2012) for Malawi.

The second step implied by the Cattaneo's (2010) approach involves the estimation of the relationship between the mean or quantiles of potential welfare outcomes and the covariates X, using Equation 12. In both the first and second step estimations, a fully interacted quadratic form is specified. We however omit these results following the argument that such results

[36] The balancing tests on the overlap or common support are shown by the density plots of the predicted probabilities (GPS) estimated from the multinomial model. The density of the probability for each treatment levels was estimated by a non-parametric kernel density estimation with a triangular kernel and optimal band with chosen by Stata (Cattaneo et al. 2013).

[37] If some predicted probabilities from the selected MLM are too close to either 0 or 1, the parameters may not be identifiable (Cattaneo et al. 2013).

cannot be given a direct economic interpretation (Cattaneo et al. 2013). The final step consists of estimating the average and quantile potential outcomes for the different treatment levels (Tables 4.A2 **a** and **b** in the Appendix). For instance, the potential outcome means of log *per capita* consumption expenditure (logPCE) for non-adopters, low intensity adopters and high intensity adopters are 5.2, 6.8 and 8.7 respectively, while the poverty headcount for the same categories are 71.7%, 61. 2% and 49.1%, respectively. Table 4.3 reports the ATE estimates for the four outcome variables at the respective treatment (adoption intensity) levels. The results generally indicate that logPCE increases with increasing intensity of adoption of SLM practices.

Table 4.3: Multivalued treatment effect (ATE)[38] of treatment level *m* relative *l*

	logPCE		Poverty HC	Poverty-gap	Poverty-gap-squared
From *m* to *l*	ATE	% change	ATE	ATE	ATE
Non-adoption to low intensity	1.602*** (0.215)	30.72	-0.106 ** (0.052)	-0.076** (0.028)	-0.067** (0.023)
Non-adoption to high intensity	3.472*** (0.587)	66.57	-0.226*** (0.061)	-0.091** (0.038)	0.012 (0.030)
Low to high intensity	1.870*** (0.651)	27.42	-0.120*** (0.071)	-0.071* (0.040)	-0.055 (0.032)

***, **, * represent 1%, 5%, and 10% significance level, respectively. Values in square brackets are p-values
Note: % change is calculated by expressing the ATE as percentage of the POM in Table 4.A2 (a) in the appendix

Specifically, the ATE of moving from one intensity level to another level, *m* versus *l* (e.g. non-adoption to low intensity adoption), is increase in logPCE by 1.6 (about 30.6% of the potential outcome means of non-adopters). This is also reflected in the reduction in the poverty headcount from 10.6% to 22.6% as farmers move from non-adoption to low intensity and high intensity, respectively. Furthermore, there is an increase in per capita consumption expenditure of more

[38] Estimations were done within multivalued TE and QTE framework using *poparms command*

than 66% for households that are able to move from low to high intensity adoption level. This finding confirms earlier findings by Nkonya et al. (2016) that SLM can be used as a tool for alleviating poverty among vulnerable smallholder farmers. Our findings also debunk the assertion that adoption of SLM worsens poverty situation among farm households (World Bank 2009). The greater positive impact on consumption at the higher intensity level of adoption is an indication that given assistance to overcome adoption barriers, smallholders can achieve improved livelihoods through increased per capita consumption and reduced vulnerability to poverty. As argued by Barbier and Hochard (2018), targeting and investing in less favored lands, though sustainable land management, is the surest way to lift rural populations out of poverty in developing countries.The drop in the poverty gap and severity of poverty (poverty gap squared) is between 7% and 9%, as intensity of adoptions moves from low to high. These findings support earlier findings about the impact of adoption of sustainable land management practices in improving farm productivity and reducing poverty (Tesfaye et al. 2016; de Janvry and Sadoulet 2001).

To clarify the nature of heterogeneity in the impact of adoption intensity on the logPCE, we report the quantile treatment effects (QTE) estimates in Table 4.4 and Figures 4.2b1-4.2b3, for 0.25, 0.5 and 0.75 quantiles[39]. The results indicate that increasing intensity of adoption of SLM practices positively influences the logPCE among farm households across all quantiles of logPCE. Based on the potential outcome means (in Tables 4.A2 (**a)** and (**b)** in the appendix), the ATE in percentage terms of moving from non-adoption to low intensity (only manure), is 30% across all quantiles, but this increases to 53%, 70% and 64% in the 0.25, 0.5 and 0.75 quantiles of PCE respectively, if we consider high intensity adopters and non-adopters. The results also suggests that response to adoption intensity is generally significant with the

[39] In estimating the QTE, the variance matrix estimator was bootstrapped with 2,000 repetitions (Cattaneo et al. 2013).

exception of poverty gap-squared where impact of adoption disappears at higher intensity levels (last column of Table 4.3).

Table 4.4: Quantile treatment effect (QTE)[40] of treatment *m* relative to *l*

	Q25		**Q50** (Median)		**Q75**	
From *m* to *l*	QTE	%Δ	QTE	%Δ	QTE	%Δ
Non-adoption to low int.	1.431*** (0.267)	30.45	1.542*** (0.240)	29.56	1.696*** (0.308)	29.93
Non-adoption to high int	3.230*** (0.578)	52.67	3.289*** (0.528)	69.72	3.643*** (0.502)	64.29
Low to high int	1.799*** (0.650)	22.68	1.747*** (0.602)	25.82	1.947*** (0.601)	26.44

***, **, * represent 1%, 5%, and 10% significance level, respectively. Values in parentheses are standard errors

[40] The QTE estimation was done in respect of 0.25, 0.5 and 0.75 quantiles of PCE. The QTE could not be done for the poverty headcount (PHC), poverty gap and poverty gap squared due to lack of sufficient observations.

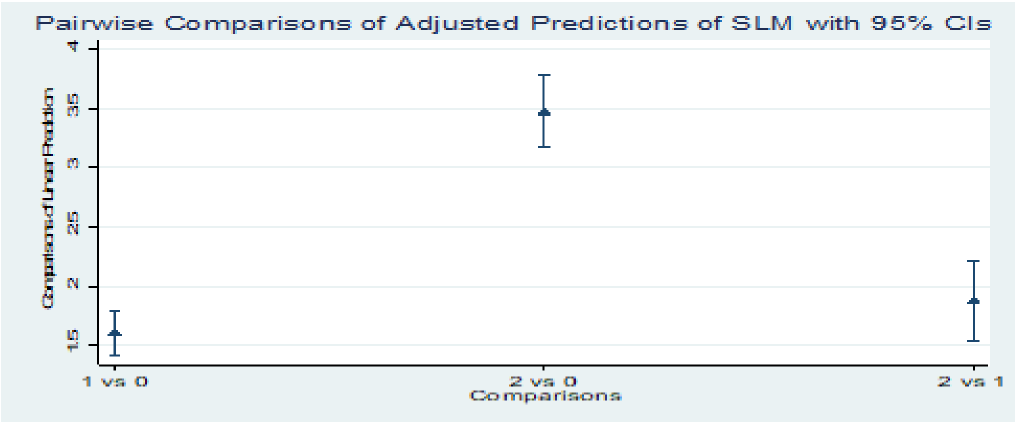


Fig 4.2b1: ATE comparisons in the 25th percentile

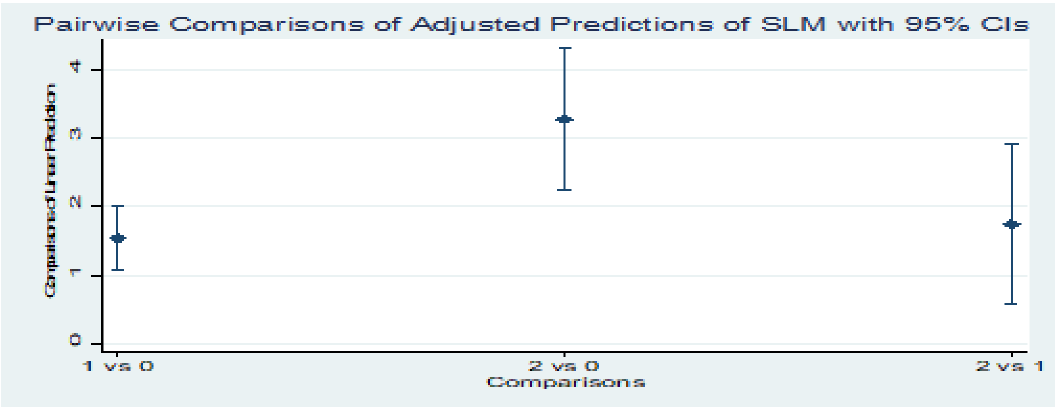


Fig 4.2b2: ATE comparisons in the Median

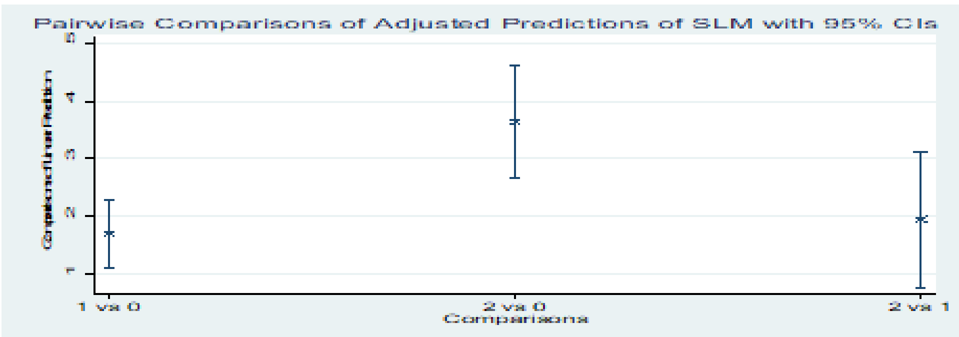


Figure 4.2b3: ATE comparisons in the 75th percentile

1vs 0 = moving non-adoption to low intensity adoption level, 2vs 1 =moving from low adoption to high adoption intensity level. SLM = Sustainable land management

Figure 4.2: b1-4.2b3 Marginal plots of pairwise comparisons of multivalued TE of adoption intensity levels at the mean and within quantiles of per capita consumption expenditure.

Dose-response function results

In this section, we examine the impact of adoption intensity on consumption and poverty outcomes in a dose-response context. Out of 207 sub-sample of adopters, 185 farmers were on common support, representing 89% for which we have enough data to estimate the dose-response functions for the outcomes (per capita consumption expenditure [PCE], poverty headcount, poverty gap and poverty gap-squared). The dose-response functions were estimated using equation 14. However, as pointed out by Hirano and Imbens (2004), the estimated regression coefficients do not have any direct meaning and are therefore not discussed here, but are reported in Table 4.A4 in the Appendix.

Figure 4.3 shows the dose-response function of the impact of adoption intensity on per capita consumption expenditure among farm households. We concentrate on the average treatment effect function, since the log transformed *per capita* expenditure on the DRF (left panel in Figure 4.3) is difficult to interpret.

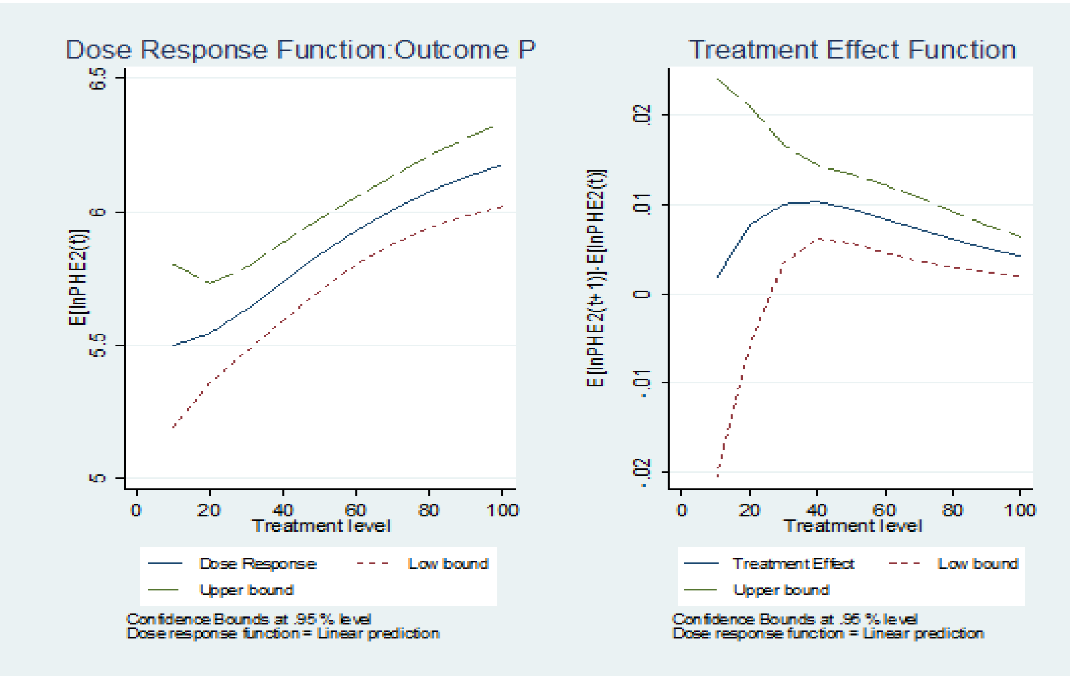


Figure 4.3: Estimate dose-response function and corresponding estimated marginal treatment effect on per capita expenditure

The ATE function of the DRF (right panel in figure 3) shows average effect of adoption on *per capita* expenditures (in percent) when adoption intensity increases by one percentage point. The result shows a non-linear relationship with an initial increase in per capita consumption due to increasing adoption intensity up to the 40% points. After this point, the rate of increase in consumption due to adoption intensity declines, although the ATE remains positive. The shape of the ATE function further explains the reason behind a greater concentration of low intensity adopters shown earlier in Figure 4.1 (**a**) and (**b**). The non-linear relationship between SLM adoption intensity and poverty measures are reported in Figures 4 A-C. Figure 4A shows the DRF of the effects of adoption intensity and the household's probability of falling below the poverty line. The results generally show a negative relationship between increasing adoption intensity and poverty outcomes.

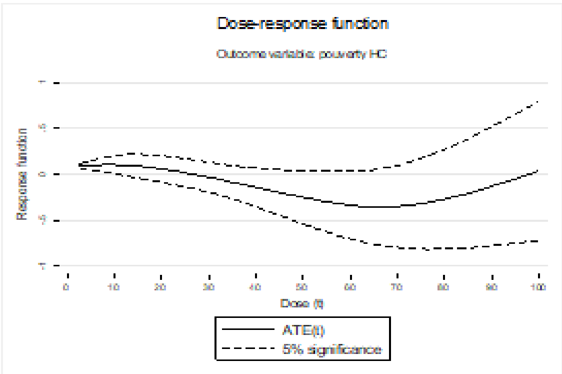


Figure 4A Poverty headcount

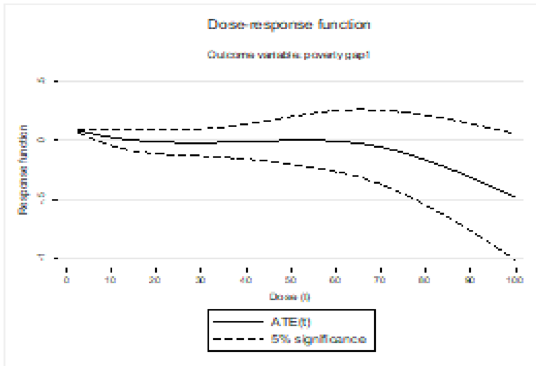


Figure 4B: poverty gap

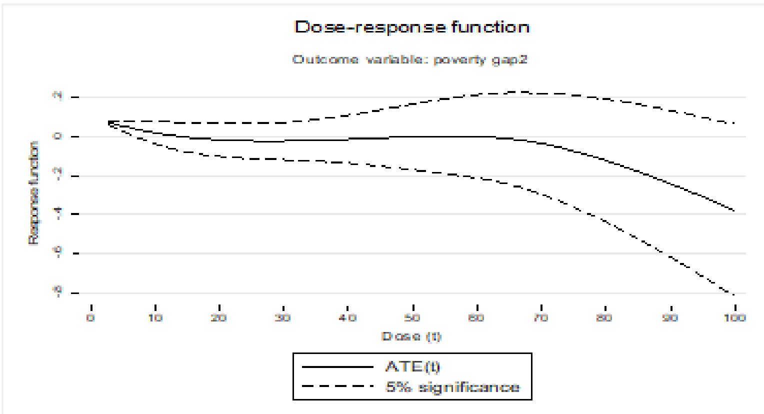


Figure 4C: Poverty gap-squared

Figures 4A-C: Estimated dose-response functions (ATE) treatment effect functions on per poverty measure.

However, in the cases of poverty gap and poverty gap-squared, the effect of adoption is quite stable (almost zero), until after 70% point increase in adoption intensity, where these poverty indices begin to decrease. The implication of this is that poverty intensity among the poor only experiences a decline at higher intensity levels of adoption. Thus, the possibility of using sustainable land management as a poverty alleviation mechanism is possible if poor farmers can be assisted to move higher up the adoption ladder (from low intensity to high intensity levels). These findings support the multivalued TE analyses, as well as previous findings that adoption of sustainable land management practices can directly or indirectly reduce household poverty levels (de Janvry and Sadoulet 2001).

4.4 Conclusions and policy implications

Analyzing adoption impacts on welfare using binary adoption frameworks may result in loss of vital information about the nature of the impact of adoption, especially when the efforts put into adoption is clearly uneven among adopters. In this paper, we employed recently developed multivalued treatment effects approaches to assess the impact of sustainable land management adoption intensity on household poverty measures, using recent farm household level survey data from Ghana. We employed generalized propensity scores with multivalued treatment effects approaches, as well as a dose-response function approach to investigate the effect of adoption intensity on these welfare outcomes. The empirical results show that adoption intensity increases household per capita consumption and reduces poverty. The impact of adoption appear to be non-linear, especially with respect to poverty measures, with poverty headcount and poverty-gap dropping significantly at the initial stages, but the effect of increasing adoption intensity on poverty-gap squared diminishes as farmers move from low intensity to higher intensity levels.

These findings are in line with the idea that sustainable land management, involving the use of organic manure and stone/soil bunds[41], improves land/soil quality, increases yields and improves household welfare. The results also showed that the average treatment effect of moving from low intensity to high intensity adoption levels differ across expenditure quantiles. For instance, adoption at high intensity levels tend to positively affect *per capita* consumption at the middle and upper quantiles than at the lower quantiles. This finding indicates a potential adoption gap that could be attributed to the constraints enumerated by farmers (e.g. tenure security, unpredictable climate or access to credit). Such a gap can deny low intensity adopters from obtaining the optimum benefits associated with adoption based on recommended practice. The findings of this study have implications for policy and investment in sustainable land management to address vital development challenges. It is imperative to state that poor smallholder farmers may not be able to fully benefit from the yield gains offered by recent advancements in crop improvement, if sustainable land management is ignored. In particular, continued cropping with unsustainable farming practices, without sufficient inputs of nutrients and organic matter, leads to *in situ* albeit extensive soil degradation that renders many farm lands in a non-responsive state. To enhance the poverty-alleviation effect of sustainable land management, poor farm households should be assisted through provision of credit, access to alternative livelihoods to improve effective adoption of SLM practices. Since education has positive influence on adoption at different intensity levels, improving education access, as well as extension services will facilitate effective adoption of sustainable land management practices.

Besides, the nonlinear effects of adoption intensity on welfare and poverty outcomes signals some level of inefficiency in the application of SLM practices, particularly at the high intensity level. This implies, improving farmer training on the efficient application of SLM will be an

[41] This is even critical in places where the agricultural lands exposed to threat of degradation, due to continues nutrient mining.

option for policy consideration. For instance, a replication of ecological friendly agricultural model of B-BOVID[42] agribusiness (in the Western region of Ghana) in the Savannah agro-ecological zones will help address problems of land degradation, climate change impacts and poverty alleviation. Provision of irrigation facilities will also enable farmers reap the full benefits of sustainable land management and reduce the crop yield gaps resulting from the biophysical limitations caused by land degradation and water deficits.

References

Abdulai, A., Huffman, W. (2014). The Adoption and Impact of Soil and Water Conservation Technology: An Endogenous Switching Regression Application, *Land Economics* 90 (1), 26–43.

Abdulai, A., Owusu, V. & Goetz, R. (2011). Land Tenure Arrangements and Investment in Land Improvement Measures: Theoretical and Empirical Analysis, *Journal of Development Economics*, 96(1) 66-78.

Amare, M., Asfaw, S., Shiferaw, B. (2012). Welfare impacts of maize–pigeon pea intensification in Tanzania, *Agricultural Economics* 43(1), 27-43.

Arslan, A., McCarthy, N., Lipper, L., Asfaw, S., Cattaneo, A. & Kokwe, M. (2015). Climate Smart Agriculture? Assessing the Adaptation Implications in Zambia, *Journal of Agricultural Economics*, 66 (3):753-780

Asfaw, S., Di Battista, F. & Lipper, L. (2016). Agricultural technology adoption under climate change in the Sahel: Micro-evidence from Niger, *Journal of African Economies* 25 (5): 637-669.

Babatunde, R. O. & Qaim, M. (2010). Impact of off-farm income on food security and nutrition in Nigeria, *Food Policy* 35: 303–311.

Barbier, E. B. & Hochard, J. P. (2018). The Impacts of Climate Change on the Poor in Disadvantaged Regions, *Review of Environmental Economics and Policy*, 12(1):26–47

Barrett, C. B., Christiaensen, L., Sheahan, M. & Shimeles, A. (2017). On the Structural Transformation of Rural Africa, *Journal of African Economies*, 26 (1):11–35.

[42] The B-BOVID model is an agribusiness in the Western region of Ghana that combines agro-forestry, organic farming and mechanization with ecological bio-diversity and ecotourism. The UN in 2012 awarded it for "sustainable and ecological learning practices and seeking to reduce poverty and create wealth by providing training and support for local farmers in Ghana" Business and Financial Times (Feb., 2018). https://thebftonline.com/business/sustainable-agriculture-the-b-bovid-model/
B-BOVID refers to Building Business on Values, Integrity and Dignity.

Becerril, J. & Abdulai, A. (2010). The Impact of Improved Maize Varieties on Poverty in Mexico: A propensity score-Matching Approach, *World Development*, 38(7): 1024-1035.

Bia, M. & Mattei, A. (2012). Assessing the effect of the amount of financial aids to Piedmont firms using the generalized propensity score, *Statistical Methods Applications*, 21:485-516.

Bia, M., Flores, C. A. & Mattei, A. (2014). A Stata package for the application of semi-parametric estimators of dose–response functions, *The Stata Journal*, 14(3):580-604.

Bourguignon, F., Fournier, M. & Gurgand, M. (2007). Selection Bias Corrections Based on the Multinomial Logit Model: Monte Carlo Comparisons. *Journal of Economic Surveys* 21(1): 174-205.

Cattaneo, M.D. (2010). Efficient semiparametric estimation of multivalued treatment effects under ignorability. *Journal of Econometrics* 155: 138–154.

Cattaneo,M.D.,Drukker ,D.M. & Holland, A. D. (2013). Estimation of multivalued treatment Effects under conditional independence, *The Stata Journal*, 13: 407–450.

Cerulli, G. (2015). Ctreatreg: Command for fitting dose-response models under exogenous and endogenous treatment, *Stata Journal* 15: 1019–1045.

Chomitz, K. M., Buys, P., De Luca, G., Thomas, T. S. & Wertz-Kanounnikoff, S. (2007). *At Loggerheads: Agricultural Expansion, Poverty Reduction, and Environment in the Tropical Forests*. World Bank, Washington, D.C.

de Janvry, A., & Sadoulet, E. (2001). World poverty and the role of agricultural technology: Direct and indirect effects, *Journal of Development Studies*, 38(4), 1–26.

Di Falco, S., Veronesi, M., Yesuf, M. (2011). Does adaptation to climate change provide food security? A micro-perspective from Ethiopia, *American Journal of Agric. Econ*. 93(3), 829–846.

Erikson, S. H. & O’brien, K. (2007). Vulnerability, poverty and the need for sustainable adaptation measures, *Climate Policy*, 7: 337-352.

Esposti, R. (2017). The heterogeneous farm-level impact of the 2005 CAP-first pillar reform: A multivalued treatment effect estimation, *Agricultural Economics* 48: 373–386.

Flores, C. F., Flores-Lagunes, A., Gonzalez, A. & Neumann, T.C. (2012). Estimating the effects of length of exposure to instruction in training program: The case of Job Corps, *The Review of Economics and Statistics*, 94(1): 153-171.

Foster, J., Greer, J. & Thorbecke, E. (1984). A class of decomposable poverty measures, *Econometrica*, 52(3): 761-765.

Ghana Statistical Service (GSS) (2015). *Ghana Poverty Mapping Report*, Ghana Statistical Service, Accra, Ghana.

Gondo, P. (2010). A review of forest financing in Africa. United Nations Forum on Forests.

Hirano, K. & Imbens, G.W., (2004). The propensity score with continuous treatment. In Gelman A., Meng X.L. (Eds.), *Applied Bayesian Modeling and Causal Inference from Incomplete-Data Perspectives*. Wiley Inter Science, West Sussex, pp. 73–84.

Holden, S. & Lunduka, R. (2012). Do fertilizer subsidies crowd out organic manures? The case of Malawi, *Agricultural Economics*, 43: 303-314

Imbens, G., and J. Wooldridge. (2009). Recent Developments in the Econometrics of Program Evaluation, *Journal of Economic Literature* 47(1):5-86.

Imbens, G. W. (2000). The role of the propensity score in estimating dose-response functions. *Biometrika*; 87(3):706-710.

IPCC (Intergovernmental Panel on Climate Change). (2014). *Climate change 2014: Impacts, adaptation, and vulnerability. Part A: Global and sectoral aspects. Contribution of working group II to the fifth assessment report of the Intergovernmental Panel on Climate Change*. Cambridge, UK: Cambridge University Press.

Kabore, P. D. & Reij, C. (2004). The emergence and spreading of an improved traditional soil and water conservation practice in Burkina Faso, *IFPRI Discussion Paper* 114. Environment and production technology division, Washington D.C.

Kassie, G. T., Abdulai, A., Green, W. H., Shiferaw, B., Abate, T., Tarekegne, A. & Sutcliffe, C. (2017). Modeling Preference and Willingness to Pay for Drought Tolerance (DT) in Maize in Rural Zimbabwe, *World Development* 94: 465-477.

Linden, A., Uysal, S. D., Ryan, A. & Adams, J. L. (2016). Estimating causal effects for multivalued treatments: a comparison of approaches, *Statistics in Medicine* 35(4): 534-552.

Lokshin, M., & Sajaia, Z., (2004). Maximum Likelihood Estimation of Endogenous Switching Regression Models. *Stata Journal* 4 (3): 282–89

Nkonya, E., Mirzabaev, A. & von Braun, J. (2016). Economics of Land Degradation and Improvement: An Introduction and Overview, in Nkonya, E., Mirzabaev, A. & von Braun, J (Eds.), *Economics of Land Degradation and Improvement: A Global Assessment for Sustainable Development*, IFPRI, Washington, D.C.

Rosenbaum, P., & Rubin, D. (1983). The Central Role of the Propensity Score in Observational Studies for Causal Effects. *Biometrika* 70:41-55.

Shiferaw, B., Holden, S., (1998). Resource degradation and adoption of land conservation technologies in the Ethiopian Highlands: A case study in Andit Tid, North Shewa, *Agricultural Economics* 18 (3), 233-247.

Tesfaye, A., Brouwer, R., Van der Zaag, P. & Negatu, W. (2016). Assessing the cost and benefits of improved land management practices in three watershed areas in Ethiopia, *International Soil and Water Conservation Research* 4:20-29.

Tol, R. S. J. (2018). The Economic Impacts of Climate Change. *Review of Environmental Economics and Polic*y, 12 (1): 4-25.

World Bank (2009). Republic of Niger: Impacts of Sustainable Land Management Programs on Land Management and Poverty in Niger, *The World Bank*, Report No. 48230-NE.

Wossen, T., Berger, T., Swamikanu, N. & Ramilan, T. (2014). Climate Variability, Consumption Risk and Poverty in Semi-Arid Northern Ghana: Adaptation Options for Poor Farm Households, *Environmental Development* 12:2–15.

Yang, S., Imbens, G. W., Cui, Z., Faries, D. E. & Kadziola, Z. (2016). Propensity Score Matching and Sub-classification in Observational Studies with Multi-Level Treatments, *Biometrics* 72, 1055-1065.

Zereyesus, Y. A., Embaye, W. T., Tsiboe, F. & Amanor-Boadu, V. (2017). Implications of Non-Farm Work to Vulnerability to Food Poverty-Recent Evidence from Northern Ghana, *World Development* 91: 113–124.

Zougmore, R., Jalloh, A. & Tioro, A. (2014). Climate-smart soil water and nutrient management options in semiarid West Africa: a review of evidence and analysis of stone bunds and Zaï techniques, *Agriculture and Food Security,* 3:16.

Appendix

Table A1: GPS function model estimation of multivalued treatment on the covariates

Non-adoption=0	(Base outcome)			
	Low Intensity=1		High intensity=2	
Variable	Est	SE	Est	SE
Fertilizer	0.555**	0.259	0.234***	0.031
Offfarm	0.732***	0.261	0.459***	0.130
Rfconditon	0.468*	0.281	1.212***	0.395
Farm size	0.553*	1.048	0.172**	0.077
HH_size	1.073**	0.575	0.321	0.628
Education	1.114***	0.392	1.087**	0.546
Livestock	0.115**	0.0442	0.431***	0.0389
Location_Altit	-0.003***	0.001	-0.004**	.002
Offarm_resid	-1.015***	0.050	-1.020	0.760
Log likelihood	-441.643	[0.000]		
N	476			

***, **, * represent 1%, 5%, and 10% significance level, respectively. Values in square brackets are p-values

Table A2 (a): Potential outcome means of Poverty measures at different adoption intensity levels

	Log PCE		*Poverty Headcount*		*Poverty gap*		*Poverty gap^2*	
POmean								
	Est	Boot SE	Est	Boot SE	Est	Boot SE	Est	Boot SE
Non-adoption	5.215	0.111	0.717	0.027	0.422	0.020	0.285	0.016
low intensity	6.818	0.199	0.612	0.045	0.351	0.024	0.231	0.020
High intensity	8.688	0.583	0.491	0.057	0.347	0.034	0.218	0.026

Table A2 (b): Potential Outcome means of PCE at different adoption intensity levels within Quantiles of PCE

	25th percentile		Median		75th percentile	
	POM	SE	POM	SE	POM	SE
Non-adoption	4.700	0.129	5.225	0.116	5.666	0.178
low intensity	6.132	0.240	6.767	0.222	7.362	0.275
High intensity	7.931	0.563	8.514	0.524	9.309	0.473

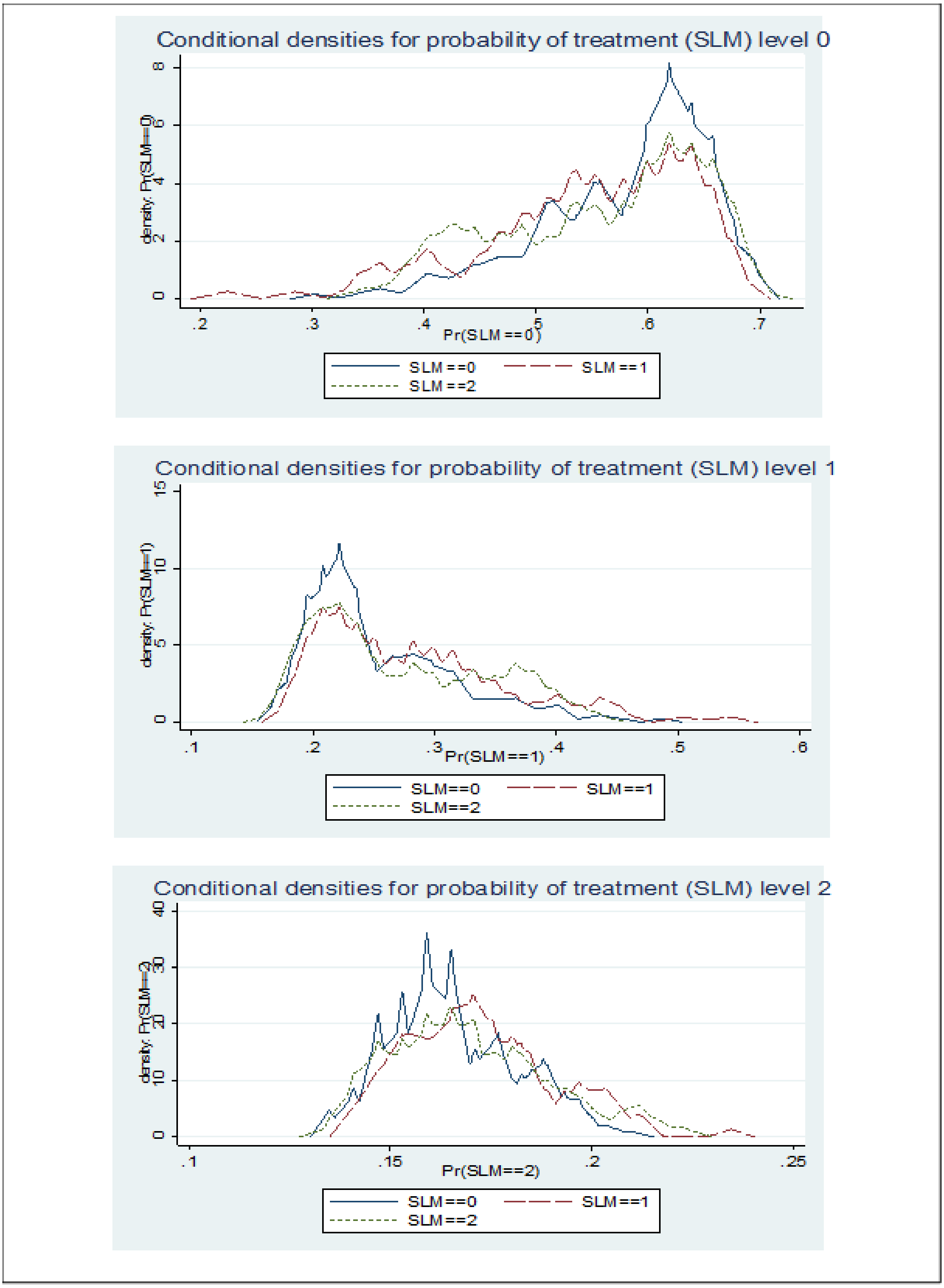


Figure 4.A1: The balancing tests on the overlap or common support as shown by the density plots of the predicted probabilities (GPS) estimated from the MLM.

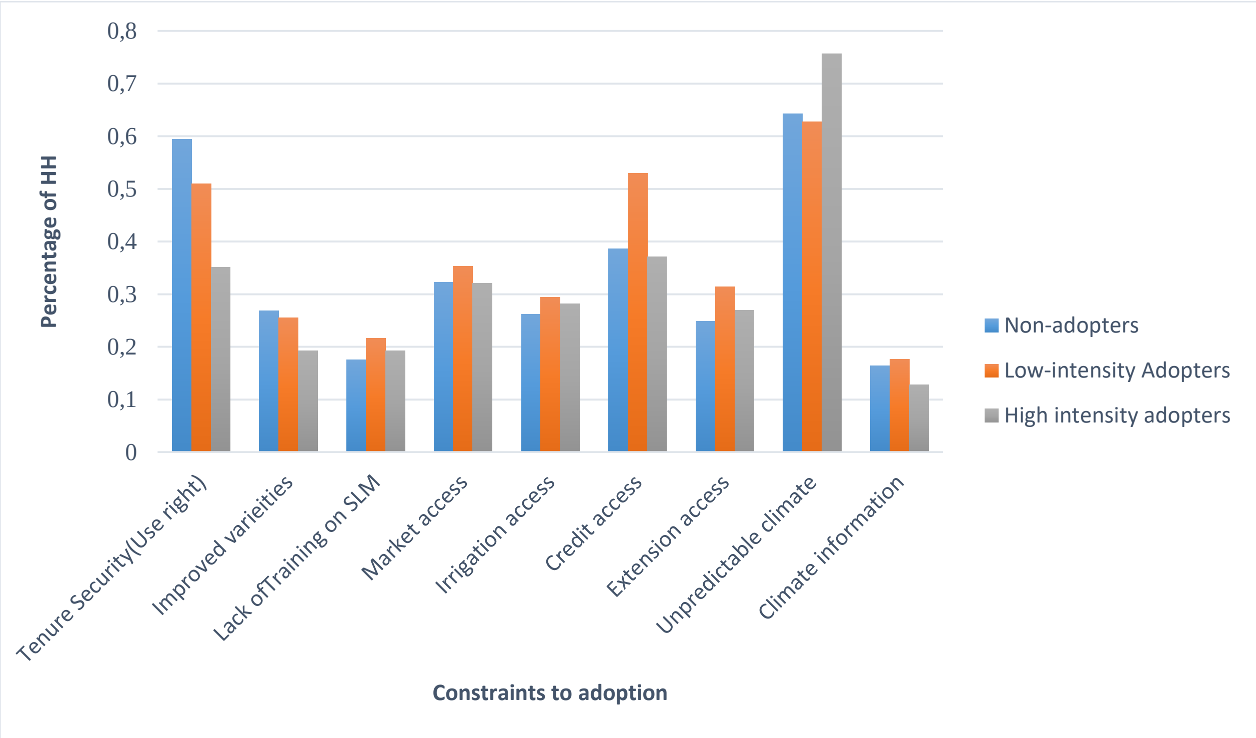


Figure 4.A2: Constraints to adoption of SLM practices

Table 4.A3: Balancing test of estimated GPS: *t*-statistics for mean difference between treatment intervals: for the DRF

Variable	Treatment 1		Treatment 2		Treatment 3	
	MD	t-value	MD	t-value	MD	t-value
Hh_Size	0.451	0.828	-0.620	-0.904	-0.398	-0.577
Education	-0.549	-0.817	0.380	0.474	0.275	0.306
Farm size	-0.131	0.359	0.272	0.725	0.052	0.210
Offfarm	-0.015	-0.246	0.052	0.694	0.024	0.282
Fertilizer	-0.016	-0.221	0.005	0.062	0.009	0.095
Rfconditon	0.121	0.539	-0.028	-0.102	-0.048	-0.165
Extension	-0.153	-0.606	0.235	0.782	-0.014	-0.042
Climateinfo	-0.041	-0.553	-0.054	-0.592	0.015	0.159
Credit cons	0.027	0.245	-0.044	-0.392	-0.052	-0.465
Livestock	0.021	0.024	-0.934	-0.908	1.052	0.885
Machinery	-0.031	-0.522	0.059	0.798	-0.126*	-1.727
Fbo_Memb	-0.015	-0.233	-0.057	-0.706	0.006	0.083
Altitude	2.577	1.295	-4.88**	2.823	0.696	0.493

**, * represent 5%, and 10% significance level, respectively.

Table 4.A4: Estimation results of the coefficients of the dose-response function

	PCE		*Poverty HC*		*pgap*		*Pgap2*	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
T	0.075**	0.038	-0.002**	0.001	-0.002**	0.001	-4.3E-5	1.0E-4
T^2	-0.001	0.0008	3.14E-07	2.16E-07	-0.003	0.025	-1.04E-08	2.36E-08
GPS	-1.470**	0.919	-1.67***	0.980	0.002	0.906	0.532	0.836
*T*GPS*	0.013**	0.002	-0.006	0.005	-0.001	0.001	-0.054**	0.005
Cons	5.510***	0.369	3.220***	1.066	0.610***	0.089	-0.432***	0.082
No. obs	185							

***, **, * represent 1%, 5%, and 10% significance level, respectively.

Chapter 5

Sustainable land management and environmental efficiency among smallholder farmers in Ghana

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Abstract

Sustainable land management (SLM) practices have been promoted to help address problems with declining soil fertility, crop yields and adverse impacts of climate change. In this study, we examine the effects of adoption of SLM practices on farm households' technical efficiency and environmental efficiency using household-level data from Ghana. We employ matching techniques and selectivity biased-corrected stochastic production frontier to account for bias from both observed and unobserved factors. The empirical results show that farmers adopting SLM technology exhibit higher levels of technical efficiency and output, compared to the non-adopters. However, the results reveal that adopters are found to use excess herbicides that could have adverse environmental consequences. The results also reveal that extension services and access to credit positively and significantly correlate with technical efficiency.

Key words: Sustainable land management; Stochastic production metafrontier; Technical and environmental efficiency; Environmental impact quotient.

5.0 Introduction

The agricultural sector in Ghana is dominated by smallholders cultivating less than 2.5 hectares on average (Ghana Ministry of Food and Agriculture [MoFA], 2016). These farmers grow mainly food and cash crops with low technical and operational efficiencies. They also encounter many challenges including declining soil fertility, land degradation, low level of technology that result in lower productivity and output, farm incomes and food insecurity (Nkonya et al., 2016; MoFA, 2016). To address the low agricultural productivity and environmental problems, government with the support of multilateral institutions, has undertaken policies and initiated projects that aim at conserving agricultural land resources and reducing rural poverty (Nkonya et al., 2016; MoFA, 2016). Examples of such projects include the Ghana Environmental Management Project (GEMP) 2004-2009, National Biodiversity Strategy and Action Plan 2004, National Climate change Policy 2015 and more recently the Ghana Strategic Investment Framework (GSIF) for Sustainable Land Management (SLM) 2011-2025 (Environmental Protection Agency [EPA], 2011). To accomplish the goals of achieving sustainable food production and poverty reduction, these policies and projects aim at improving household incomes by promoting sustainable land management (SLM) practices including the use of cover-cropping, crop diversification and soil and water conservation practices (such as stone and soil bunds, minimum tillage and organic manures) (for example, FAO, 2011; Zougmore et al., 2014).

Thus, promoting productive and efficient use of arable land and other resources is an important policy issue that is essential for sustainable food production and poverty alleviation in Ghana. Some studies have found that adoption of SLM practices contribute to enhanced productivity and efficiency, as well as carbon sequestration (FAO, 2011; Khanal et al., 2018). Other studies have indicated that adoption of SLM practices enables farmers to produce enough food even under climate uncertainty, with yield increases of up to 200 per cent (FAO, 2011; Zougmore et al. 2014; Nkonya et al., 2016). However, findings from some studies suggest that adoption of SLM practices leads to temporary decline in yields and higher poverty, especially among poor farmers in some parts of SSA, resulting in low adoption rates (World Bank, 2009; Kassam et al., 2009). The contrasting findings about the adoption impacts of SLM suggests the need for further empirical research on the subject. In particular, it is not quite clear whether it is the adoption of SLM technology that improves efficiency or confounding factors that account for this relationship.

Furthermore, an important issue worth considering in relation to SLM and smallholder crop production, is the recent increase in herbicide use. As part of measures to reduce the drudgery associated with manual land preparation and weeding, many farmers are increasingly employing herbicides (Watkins et al., 2018). For example, studies in Ghana have shown that the import of herbicides into the country grew from 610,000 liters in 2008 to over 22 million liters in 2015 (MoFA, 2016). Globally, it has been found that glyphosate-based herbicides account for about 54 per cent of total agricultural herbicides (Coupe and Capel, 2015). Farmers in Ghana use Roundup (glyphosate-based herbicide) for weed control and sometimes apply it to facilitate drying of plants for harvesting purposes. It is also employed by many farmers as the main land preparation method in minimum and zero-tillage farming systems, with significant economic benefits in terms of reduction in labour costs (Boahen et al., 2007). Although negative externalities due to herbicides and other pesticides use cannot be entirely eliminated, their intensity of use can be minimized through development, dissemination and promotion of ecologically friendly crop production technologies (Kurgat et al., 2018). Some studies suggest that SLM practices such as cover-cropping and minimum tillage can be effective in suppressing weed growth and therefore reducing the use of herbicides in crop production (Price and Norsworthy, 2013; Watkins et al., 2018). Other studies suggest that adoption of some SLM practices, such as zero-tillage is enhanced through the use of herbicides (Adnan et al., 2017). In SSA countries, including Ghana, studies that discuss the effects of adoption of SLM practices on farmers' technical efficiency and excess herbicide use (environmental inefficiency) are quite rare. Recent findings indicate that the application of herbicides (Roundup) to control weeds could harm, or induce unintended harmful effects on the environment, soil organisms, water and air pollution, as well as human health (Myers et al. 2016; Watkins et al., 2018). Such findings suggest that the world's most widely used herbicide may have much effect on non-target species than previously considered (Myers et al., 2016; Williams et al., 2016).

Our aim in this study is two-fold. First, we examine the impact of adoption of SLM technology on technical efficiency, using the stochastic production metafrontier framework while accounting for selection bias (Greene, 2010; Huang et al., 2014). Second, we employ the Data Envelope Analysis (DEA) to derive environmental impact quotient (EIQ) slacks (our proxy for environmental efficiency). We then use fractional regression models (FRM) (Ramalho et al., 2010) to identify the drivers of technical and environmental efficiency. The determination of the EIQ is explained later in the data and descriptive statistics section. We employ recent data from Ghana to realize these research objectives.

Our study fills the gap among studies on the adoption of SLM practices among farm households by drawing a link between adoption and technical and environmental efficiency. This assessment may impact on policy concerning herbicide use, as well as environmental regulation in general. The study also contributes to the debate on the role of glyphosate-based herbicides within the context of conservation agriculture (Watkins et al., 2018). To the best of our knowledge, this study is among the few, or the first in SSA that attempts to assess the relationship between SLM and environmental efficiency, using the excess EIQ (slacks) of Roundup, one of the most commonly used herbicide.

The rest of the study proceeds as follows. In the next section, we discuss the conceptual and econometric framework employed in the study. The data and descriptive statistics are discussed in section three. This is followed by the results and discussions. The final section presents conclusion and policy implications.

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5.1 Conceptual and Econometric Framework

Several studies on efficiency in agriculture have shown that inefficiency is a common phenomenon among farmers in developing countries (e.g. O'Donnell and Rao 2009; Battesse and Coelli 1992). In this regard, adoption of SLM practices may reduce technical inefficiency and production costs and make farms more productive and sustainable (FAO 2011). In addition, farmers need to ensure environmental sustainability to maintain the value of productive resources (Reinhard et al. 2002; Veettil et al. 2017; Watkins et al. 2018). This is necessary to ensure the preservation of energy balance and the fundamental law of nature concerning energy conservation. The use of herbicides reduces the energy requirement for weed control and for land preparation in crop production. It also minimizes the frequency of mechanical tillage and damage to the soil structure. In zero-tillage systems, chemical herbicides especially roundup and other inputs facilitate adoption (Adnan et al. 2017). However, this may be achieved at the expense of high level of glyphosate (the active ingredient in roundup herbicides) that is environmentally hazardous (Gibbons et al. 2014; Myers et al. 2016). Adoption of SLM (e.g., cover-cropping, soil and water conservation, mulching, etc.) may promote effective use of soil resources and suppresses weed growth that can lead to high crop productivity and high level environmental efficiency. As indicated by Lee (2005), while outputs of many agricultural systems that are often considered in measuring success in terms of household food and livelihood security, sustainable agricultural systems are often identified by levels and efficiency of inputs use.

On the other hand, some SLM practices that rely on the use of herbicides to control weeds may result in long-term accumulation of glyphosate and hence, lead to environmental inefficiency. In this study we assess the efficiency levels of farm households using SLM technology and those who are not. In addition, we examine whether adoption is associated with lower or higher levels of herbicide environmental impact quotient (EIQ). Although plot-level analysis of excess EIQ of all pesticides with their active ingredients (AI) biological half-lives would have been the preferred measure of environmental efficiency (Kovach et al. 1992), we lack information about other pesticides applied by farmers. We therefore rely on reported quantities of roundup herbicide used by farmers to calculate the environmental impact quotient (EIQ). In a DEA framework, excess of inputs (input slacks) are indications of inefficiency with the respect of these inputs. Thus, in the case of excess EIQ from roundup, this would be an indication of environmental inefficiency (Mal et al. 2011).

Adoption decision

Assume that farmers are risk-neutral in their decision to adopt SLM technologies[43] or not, and as such compare the expected utility of adoption (U_{iA}^{*}) and (U_{iN}^{*}) for adopters and non-adopters that may be denoted as A^{*}, such that a utility maximizing household i will choose to adopt SLM if the utility gained from adopting is greater than the utility of not adopting ($A^{*} = U_{iA}^{*} - U_{iN}^{*} > 0$). Given that household utility level is latent and cannot be directly observed, we express it as a function of observed factors in the following latent variable model:

[43] The SLM technology considered in this study include a set of land management practices - soil and stone bunds, organic manure, minimum/zero-tillage and covercropping. We classify a farmer as an adopter if he/she reported using one or combination of these pactices during the last five seasons.

$A_i^* = \gamma Z_i + \omega_i$ with $A_i = \begin{cases} 1\ if\ A^* > 0 \\ 0\ \ otherwise \end{cases}$ (1),

where A is the a dummy indicating the adoption decision, Z is vector of explanatory variables, γ is a vector of parameters to be estimated and ω is the error term. The probability that a farmer adopts the SLM practices can be expressed as:

$Pr(A_i = 1) \ = pr\ (\omega_i > -\gamma Z_i \ = 1 - F(-\gamma Z_i)$ (2)

where F is the cumulative distribution function of error term.

The possibility and ease of farmers switching from non-adoption to adoption is greatly contingent upon the capacities and constraints faced by farm households in terms of capital, technological, biophysical and information, as well as the existing institutional environment (Reinhard et al. 2002; Barrett et al. 2017).

Impact of SLM adoption

In this study, we employ SPF method to estimate the TE and productivity of food crop farmers with the assumption that farmers either produce food crops using SLM technology or non-sustainable practices (conventional technology). We start with the stochastic production frontier (SPF) model that is stated as:

$Y_{ij} = f(X, A) + \varepsilon_{ij}$, where $\varepsilon_{ij} = v_{ij} - u_{ij}$ (3)

where Y_i denotes output of farmer i employing technology j; X refers to a vector of inputs and other environmental variables; A is as earlier defined. The error term ε_{ij} is composed of two parts, the random noise (v_{ij}) and the one sided inefficiency term (u_{ij}) (Battese and Coeli 1992). It is essential to note that farmers self-select themselves into adoption and non-adoption of SLM technology, which implies that sample selectivity bias from both observable and unobservable factors, is an important issue that needs to be addressed. According to Maddala (1998), partitioning of data into subsamples of farmers with different technologies leads to observations that are no longer random draws from the population, since the observations in each subsample might depend on the variables influencing adoption of the technology under analysis.

Accounting for sample selectivity bias in this study is necessary to ensure unbiased and consistent estimates of adoption impacts (Greene 2010; Villano et al. 2015).

Sample selectivity corrected SPF

A number of studies have employed SPF approaches to assess productivity and technical efficiencies among firms in industry and agriculture (Battese et al. 2002; Villano et al. 2010; O'Donnell et al. 2008; Kouser and Qaim 2015). The limitation of a large body literature that has employed SPF approaches to compare adopters and non-adopters is the failure to account for selectivity bias especially from unobservable factors (e.g., Mal et al. 2011; Khanal et al. 2018). The advancement in econometric approaches to handle sample selectivity issues in SPF models has generated interest in the use of these approaches in efficiency analysis (e.g., Villano et al. 2015; Gonzales-Flores et al. 2014; Abdulai and Abdulai 2017). These studies have all employed the sample selection bias-correction approach by Greene (2010). We employ this analytical approach to estimate effect of adoption of SLM on TE among food crop farmers. This model assumes that the unobserved characteristics in the selection equation (decision to adopt SLM technology) are correlated with the conventional error term in the stochastic frontier model. The sample selection SPF model by Greene (2010) is specified as follows:

$$A_i = 1[\gamma Z_i + \omega_i > 0], \omega_i \sim N(0,1) \quad (4)$$

$$Y_i = \vartheta' X_i + \epsilon_i, \epsilon_i \sim N(0, \sigma_\varepsilon^2), \quad \epsilon_i = v_i - u_i \quad (5)$$

where Y_i and X_i are observed only when $A_i = 1$

$v_i = \sigma_v V_i$ with $V_i \sim N(0,1)$

$u_i = |\sigma_u U_i| = \sigma_u |U_i|$ with $U_i \sim N(0,1)$

$(\omega_{i,} v_i) \sim_i N_2(0,1), (1, \rho\sigma_v, \sigma_{v)}^2]$

where Y_i denotes the logarithmic farm revenue of farmer $i = 1,2 \ldots, N$; X_i is a vector of logarithmic input quantities, A_i is a binary dummy variable that equals one for adopters of SLM practices and zero otherwise, Z_i is a vector of covariates in the sample selection equation, ϵ_i is the composed error term of the stochastic frontier model that takes into account the conventional error (v_i) and inefficiency term (u_i), ω_i is the error term of the selection equation, while γ and ϑ are parameters to be estimated. It is assumed that the inefficiency term u_i follows a half-normal distribution with the dispersion parameter σ_u, while ω_i and v_i follow a bivariate normal distribution with variances 1 and σ_v^2, respectively. The correlation coefficient, $\rho\sigma_v$ (if significant), indicates self-selection bias implying that estimates of the standard SPF model would be inconsistent (Kumbhakar et al., 2009; Greene, 2010). The two-stage estimation procedure, as well as the log-likelihood function of this model are described in Greene (2010). Thus, two separate selectivity corrected SPF's are estimated. From the two estimated stochastic frontier models, we can derive the group-specific technical efficiency estimates ($TE_{ij} = E[e^{-u_{ij}},\ j = 1,0]$ for adopters and non-adopters, respectively.

By comparing these technical efficiency estimates, we are able to assess whether or not the farm productivity of adopters and of non-adopters is closer to the production frontier of their respective groups. However, the group technical efficiency estimates do not allow for effective comparison of the productivity to be made about the adopters and non-adopters of SLM technology as it does not account for technological differences (O'Donnell et al. 2008). The adoption of SLM practices generally results in heterogeneous production technologies undertaken by smallholder farmers (O'Donnell et al 2008; Khanal et al. 2018). Such technology differences can be measured by the gap between the metafrontier and group-specific frontiers. Therefore, we follow Huang et al.'s (2014) approach to obtain a meta-frontier that envelopes the production frontiers of the two groups of farmers.

Stochastic meta-frontier framework

According to Huang et al. (2014), technical efficiency is derived from estimating a production frontier for each group (adopters and non-adopters) as follows:

$$Y_{ij} = f^j(X_{ij}, \vartheta_j)e^{v_{ij}-u_{ij}}, \qquad j = \text{adopters, nonadopters} \tag{6}$$

where Y_{ij} denotes the farm revenue and X_{ij} refers to the vector of inputs of the ith farm household in the jth group, v_{ij} is the conventional error term that captures stochastic noise; u_{ij} represents technical inefficiency and ϑ_j are parameters to be estimated. It is assumed that v_{ij} and u_{ij} and uncorrelated and u_{ij} follows a truncated-normal distribution (Huang et al. 2014). Consequently, TE derived from the model specific to each household and adoption status can be stated as:

$$TE_{\boldsymbol{i}}^{\boldsymbol{j}} = \frac{Y_{ij}}{f^j(X_{ij}, \vartheta_j)e^{v_{ij}}} = e^{-u_{ij}} \tag{7}$$

Let $f^M(X_{ij}, \vartheta_j)$ denotes the common meta-frontier (MF), which envelops the group frontiers of both adopters and non-adopters. This is expressed relative to the group frontier as:

$$f^j(X_{ij}) = f^M(X_{ij}, \vartheta_j)\boldsymbol{e}^{-\boldsymbol{u}_{\boldsymbol{ij}}^{\boldsymbol{M}}}, \forall\, i, j \tag{8}$$

where $u_{ij}^M \geq 0$. Thus, $f^M(X_{ij}, \vartheta_j) \geq f^j(X_{ij}, \vartheta_j)$ and therefore, the ratio of the group frontier to the MF referred to as the meta-technology gap ratio (TGR) can be expressed as:

$$TGR = \frac{f^j(X_{ij}, \vartheta_j)}{f^M(X_{ij}, \vartheta_j)} = \mathrm{e}^{-\mathrm{u}_{\mathrm{ij}}^{\mathrm{M}}} \leq 1 \tag{9}$$

The technical efficiency with respect to the meta-frontier production technology $f^M(.)$ (MTE) is determined as:

$$MTE = \frac{Y_{ij}}{f^M(X_{ij}, \vartheta_j)e^{v_{ij}}} = TGR_{ij} * TE_{ij} \tag{10}$$

Thus, a relatively high average TGR for a specific technology group (e.g. adopters) suggests a lower technological gap between farmers in that group compared to all available set of production technology represented in the all-encompassing production frontier.

DEA approach and environmental efficiency

In this section we present data envelopment analysis (DEA) approach for relative productivity efficiency scores, as well as environmental efficiency analyses (from EIQ slacks). The DEA is a nonparametric method that enables us to handle multiple inputs and outputs in efficiency analyses. In this study we employ an input-output oriented DEA as presented in Ji and Lee (2010). The model uses available data on K inputs and M outputs for each of the N decision-making units (DUM's) to obtain efficiency scores and slacks for inputs and output. Input and output vectors are represented by the vectors x_i and y_i, respectively for the ith farm. The data for all farms may be denoted by the $K\ x\ N$ input matrix (X) and $M\ x\ N$ output matrix (Y). The envelopment form of the input-oriented DEA model is specified as:

$$\min_{\theta,\lambda} \theta \tag{11}$$

subject to: $\theta x_i - X\lambda \geq 0, \;\; Y\lambda \geq y_i, \lambda \geq 0,$

where λ is semipositive vector in R^k and θ is a DEA efficiency score. An efficiency value (θ) of one indicates that the farm is technically efficient. In the DEA procedure, equation 11 is presented as:

$$\min_{\theta,\lambda} \theta \tag{12}$$

subject to: $\theta x_i - X\lambda - s^- = 0,\; Y\lambda + s^+ = y_i$

$\lambda \geq 0$, where s^+, s^- and λ are semipositive vectors (DEA reference weights). Input *excesses* (s^-) and the output *shortfalls* (s^+) are identified as "slacks" as indicated by Cooper et al. (2007). Thus, slacks (s^-) in herbicide captured by EIQ can be an indication of environmental inefficiency.

Determinants of technical efficiency and environmental inefficiency

The choice of regression model for the second-stage of DEA analysis is not a trivial econometric problem, as the standard OLS is generally considered inappropriate (McDonald 2009). Many previous studies employed the Tobit in the second-stage DEA (e. g., Bravo-Ureta et al. 2007; Veettil et al. 2017) to relate socioeconomic variables to efficiency scores. To address the problem of inconsistent estimates associated with OLS and Tobit, McDonald (2009) and Ramalho et al (2010) proposed fractional regression models (FRM) in the second-stage analyses of the determinants of efficiency scores. Contrary to the generalized linear and Tobit models, the FRM deals with dependent variables defined on the unit interval, irrespective of whether or not the boundary value (0, 1) is observed (Ramalho et al. 2010). Thus, guided by the preceding arguments and in addition to the fact that FRM's can be estimated by qausi-maximum likelihood (QML) methods that do not require assumptions about the distribution of the DEA efficiency scores (Ramalho et al. 2010), the present study employs the FRM to assess the determinants of technical and environmental efficiency scores (slacks of EIQ).

From the DEA analysis we extracted the efficiency scores and input slacks which signify inefficiencies with respect to input allocation. As argued by Cooper et al. (2007), a DMU (i.e., farm in our case) is considered to be fully efficient when the DEA score equals one and all slacks are zero (0). Let the relationship between the DEA scores (efficiency scores and slacks of EIQ) ($\boldsymbol{DEA_{EFFi}}$) and a vector of socio-economic variables be expressed as:

$$\boldsymbol{DEA_{EFFi}} = \vartheta z_i + \Gamma_i \quad (13)$$

where z is a vector of explanatory variables such as age, household size, extension access, credit access and participation in off-farm work, ϑ is a vector of coefficients to be estimated and Γ is the error term. Since the DEA scores fall within the boundaries of 0 and 1, we employ FRM to estimate equation 13. Ramalho et al. (2010) employed the following Bernoulli Log-likelihood specification:

$$L_i(\beta, \alpha) = y_i \ln(G(\vartheta z_i)) + (1 - y_i)\ln(1 - G(z_i)) \quad (14)$$

where $0 \leq y_i \leq 1$ denotes the dependent variable equivalent to $\boldsymbol{DEA_{EFF}}$ in our study, while z is as defined earlier. As indicated by Solis et al (2007), z includes managerial characteristics such as adoption status, experience (age), gender of farmer (DMU), access to credit, extension contacts, off-farm work participation and the land usufruct right[44] operated by the DMU. Thus, the estimation in equation 13 is well defined for $0 < G(z_i) < 1$. According to Papke and Wooldridge (1996), the Bernoulli QMLE β or α is consistent and $\sqrt{N}$ asymptotically normal regardless of the distribution of the DEA efficiency scores, $\boldsymbol{DEA_{EFFi}}$ or y_i, conditional on z, and no special need for adjustments for extreme values of zero and one for y_i. Therefore, the second-stage QML regression used for the empirical analysis is specified as:

$$\boldsymbol{E}(\boldsymbol{DEA_{EFFi}}|z) = G(\delta_0 + \sum_{k=1}^{k} \vartheta_k z_{ki} + \eta_i), \qquad (15)$$

where $\mathrm{DEA_{EFFi}}$ and z are as earlier defined and G(.) is the logistic function. We used the DEA-efficiency scores, as well as the slacks for (excess EIQ expressed as fraction of the mean) as dependent variables in equation 15 above. In this study, we considered different variants of the FRM, particularly the logit, probit, loglog and complementary loglog (cloglog) functional specifications (see Ramalho et al. 2010 for the various specifications). The marginal effects irrespective of the specification is stated as $\frac{\partial E(y|z)}{\partial z_k}$ (see, Ramalho et al. 2010). The adoption variable, which is captutred as part of $\boldsymbol{z}$ in equation 15 may be endogenous because some SLM practices (e.g., zero-tillage and minimum tillage) rely mainly on the use of herbicides to control weeds and such farmers will tend to generate higher excess EIQ. On the other hand, lower slacks of EIQ may be associated with non-adopting farmers, as they may be employing more non-herbicide weed control measures. We employed Wooldridge's (2015) control function (CF) approach to address the pontential endogeneity of adoption in this context.

[44] Farm land in the northern Savannah agro-ecological zones is considered a community property and its use is often governed by customary rights or usufruct rights (see Kansanga et al. 2018). Thus, the duration of usufruct right may influence farmer investment and for that matter the efficiency level of the household

In the CF approach, the adoption variable is expressed as function of the rest of the variables in z, together with an instrument. The generalized residual in the auxiliary probit regression is retrieved. The adoption variable and the residual are then included as explanatory variables in equation 15. We used farmer's perceived vulnerability to drought as an instrument in the first-stage. Farmer's perceived vulnerability to drought has been found to significantly influence their decisions to adopt SLM, but it (vulnerability to drought) may not necessarily influence efficiency or EIQ slacks.

5.2 Data and descriptive statistics

The data for this study came from a survey that was conducted in 2016 between June and July in 25 communities across five districts in Ghana. A multistage random sampling procedure was employed to select and interview 476 households across three regions; Upper East (UE), Northern Region (NR) and Brong-Ahafo (BA) regions. Based on agroecology, we selected five districts (Bongo and Talinse in UE, Tolon and Kumbungu in NR, and Techiman-South in BA). We took into account the land size and farmer population of the Guinea Savannah and put greater weight on the sub-sample from the NR. Finally, we obtained 203 households for NR, 147 households for the UE and 126 households for the BA.

We analyze a household-level productivity model. As such, the dependent variable in the production function is the total value of household food crop production. This variable, measured in Ghana cedis (GHS), represents the sum of household's crop production (including self-consumption), following the examples of Solis et al. (2007) and Kato et al. (2011) for mixed-crop farming situations. Following common practice, the control variables in the household production function reflect mainly production inputs and farm characteristics (Coelli and Battese 1992; Solis et al. 2007). Inputs include the area of land cultivated measured in hectares, labor (value of hired and family labor) and capital inputs (value of fertilizer and seed) also measured in Ghana cedis, as well as the quantity of Roundup herbicide used. In addition, we determined the environmental impact quotient (EIQ) values in Roundup based on the quantity (volume, mass) of herbicide used, the active ingredient (glyphosate) and rate of application. This variable is constructed using equation 16 below that has been configured into an online calculator for easy application (see Figure A2 in the Appendix).

Glyphosate environmental impact quotient (EIQ)

As noted earlier, the EIQ is regarded as a comprehensive index for assessing pesticides[45] risks in agricultural production systems (Kovach et al. 1992). The EIQ captures three components, namely farm worker, consumer and ecological effects, and it is calculated as:

$$EIQ = C[(DT * 5) + (DT * P)] + \left[\left(C * \frac{S+P}{2} * SY\right) + L\right] + \left[(F * R) + \left(D * \frac{(S+P)}{2} * 3\right) + (Z * P * 3) + (B * P * 5)\right]\}/3 \quad (16)$$

Where C is chronic toxicity, DT is dermal toxicity, SY is systemicty, F is fish toxicity, L is leaching potential, R is surface loss potential, D is bird toxicity, S is soil half-life, Z is bee toxicity, B is beneficial arthropod toxicity and P is plant surface half-life. We used the calculated field EIQ[46] values as the potentially detrimental input in a DEA approach to estimate efficiency scores and EIQ input slacks. The EIQ field use rating is expressed as $EIQ_{field\ use} = EIQ * \ AI * \ rate\ of$ application. From the Table 5.1, the mean field-use EIQ values are 15.9 and 10.7 for adopters and non-adopters respectively, suggesting that adopters use more Roundup herbicide.

We also captured information on socio-economic variables including education of household head, household size, age of household head, membership in a farmers' group and access to

[45] Pesticides include weedicides (herbicides)
[46] The calculation was done using the online EIQ calculator of the New York State Integrated Pest Management Website at: nysipm.cornell.edu/eiq/calculator-field-use-eiq/, based on quantity of weedicide farmers reportedly used in the previous season.

extension. Farmers' credit constraint[47] was measured as a dummy variable to capture access to credit. The descriptions, means and standard deviations of variables are captured in Table 5.1. The mean age of the household head of adopters and non-adopters is about 40 years, with an average of 5 years of schooling. The reported mean schooling of both groups in our sample reflects the generally low level of education among Ghanaian farmers (GSS 2012). The household size of both groups 6.1 and 5.5 persons for adopting and non-adopting households, respectively, also reflects the high average household size (about 6 persons) in the study area, compared to the national average of 4.5 (GSS 2012).

Table 5.1: Definition of variables and descriptive statistics

Variable	Description	Adopter	Non-adopter	Pooled	SD
Output					
Farm revenue	Total value of household production including self-consumption in GHS	2751.98	1965.57	2474.37	2141.67
Inputs					
land	Farm size in hectares	2.10	1.69	1.96	1.48
Labour	Value of labour (hired and family)	219.62	109.88	182.73	530.66
Capital	Expenditure on fertilizer and seed (GHS)	157.49	92.35	135.59	320.74
Herbicides	Monetary value of Roundup herbicide	68.66	37.46	58.17	204.49
EIQ value	Environmental impact quotient (EIQ) field use value of Glyphosate-based herbicide; calculated using the EIQ-calculator (see Figure A2)	15.91	10.69	14.16	43.79
Farm and HH characteristics					
Age	Age of farmer in years	39.49	39.92	39.64	13.83
Education	Number of years of formal education	5.96	4.96	5.62	4.70
Household size	Number of household members	6.15	5.47	5.92	3.02
Offarm	Farmer participates in off-farm work=1, 0 otherwise	0.35	0.45	0.39	0.49
Extension	Number of contacts with extension personnel	0.55	0.26	0.45	0.50
FBO-Memb	Farmer belongs to a group/ association =1, 0 otherwise	0.17	0.14	0.16	0.36
Vulnerability to drought	Perceived high vulnerability to drought=1, 0 otherwise	0.24	0.41	0.30	0.46
weatherinfo	Farmer is informed about local weather =1, 0 otherwise.	0.50	0.43	0.45	0.50

[47] Credit constraint farmers are those who failed to obtain any amount or only got part of what they requested.

Credit constraint	Farmer applied for credit and did not get enough or failed to get it =1, 0 otherwise	0.42	0.36	0.40	0.49
Farm machinery	Farmer owned tractor, power-tiller/motorking=1, 0 otherwise	0.10	0.21	0.17	0.38
Tenure type	Farmer has user right over farm land for five or more years = 1, 0 otherwise	0.72	0.61	0.68	0.47
SS	Sudan savanna=1,0 otherwise	0.26	0.41	0.31	-
GS	Guinea savanna=1, 0 otherwise	0.49	0.31	0.43	-
TZ	Transitional zone=1, 0 otherwise	0.26	0.28	0.26	-

5.3 Analytical Strategy

We start with the PSM method following Bravo-Ureta et al. (2012) and Villano et al. (2015). First, a probit model was estimated using observable farm and household characteristics in order to generate an adoption propensity score. Information on socio-demographic and farm characteristics was included in the probit model used for the propensity score matching. We employed the nearest neighbor matching algorithm with a maximum of five matches and caliper of 0.01. The matching procedure yielded a sample of 466 matched observations, made up of 307 adopters and 159 non-adopters, respectively. Table 5.A1 in the appendix presents the descriptive statistics for the matched and unmatched samples of adopters and non-adopters. As opposed to the significant differences between adopters and non-adopters in most of the variables in the unmatched sample, no significant differences in the observed characteristics are found in the matched sample, an indication that the balancing condition is satisfied (Caliendo and Kopeinig 2008). As expected, the common support condition is also satisfied and the interval of the estimated propensity scores is between 0.2 and 0.8 as shown in Figure 5.1.

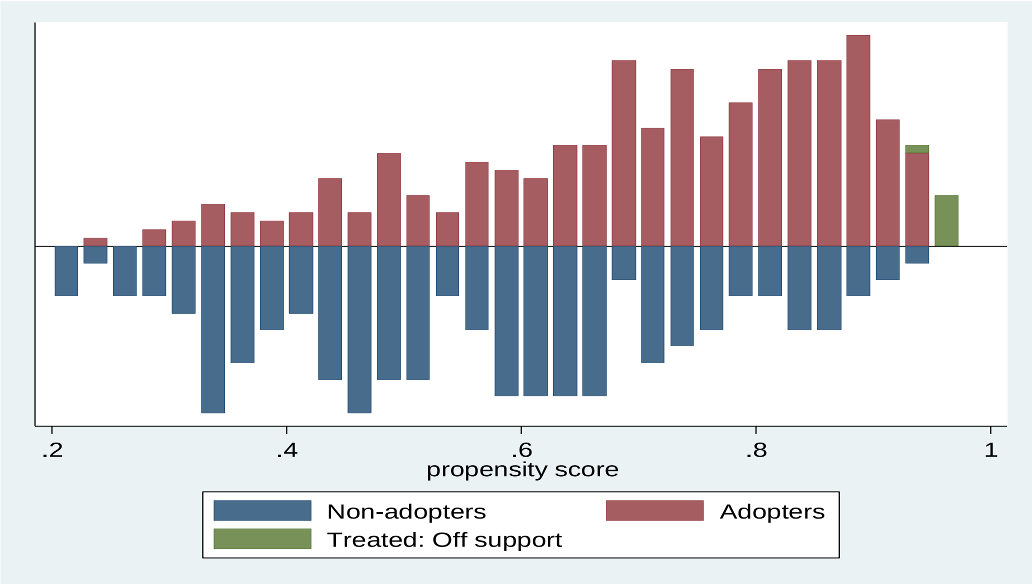


Figure 5.1. Propensity score distribution and common support for propensity score estimation

After generating the matched samples we estimated the sample selectivity bias corrected SPF model. The adoption equation is first estimated using a Probit model. According to Greene (2010) the SPF for an adopter is observed when $A = 1$. Therefore, for the sub-sample where $A = 1$, the SPF for adopters is estimated. In the same way, we estimated the selection model for non-adopters where the dependent variable for non-adopters in the adoption equation is 1 for non-adopters and 0 for adopters (see Green 2010, Gonzalez-Flores et al. 2014 for detail description of the approach).

In order to obtain the TE measures that come from models that have been corrected for biases arising from both observable and unobservable variables, we estimated a series of models, including a conventional unmatched pooled sample model with SLM adoption dummy as an independent variable. However, we focus on (a) matched sample pooled model, with SLM adoption as an explanatory variable. This type of estimation corrects for selection bias from observable characteristics only; (b) two SPF models, one for adopters of SLM and one for non-adopters, using the Greene's (2010) sample selection model, which corrects for selection biases from both observable and unobservable variables.

Preliminary comparisons led to the rejection of the Cobb-Douglas (CD)[48] in favour of the translog (TL) functional form. Thus, the specification of the TL function for the stochastic frontier used in our analyses is expressed as:

$$lnY_i = \alpha_0 + \sum_{k=1}^{4} \alpha_k lnX_{ik} + \frac{1}{2}\sum_{j=1}^{4}\sum_{k=1}^{4} \alpha_{jk} lnX_{ij}\, lnX_{ik} + \sum_{l=1}^{2} \beta_l lnD_l + v_i - u_i \qquad (17)$$

where Y_i represents output (total value of production) of the ith household, X_{ij}, X_{ik} is the quantity of input j or k, for $j \neq k$; D captures dummy variables; α and β are parameters to be estimated; v_i and u_i are the components of the composed error term ε. The four inputs land cultivated, labor, capital and herbicide, as well as agro-ecological zone dummies (D_l) were employed in the TL function. The estimation of the conventional SPF for both matched and unmatched samples were performed using STATA 13 while NLOGIT 5 was used to estimate the sample selection SPF models.

The second aspect of the empirical analysis involves nonparametric estimation of environmental efficiency. To do that we run a DEA to obtain efficiency scores and the input slacks. We employed the procedure developed by Ji and Lee (2010) in STATA, where we capture the four inputs (land, labor, and capital and EIQ and one output (total revenue). Higher slacks with respect to field EIQ implies excess use of glyphosate herbicide, which might indicate environmental inefficiency (Myers et al. 2016; Watkins et al. 2018). As indicated by Tone (2001), a slacks-based measure provides a more suitable model to capture DMU's (farm) performance especially if the goal is to enhance desirable output and minimize undesirable outputs and inputs.

[48] A specification test using the pooled showed a chi-square of 73.57 at 1% p-value, rejecting the CD in favor of the TL.

5.4 Results and discussions

Tables 5.2 and 5.3 present the maximum likelihood estimates of separate SPF models for the unmatched and matched samples, respectively. For each table, column (1) contains the pooled sample estimates while columns (2) and (3) represent sample selection SPF estimates for adopters and non-adopters of SLM. The fourth column represents the estimates of the metafrontier. The group sample estimates in Table 5.2 (unmatched sample) corrected for sample selectivity bias from unobservable factors, while their counterpart in Table 5.3 (matched) corrected for selectivity bias from both observable and unobservable factors. The inefficiency terms ($\sigma(\boldsymbol{u})$) in all SPF models are significant, suggesting that most of the farmers are producing below the production frontier. The sample selectivity term (ρ) for adopters is negative and statistically significant in both the unmatched and matched samples, an indication of the presence of selectivity bias from unobserved factors and lending support to the use of the sample selectivity framework to estimate the SPF (Greene 2010). Thus, accounting for selectivity bias is essential for consistent TE estimates in this study (Bravo-Ureta et al. 2012).

The estimates of the Probit model in the SPF selection equation are presented in Table 5.A2 in the appendix. The results of matched sample in that of table showed that *Extension* access and ownership of *machinery* positively and significantly associated with farmers' decision to adopt SLM technology, signifying the role of extension access in technology adoption as observed in earlier studies (e.g. Solis et al. 2007; Abdulai and Abdulai 2017). Farmer's perceived vulnerability to drought also significantly influenced their decision to adopt SLM technology, a finding that is consistent with the study by Kurgat et al. (2018) in Kenya. As noted earlier, we concentrate our discussions concerning the SPF results on the matched sample.

The coefficients of the first order terms for most of the inputs, representing partial elasticities are positive and significant, implying that these inputs contribute to moving farm productivity to the frontier. It is important to note that the coefficient of herbicide, the input that contains the environmentally detrimental active ingredient (glyphosate), is positive in most SPF the models especially in Table 5.3. This implies that the use of herbicides is positively correlated with increased productivity.

Table 5.2: Estimates of conventional and sample selection SPF models: Unmatched sample

	Conventional		Sample selection models				Metafrontier	
LNY	Pooled (P-M)		Adopters		Non-adopters			
	Coef	SE	Coeff	SE	Coeff	SE	Coeff	SE
Constant	7.533***	0.130	7.824***	0.184	6.242***	0.374	7.489***	0.028
Ln(land)	0.126	0.093	0.116	0.120	0.102	0.136	0.127***	0.023
Ln(capital)	0.113**	0.056	0.154***	0.074	0.006	0.145	0.038***	0.014
Ln(labor)	0.132**	0.058	0.041	0.076	0.114***	0.019	0.105***	0.014
Ln(herbicide)	0.1863**	0.072	0.126	0.088	0.057**	0.012	0.070***	0.018
0.5Ln(land)^2	-0.011	0.115	-0.054	0.155	-0.220	0.338	-0.012	0.028
0.5Ln(capital)^2	-0.004	0.018	-0.005	0.028	-0.036	0.048	-0.005	0.004
0.5Ln(labor)^2	-0.031*	0.018	-0.028	0.025	-0.061	0.070	-0.008*	0.004
0.5Ln(herbicide)^2	-0.022	0.026	-0.031	0.043	-0.008	0.130	-0.033***	0.006
Ln(land) x Ln(capital)	-0.012	0.023	-0.037	0.033	-0.006	0.066	-0.013**	0.006
Ln(land) x Ln(labor)	-0.021	0.024	-0.013	0.036	-0.106	0.079	-0.027***	0.006
Ln(land) x Ln(herbicide)	0.066**	0.030	0.0731*	0.043	0.019	0.110	0.060***	0.007
Ln(capital) x Ln(labor)	-0.002	0.007	-0.001	0.010	0.009	0.019	-0.006***	0.002
Ln(capital) x Ln(herbicide)	-0.010	0.008	-0.017	0.011	0.001	0.034	-0.012***	0.002
Ln(labor) x Ln(herbicide)	-0.007	0.007	-0.007	0.009	0.003	0.026	-0.008***	0.002
Adoption	0.345***	0.085	-	-	-	-	-	-
SS	-0.600***	0.102	-0.541***	0.132	-0.624***	0.183	-0.574***	0.025
GS	-0.343***	0.107	-0.291**	0.147	-0.425*	0.250	-0.349***	0.027
$\boldsymbol{\lambda}$	1.246***	0.002					0.282***	0.000
$\boldsymbol{\sigma^2}$	2.118***	0.228					1.632***	0.141
Sigma(u)			1.149***	0.131	1.206***	0.262		
Sigma(v)			0.526***	0.111	0.561***	0.150		
$\boldsymbol{\rho}$(w,v)	-	-	-0.730***	0.212	0.203	0.412	-	-
N	476		316		160		476	
Log likelihood	-597.54		-493.749		-362.83		80.304	

*, ** and *** refers 10%, 5% and 1% significant levels, respectively.

Table 5.3 Estimates of conventional and sample selection SPF models: Matched sample

	Conventional		Sample selection models				Metafrontier	
	Pooled sample		Adopters		Nonadopters			
	Coef	SE	Coeff	SE	Coeff	SE	Coeff	SE
Constant	6.968***	0.362	7.420***	0.290	7.751***	0.507	6.717***	0.290
Ln(land)	0.289***	0.052	0.367***	0.058	0.391***	0.045	0.306**	0.153
Ln(capital)	0.110	0.070	0.065	0.041	0.040**	0.011	0.117***	0.028
Ln(labor)	0.142**	0.062	0.070***	0.018	0.092	0.217	0.092***	0.029
Ln(herbicide)	0.121***	0.015	0.082***	0.026	0.027*	0.014	0.122**	0.033
0.5Ln(land)^2	-0.103	0.179	-0.138	0.099	-0.738	0.977	0.013	0.138
0.5Ln(capital)^2	-0.898*	0.461	0.003	0.019	-0.033	0.047	-0.004	0.008
0.5Ln(labor)^2	-0.008	0.019	-0.019	0.034	-0.069	-0.074	-0.047***	0.008
0.5Ln(herbicide)^2	-0.125***	0.034	-0.026	0.018	- 0.301**	0.132	0.045***	0.011
Ln(land) x Ln(capital)	-0.043	0.077	0.040*	0.022	-0.043	0.117	-0.072***	0.017
Ln(land) x Ln(labor)	0.171**	0.063	0.041	0.036	-0.147***	0.038	-0.012	0.018
Ln(land) x Ln(herbicide)	0.030	0.045	0.050	0.101	0.063	0.195	0.118***	0.021
Ln(capital) x Ln(labor)	0.027	0.062	0.007	0.002	0.009	0.018	0.001	0.003
Ln(capital) x Ln(herbicide)	0.241	0.132	0.011	0.008	1.3E-3	0.037	-0.021***	0.003
Ln(labor) x Ln(herbicide)	-0.300	0.149	0.007	0.007	0.002	0.027	-0.010***	0.003
Adoption	0.346***	0.085	-	-	-	-	-	-
SS	-0.510***	0.107	-0.112	0.337	-0.623***	0.183	-0.337***	0.111
GS	-0.209***	0.018	-0.625***	0.106	-0.428*	0.254	-0.625***	0.106
λ	0.310***	0.090					0.292***	0.001
σ^2	1.480***	0.761					1.532***	0.141
Sigma(u)			1.27***	0.117	1.108***	0.283		
Sigma(v)			0.495***	0.115	0.677***	0.138		
ρ(w,v)	-	-	-0.709***	0.225	0.274	0.372		
N size	466		307		159		466	
Log likelihood	-597.54		-496.33		-368.139		-7.732	

*, ** and *** refers 10%, 5% and 1% significant levels, respectively.

It is also important to mention that farmers in the Transitional agro-ecological zone (the reference location) are likely to be more productive compared to their counterparts in the Sudan Savannah (SS) or Guinea Savannah (GS) agro-ecological zones. This indicates the importance of capturing agro-ecological differences in specifying agricultural production functions (Mayen et al. 2010). Apart from capturing climatic effects the agro-ecological zone differences may also capture unmeasured location specific institutional differences that may influence productivity.

Technical efficiency (TE) and technology gap ratios (TGR)

Table 5.4 presents the TE scores and TGR obtained from the estimated sample-selectivity SPF and meta-frontier models. In the unmatched sample, the TE estimates for adopters (55%) appear to be significantly higher than non-adopters (49%).

Table 5.4 TE scores with the estimated models

	Unmatched Sample				Matched Sample			
Item	Mean	sd	min	max	Mean	Std. Dev.	Min	Max
Adopters								
TE	0.550*** [2.826]	0.181	0.083	0.863	0.470 [0.494]	0.220	0.050	0.860
TGR	0.869*** [15.165]	0.030	0.765	0.973	0.95*** [21.00]	0.070	0.630	1.000
MTE	0.474*** [6.06]	0.159	0.070	0.767	0.430* [1.820]	0.180	0.054	0.800
Non-adopters								
TE	0.490	0.206	0.461	0.526	0.460	0.170	0.080	0.800
TGR	0.768	0.110	0.471	0.969	0.883	0.012	0.140	0.984
MTE	0.378	0.169	0.035	0.737	0.397	0.170	0.049	0.750
Pool (adopters and Non-adopters)								
TE	0.460	0.192	0.056	0.850	0.440	0.200	0.050	0.860
MTR	0.835	0.083	0.471	0.973	0.800	0.230	0.140	1.00
MTE	0.442	0.169	0.035	0.767	0.350	0.200	0.030	0.860

*, ** and *** refers 10%, 5% and 1% significant levels, respectively

With the matched sample however, the difference in TE between adopters and non-adopters appear to have vanished (i.e. 47% and 46% for adopters and non-adopters, respectively). To make a more reasonable comparisons across groups, a meta-frontier regression was ran using

Huang et al.'s (2014) approach and the gaps between the meta-frontier and the individual group frontiers (meta-technology gap ratio (TGR)) was derived, with higher TGR indicating better return from technology. The technical efficiency with respect to the meta-frontier (MTE) was then calculated. The results (Table 5.4, matched sample) indicate that the average TGR for adopters is about 0.95, ranging from 0.63 to 1. However, the TGR among non-adopters ranges from 0.14 to 0.98, with an average of 0.88.

The MTE scores indicate that on average, SLM technology farms are about 43% technically efficient, while the non-SLM technology farms are 40% technically efficient. In the unmatched sample however, the MTE scores for adopters and non-adopters of SLM technology are 47% and 38%, respectively. With respect to the matched sample, these findings suggest that with same level of inputs, SLM technology tends to increase TE by 7.5% among adopters compared to non-adopters. Although the differences in TE between adopters and non-adopters appear marginal, compared to experimental reported yield difference between adopters and non-adopters, our results are still consistent with the previous findings of positive impact of SLM on farm performance (Zougmore et al. 2014; MoFA 2016). Farmers who shift from conventional farming to apply SLM practices (stone and soil bunds, organic manure and cover crops) might be the ones with higher managerial abilities and who are also more environmentally conscious. To show how the two groups perform in terms of expected farm revenues, we predicted and compared their frontier outputs for both unmatched and matched samples (Table 5.5). The results showed that adopters performed better in terms of expected farm revenues with much higher performance coming from the matched sample, confirming output enhancement potential of SLM.

Table 5.5 Predicted frontier of log farm revenues of adopters and non-adopters in unmatched and matched samples

	Adopter	non- adopter	ATT	% change log farm revenue	t-statistic
Unmatched sample	8.320	8.042	0.278***	3.5	7.37
Matched sample	8.710	8.025	0.685***	8.5	19.42

*, ** and *** refers 10%, 5% and 1% significant levels, respectively. T-statistic is based on the mean difference between the predicted frontiers of adopters and non-adopters.

DEA analysis and Input slacks among adopters and non-adopters

The distribution of the DEA efficiency scores are shown in Figure 5.A1 in the appendix. The results confirmed that adopters generally obtained higher efficiency scores than non-adopters. The TE scores of the pooled sample appear to be normally distributed, but the distributions are negatively skewed among adopters and non-adopters, with higher number of adopters (42%) compared to 36% of non-adopters obtaining efficiency scores 60%-80%. The DEA analysis also revealed the existence of slacks in some inputs. Since a slack indicates excess of an input, a farm household can reduce its use of such input by the quantity of slack without reducing its output. From Figure 5.2, it is obvious that adopters and non-adopters make excess use of herbicides (excess field EIQ) at an average of 57% and 26%, respectively.

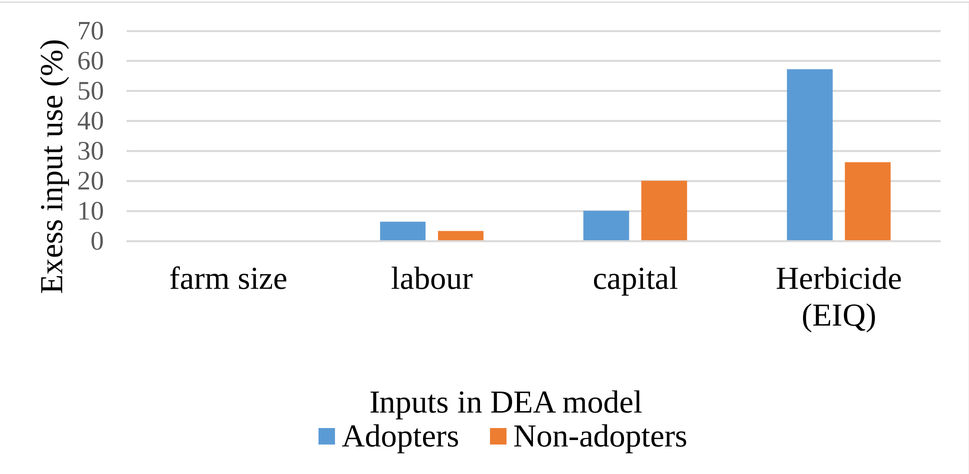


Figure 5.2: Input slacks from DEA model by adoption status

Since excess use of herbicides has environmental implications, we discuss the determinants of excess field EIQ (excess glyphosate) in the next section.

Determinants of technical and environmental efficiency

In the context of policy, it is more useful to determine what influences efficiency/inefficiency (i.e., the variables to which TE and environmental inefficiency are related). Thus, the DEA scores were regressed on specific household socioeconomic characteristics variables using the fractional regression models (FRM), following the example of recent studies (e. g., Ramalho, Ramalho and Henriques 2010; Ogundari 2014) and Abdulai and Abdulai (2017). For each of the FRM's in Table 5.6, we report the specification test statistic[49]. All the models of the FRM (with respect to the TE scores) show similar test statistics, an indication that all the competing models fit out data (Ramalho et al. 2010). We address potential endogeneity of some explanatory variables (particularly, adoption status and off-farm work participation) using the CF approach by Wooldridge (2015). Based on the *RESET* test for misspecification, we discuss the determinants of DEA efficiency scores using the complimentary log-log (cloglog) specification (Table 5.6, column 4).

The estimates show that TE scores are significantly influenced by adoption status, credit access, extension access, as well as household size. On the on the other hand, environmental inefficiency appears to be influenced also by adoption of SLM, credit access and usufruct right/tenure security.

[49] We used the RESET test statistic based on the fitted power of the response index (Ramalho et al 2010).

Table 5.6 Determinants of technical efficiency and environmental inefficiency (excess EIQ)

	(1) Logit		(2) probit		(3) loglog		4 cloglog	
Variable	Coef	SE	Coef	SE	Coef	SE	Coef	SE
Determinants of technical efficiency								
Age	-0.001	0.003	0.000	0.002	-0.001	0.002	0.000	0.002
Adoption	0.308***	0.090	0.190***	0.055	0.198***	0.059	**0.242*** **	0.070
Household size	0.054***	0.014	0.034***	0.008	0.037***	0.010	**0.039*** **	0.010
Education	0.006	0.008	0.004	0.005	0.004	0.005	0.005	0.006
Offarm	-0.001	0.080	0.000	0.049	0.004	0.053	-0.003	0.060
Credit_const	-0.143*	0.080	-0.088*	0.050	-0.091*	0.055	**-0.112* **	0.060
Extension	0.315***	0.083	0.196***	0.052	0.214***	0.057	**0.238*** **	0.062
Tenuretpye	-0.020	0.085	-0.012	0.053	-0.013	0.057	-0.015	0.064
Adopt_resid	-0.110	0.210	-0.111	0.230	-0.110	0.210	-0.120	0.210
Offfarmresid	0.008	0.011	0.008	0.012	0.010	0.021	0.009	0.013
Constant	-1.086***	0.194	- 0.674***	0.119	-0.360**	0.125	- 1.191***	0.149
Test statistic[a]	1.08		0.98		2.05		**0.37**	
p-value	0.298		0.322		0.152		**0.543**	
Sample size	466		466		466		466	
Log pseudolikelihood	-314.80		-314.83		-314.9		-314.82	
Determinants of environmental inefficiency (% excess EIQ)[b]								
Age	0.006	0.005	0.003	0.003	0.003	0.002	0.006	0.005
Adoption	0.515**	0.178	0.267**	0.096	0.204**	0.078	**0.481*** **	0.163
Household size	-0.009	0.023	-0.005	0.013	-0.005	0.011	-0.007	0.021
Education	-0.021	0.016	-0.012	0.009	-0.010	0.007	-0.019	0.014
Offarm	0.005	0.143	0.005	0.081	0.007	0.069	0.004	0.128
Credit_const	0.224*	0.135	0.116	0.076	0.089	0.064	0.211*	0.122
Extension	0.043	0.142	0.019	0.080	0.011	0.067	0.045	0.128
Tenuretpye	1.012***	0.202	0.535***	0.102	0.424***	0.079	**0.944*** **	0.192
Adoptresid	-0.219	0.290	-0.203	0.280	-0.199	0.210	-0.217	0.300
Offfarmresid	0.344	0.309	0.358	0.299	0.324	0.320	0.345	0.319
Constant	-3.049***	0.388	- 1.709***	0.206	- 1.151***	0.166	- 3.057***	0.355
Test statistic	4.95		4.29		3.14		3.38	
p-value	0.031		0.032		0.066		0.076	
Sample size	183		183		183		183	
Log pseudolikelihood	-197.81		-197.95		-198.13		-197.74	

*, ** and *** refers 10%, 5% and 1% significant levels, respectively.

[a]The statistic used to assess misspecification is the Ramsey test RESET test.

[b]In the matched sample, the analysis was restricted to only farmers who applied glyphosate herbicide, because they the only farmers expected to have excess EIQ in our context.

Adoption is positively associated with DEA TE scores, confirming the results of the SPF analysis discussed earlier. This finding is line with the results reported by Khanal et al. (2018) who showed that adoption of soil and water conservation practices by households in Nepal resulted in improved farm efficiency. However, the positive correlation between adoption of SLM and environmental inefficiency (excess EIQ) calls for concern. This implies that adoption of some SLM practices (e. g., minimum/zero-tillage) might be associated with using higher levels of herbicides to control weeds and to ensure minimum soil disturbance. Although our finding is not able indicate the threshold EIQ-level that is considered environmentally unsustainable, our results confirms the heightened concern about increasing levels of glyphosate use in crop production, especially in zero-tillage practices (Myeres et al. 2016). Some recent studies are proposing the use of weed suppressing crops, cover-cropping and mixed cropping to minimize the dependence on herbicides for weed control in sustainable land management and soil conservation systems (Price and Norsworthy 2013; Watkins et al. 2018).

The results also showed a positive and significant relationship between extension access and technical efficiency, but not in the environmental inefficiency models, suggesting that farmers with lower extension contacts tend to be less efficient. Our results are consistent with that Abdulai and Abdulai (2017), who found positive effect of extension access on TE among farmers in Zambia. Although education has the expected sign, the estimate is not statistically significant. The estimate for household size is positive and statistically significant, implying that efficiency of farms are strongly associated with family size. In a meta-analysis of efficiency studies in Africa, Ogundari (2014) reported that 22% of increases in technical efficiency is attributed to household size.

In addition, the results also reveal a negative and significant (only at 10% level) relationship between the variable representing credit constraint and technical efficiency, suggesting that credit constrained farmers tend to be less efficient, a finding that is consistent with other studies in SSA countries (Ogundari 2014). It also agrees with the assertion that enhancing farmers' access to credit could significantly improve their efficiency in food production and reduce food insecurity in SSA (Barrett et al. 2017). The estimate of the variable representing farmland usufruct right/tenure arrangement is positive and significant in the environmental inefficiency models, implying that longer usufruct right is associated with higher environmental inefficiency (EIQ). This may appear strange, but given the fact that farmers with longer usufruct right may be the ones who will be prepared to invest in SLM including practices that may involve the use of more herbicides, this finding is not inconsistent. What we are unable to establish, due to data limitation, is whether organic manure accumulation and microbial activity in the soil enhanced through the SLM adoption involving herbicides, is sufficient to breakdown the excess glyphosate into harmless components.

5.5 Conclusions and implications

In this study, we examined the impact of adoption of SLM on technical efficiency and environmental inefficiency among smallholder farmers in Ghana. We used a metafrontier approach to account for technology differences among farmers practising SLM technology and those using conventional farming technology. We accounted for observable and unobservable selection bias, using PSM and Greene's (2010) sample selection SPF approach. In addition, we used environmental impact quotient of herbicide in a DEA framework to derive percentage excess EIQ scores (slacks), which we used as proxy for environmental efficiency. We then employed FRM to assess the determinants of technical and environmental efficiency.

The empirical results revealed that adoption of SLM technology resulted in increased technical efficiency, suggesting that SLM has the potential to reduce the economic drain. The meta-frontier estimates also showed that SLM technology adopters are 7.5% more technically efficient than the non-adopters. In addition, adopters obtained about 8.5% increase in farm revenues, compared to no-adopters. The results also revealed key drivers of efficiency levels of smallholder food crop famers to be credit access, extension service and household size. In addition, adoption of SLM was found be positively and significantly associated with excess EIQ. Furthermore, access to credit access and land tenure security (longer usufruct right) were also found to be significantly associated with environmental efficiency, implying that credit constraint farmers probably used less herbicides and therefore lower excess EIQ.

Given these findings, the potential role of agriculture in achieving national food security, eradicating poverty and reducing unemployment, may not materialize unless purposeful policy actions are undertaken to address the identified drivers of farmers' technical and environmental efficiency. Particularly, the findings reveal that while we focus on using production technologies that enhance land use sustainability and fertility, we should be mindful of potential harmful effects of excess herbicides, associated with some SLM practices. Thus, the use of herbicides could be driving the higher technical efficiency levels among adopters. At the same time these herbicides, if not properly applied may be the cause of the environmental inefficiency (higher EIQ), especially among adopters. This particular finding is relevant for policy on zero-tillage and other SLM options whose adoption is facilitated by the use of herbicides. For instance, promotion of non-herbicide-based SLM practices such as crop rotations and cover crops, as well as weed-suppressive crop varieties have already proven to be effective in reducing the use of herbicides among certain crops in Kenya and the USA (Kurgat et al. 2018; Watkins et al. 2018). In addition, intensifying farmer education through enhanced extension services and improving access to credit will help improve farmers' efficiency level and food productivity.

References

Abdulai, A. & Abdulai, A. (2017). Examining the impact of conservation agriculture on environmental efficiency among maize farmers in Zambia, *Environment and Development Economics* 22 (2): 177-201.

Adnan, N., Nordin, S. M., Rahman, I., & Noor, A. (2017). Adoption of green fertilizer technology among paddy farmers: A possible solution for Malaysian food security. *Land Use Policy 63*: 38-52.

Battesse, G. E. & Coelli, T. J. (1992) Frontier production functions, technical efficiency and panel data: with application to paddy farmers in India. *Journal Productivity Analysis* 3:153–169.

Barbier, E. B. & Hochard, J. P. (2018). The Impacts of Climate Change on the Poor in Disadvantaged Regions, *Review of Environmental Economics and Policy*, 12(1):26–47

Barrett, C. B., Christiaensen, L., Sheahan, M. & Shimeles, A. (2017). On the Structural Transformation of Rural Africa, *Journal of African Economies* 26 (1): 11–35.

Boahen, P., Dartey, B. A., Dogbe, G. D., Boadi, E. A., Triomphe, B., Daamgard-Larsen, S., & Ashburner, J. (2007). *Conservation agriculture as practiced in Ghana*, African Conservation Tillage Network (ACT), Food and Agriculture Organization of the United Nations, Nairobi, Keyna.

Bravo-Ureta, B. E., Solis, D., Moreira Lopez, V. H., Maripani, J. F., Thiam, A., & Rivas, T.(2007). Technical efficiency in farming: A meta- regression analysis. *Journal of Productivity Analysis*, *27*, 57–72.

Chamberlin, J. (2008). It's a Small World After All: Defining Smallholder Agriculture in Ghana, *International Food Policy Research Institute (IFPRI) Discussion Paper 00823*: 1-36.

Caliendo, M., & Kopeinig, S. (2008). Some practical guidance for the implementation of propensity score matching. *Journal of Economic Surveys*, 22(1), 31–72.

Coupe, R. H. & Capel, P. D. (2015). Trends in pesticide use on soybean, corn and cotton since the introduction of major genetically modified crops in the United States, *Pest Management Science,* 73(5):1013-1022.

Cooper, W. W., Seiford, L. M., & Tone, K. (2007). *Introduction to Data Envelopment Analysis: A Comprehensive Text with Models, Applications, References and DEA-Solver Software.* Second Edition, Springer, New York.

Environmental Protection Agency (EPA) (2011). *Ghana Strategic Investment Framework*

(GSIF) For Sustainable Land Management (SLM) 2011 – 2025, Ministry of Environment, Science and Technology, *EPA*, Accra, Ghana.

Food and Agriculture Organization of the United Nations (FAO) (2011). *Sustainable Land Management in Practice: Guidelines and Best Practices for Sub-Saharan Africa*, FAO, Rome, Italy.

FAO (2013). *Climate Smart Agriculture sourcebook*. Food and Agriculture Organization of the United Nations, Rome, Italy. Online at: www.fao.org/docrep/018/i3325e/i3325e.pdf.

Gibbons, D., Morrissey, C., Mineau, P. (2014) A review of the direct and indirect effects of neonicotinoids and fipronil on vertebrate wildlife. *Environmental Science and Pollution Research* 22:103–118.

Gonzalez-Flores, M., Bravo-Ureta, B. E., Solis, D. & Winters, P. (2014). The impact of high value markets on smallholder productivity in the Ecuadorean Sierra: a stochastic production frontier approach correcting for selectivity bias, *Food Policy* 44: 237–247.

Greene, W. (2010), A stochastic frontier model with correction for sample selection, *Journal of Productivity Analysis* 34: 15–24.

Guyton, K. Z., Loomis, D., Grosse, Y., El Ghissassi, F., Benbrahim-Tallaa, L., Guha, N., Scoccianti, C., Mattock, H., Straif, K. (2015). Carcinogenicity of tetrachlorvinphos, parathion, malathion, diazinon, and glyphosate, International Agency for Research on Cancer (IARC) Monograph Working Group, *Lancet Oncology* 16:490–491.

Huang, C. J., Huang, T. H. & Liu, N. H. (2014). A new approach to estimating the metafrontier production function based on a stochastic frontier framework *Journal of Productivity Analysis* 42:241–254.

Ji, Y. & Lee, C. (2010). Data envelopment analysis, *Stata Journal*, 10(2): 267-280.

Kato, E. Ringler, C. Yesuf, M. & Bryan. E. (2011). Soil and Water Conservation Technologies: A Buffer against production risk in the face of climate change? Insights from the Nile basin in Ethiopia, *Agricultural Economics* (42): 593-604.

Kassie, M., Teklewold, H., Jaleta, M. (2015). Understanding the adoption of a portfolio of sustainable intensification practices in eastern and southern Africa, *Land Use Policy* 42: 400-411.

Kansanga, M., Andersen, P. Atuoye, K. & Mason-Renton, S. (2018). Contested commons: Agricultural modernization, tenure ambiguities and intra-familial land grabbing in Ghana, *Land Use Policy*, https://doi.org/10.1016/j.landusepol.2018.03.047.

Kassam, A. Friedrich, T., Shaxson, F., and Pretty, J. (2009). The spread of Conservation Agriculture: Justification, sustainability and uptake, *International Journal of Agricultural Sustainability* 7(4): 292-320.

Khanal, U., Clevo, W. Boon, L. & Viet-Ngu, H. (2018) Do climate change adaptation practices improve technical efficiency of smallholder farmers? Evidence from Nepal. *Climatic Change*, *147*(3-4): 507-521.

Kovach, J., Petzoldt, C., Degni, J. & Tette, J. (1992). A method to measure the environmental impact of pesticides, in *New York's Food and Life Sciences Bulletin*: New York State Agricultural Experiment Station, No. 139: 1–8.

Kouser, A. S. & Qaim, M. (2015). Bt Cotton, pesticide use and environmental efficiency in Pakistan, *Journal of Agricultural Economics*, 66 (1):66–86.

Kumbhakar, S. C., Tsionas, E. G. and Sipilaeinen, T. (2009). Joint estimation of technology choice and technical efficiency: An application to organic and conventional dairy farming, *Journal of Productivity Analysis* 31: 151–161.

Kurgat, B. K., Ngenoh, E., Bett, H. K., Stöber, S., Mwonga, S., Lotze-Campen, H., & Rosenstock, T. S. (2018). Drivers of sustainable intensification in Kenyan rural and peri-urban vegetable production, *International Journal of Agricultural Sustainability* 16 (4-5): 385-398.

Lee, D. R. (2005). Agricultural Sustainability and Technology Adoption: Issues and Policies for Developing Countries, *American Journal of Agricultural Economics* 87(5): 1325-1334.

Maddala, G. S. (1983), *Limited-Dependent and Qualitative Variables in Economics*, New York: Cambridge University Press, pp. 257-91.

Mal, P., Manjunatha, A. V., Bauer, S., & Ahmed, M. N. (2011). Technical Efficiency and Environmental Impact of Bt Cotton and Non-Bt Cotton in India, *AgBioForum, 14* (3):164-170.

Mayen, C. D., Balagtas, J. V., & Alexander, C. E. (2010). Technology Adoption and Technical Efficiency: Organic and Conventional Dairy Farms in the United States, *American Journal of Agricultural Economics* 92 (1): 181-195.

Ministry of Food and Agriculture (MoFA) (2016). Agricultural Sector Progress Report 2015. *Ministry of Food and Agriculture*, Accra, Ghana.

Ministry of Food and Agriculture (MoFA) (2017). Planting for Food and Jobs Strategic Plan For Implementation (2017-2020), *Ministry of Food and Agriculture*, Accra, Ghana.

Myers, J. P., Antoniou, M. N., Blumberg, B., Carroll, L., Colborn, T., Everett, T. G., Hansen,

M. Landrigan, P. J., Lanphear, B. P., Mesnage, R., Vandenberg, L. N., vom Saal, F. S., Welshons, W. V. & Benbrook, C. M. (2016). Concerns over use of glyphosate-based herbicides and risks associated with exposures: a consensus statement, *Environmental Health* 15 (19):1-13.

Nkonya, E., Mirzabaev, A. & von Braun, J. (2016). Economics of Land Degradation and Improvement: An Introduction and Overview, in Nkonya, E., Mirzabaev, A. & von Braun, J (Eds.), *Economics of Land Degradation and Improvement: A Global Assessment for Sustainable Development,* IFPRI, Washington, D.C.

Nkonya, E., Pender, J., Kaizzi, K. C., Kato, E. Mugarura, S., Ssali, H. & Muwonge, J. (2008). Linkages between Land Management, Land Degradation, and Poverty in Sub-Saharan Africa, *International Food Policy Research Institute*, Report 159. Washington, D.C.

O'Donnell, C.J., Rao, D.S.P. & Battese, G. E. (2008) Metafrontier frameworks for the study of firm-level efficiencies and technology ratios, *Empirical Economics* 34:231–255.

Ogundari, K. (2014) The Paradigm of Agricultural Efficiency and its Implication on Food Security in Africa: What Does Meta-analysis Reveal? *World Development* 64: 690-702.

Papke, L. E. & Jeffrey M. Wooldridge, J. M. (1996). Econometric Methods for Fractional Response Variables with an Application to 401 (K) Plan Participation Rates, *Journal of Applied Econometrics*, 11: 619-632.

Pendell, D. L., Williams, J. R., Rice, C. W., Nelson, R. G., & Boyles, S. B. (2006). Economic Feasibility of No-Tillage and Manure for Soil Carbon Sequestration in Corn Production in Northeastern Kansas, *Journal of Environmental Quality* 35:1364–1373

Price, A. J., and Norsworthy, J. K. (2013). Cover Crops for Weed Management in Southern Reduced-Tillage Vegetable Cropping Systems, *Weed Technology* 27:212–217.

Ramalho, E. A., Ramalho, J. J. S., & Henriques, P. D. (2010). Fractional regression models for Second-stage DEA efficiency analyses. *Journal of Productivity Analysis*, 34, 239–255.

Reinhard, S., Lovell, C. A. K. and Thijssen, G. (2002). Analysis of environmental efficiency variation, *American Journal of Agricultural Economics*, 84: 1054–1065.

Singh, A., Kumar, R. & Das, D. K. (2007). An economic evaluation of environmental risk of pesticide use: a case study of paddy, vegetables and cotton in irrigated eco-system, *International Journal of Agricultural Economics* 62 (3): 492-502.

Skevas, T., Stefanou, S. E. & Lansink, A. O. (2013). Do farmers internalise environmental spillovers of pesticides in production? *Journal of Agricultural Economics*, 64: 624–640.

Tesfaye, A., Brouwer, R., Van der Zaag, P. & Negatu, W. (2016). Assessing the cost and benefits of improved land management practices in three watershed areas in Ethiopia, *International Soil and Water Conservation Research* 4:20-29.

Tone, K. (2001). A slacks-based measure of efficiency in data envelopment analysis. *European Journal of Operational Research* 130 (3): 498-509.

United Nations Development Programme (UNDP) (2018). *Northern Ghana Human Development Report 2018:* Bridging the Poverty Gap and Fostering Socio-Economic Transformation and Empowerment to Contribute to Human Development for All, UNDP-Ghana.

Van Hulst, F. J. & Posthumus, H. Understanding (non-) adoption of Conservation Agriculture in Kenya using the Reasoned Action Approach, *Land Use Policy 56*: 303-314.

Villano, R., B. Bravo-Ureta, D. Solis, and E. Fleming (2015), Modern rice technologies and productivity in the Philippines: disentangling technology from managerial gaps, *Journal of Agricultural Economics* 66(1): 129–154.

Veettil, P. C., Krishna, V. V. & Qaim, M. (2017). Ecosystem impacts of pesticide reductions Through Bt cotton adoption, *Australian Journal of Agricultural and Resource Economics*, 61: 115-134.

Williams, G. M., Aardema, M., Acquavella, J. Berry, S. C., Brusick, D., Burns, M. M., de Camargo, J. L. V., Garabrant, D. Greim, H. A., Kier, L. D., Kirkland, D. J., Marsh, G., Solomon, K. R., Sorahan, T., Roberts, A. & Weed, D. L. (2016) A review of the carcinogenic potential of glyphosate by four independent expert panels and comparison to the IARC assessment, *Critical Reviews in Toxicology*, 46 (1): 3-20.

Watkins, K. B., Gealy, D. R., Anders, M. M., & Mane, R. U. (2018). An Economic Risk Analysis of Weed-Suppressive Rice Cultivars in Conventional Rice Production, *Journal of Agricultural and Applied Economics* 50 (4):478-502.

Wooldridge, J. M. (2015). Control Function Methods in Applied Econometrics, *Journal of Human Resources*, 50 (2):420-445.

World Bank (2009). Republic of Niger: Impacts of Sustainable Land Management Programs on Land Management and Poverty in Niger, *The World Bank*, Report No. 48230-NE.

World Bank 2010. *Economics of Adaptation to Climate Change. Ghana Country Study*. World Bank: Washington, D.C.

Zougmore, R., Jalloh, A. & Tioro, A. (2014). Climate-smart soil water and nutrient management options in semiarid West Africa: a review of evidence and analysis of stone bunds and Zaï techniques, *Agriculture and Food Security*, 3:16.

Table 5.A1 Summary statistics of variables for Matched and unmatched samples

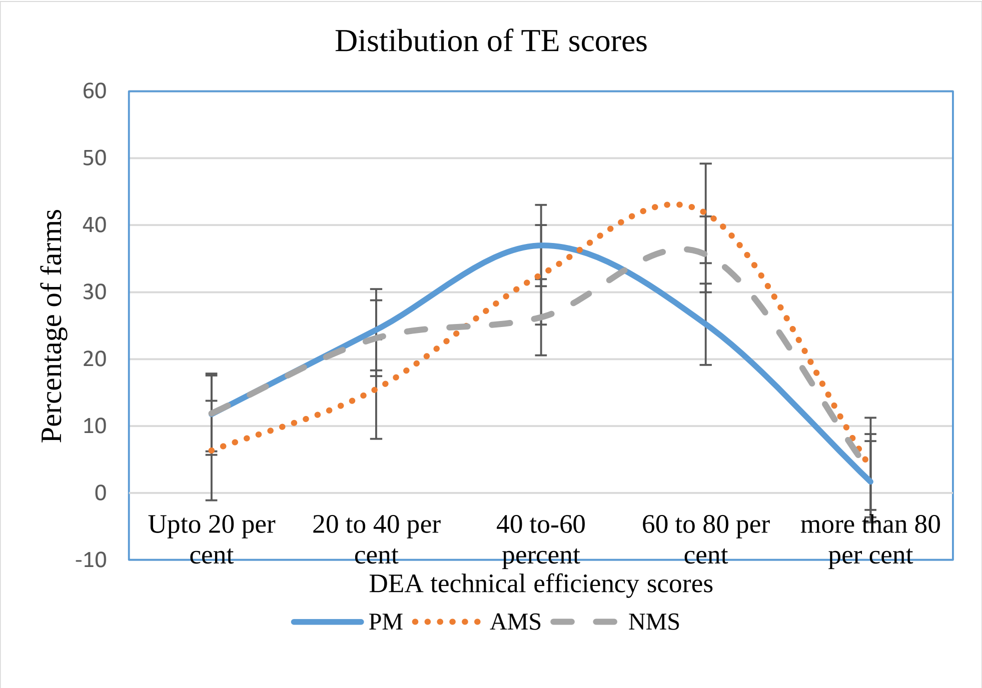
Unmatched sample						
variable	pooled	sd	Adopters	non-adopter	Diff	t-test
Gender	0.84	0.36	0.85	0.82	0.04	1.01
Age	39.64	13.83	39.49	39.92	-0.42	-0.32
Education	5.62	4.70	5.96	4.96	1.00**	2.19
Extension	0.45	0.50	0.55	0.26	0.29***	6.34
Offarm	0.39	0.49	0.35	0.45	-0.10**	-2.03
Fbomem	0.16	0.36	0.17	0.14	0.03	0.85
Weatherinfo	0.45	0.50	0.43	0.51	-0.08	-1.64
Household size	5.92	3.02	6.15	5.47	0.68**	2.34
Vulnerable	0.30	0.46	0.24	0.41	-0.16***	-3.71
Credit-const	0.40	0.49	0.42	0.36	0.06	1.36
Tenuretype	0.68	0.47	0.72	0.61	0.12***	2.64
Machinery	0.17	0.38	0.21	0.10	0.11***	2.99
Farmsize	1.96	1.11	2.10	1.69	0.41***	2.89
Sample size	476		316	160		
Matched Sample						
Gender	0.84	0.37	0.86	0.85	0.01	0.3
Age	39.66	13.88	39.81	40.94	-1.13	-0.93
Education	5.56	4.69	5.79	5.53	0.26	0.67
Extension	0.44	0.50	0.52	0.52	0.00	0.00
Offarm	0.39	0.49	0.16	0.42	-0.27	-1.2
Fbomem	0.15	0.36	0.16	0.17	-0.02	-0.6
Weatherinfo	0.46	0.50	0.45	0.43	0.03	0.64
Household size	5.86	2.88	6.01	6.09	-0.08	-0.36
Vulnerable	0.30	0.46	0.26	0.22	0.04	1.1
Credit-const	0.39	0.49	0.41	0.41	0.00	0.1
Tenuretype	0.68	0.47	0.71	0.72	-0.01	-0.17
Machinery	0.16	0.37	0.18	0.21	-0.03	-1.03
Farmsize	1.90	1.22	1.97	1.83	0.14	1.2
Sample size	466		307	159		

*, ** and *** refers 10%, 5% and 1% significant levels, respectively.

Table 5.A2 Estimates of the Probit selection equation using unmatched and matched samples

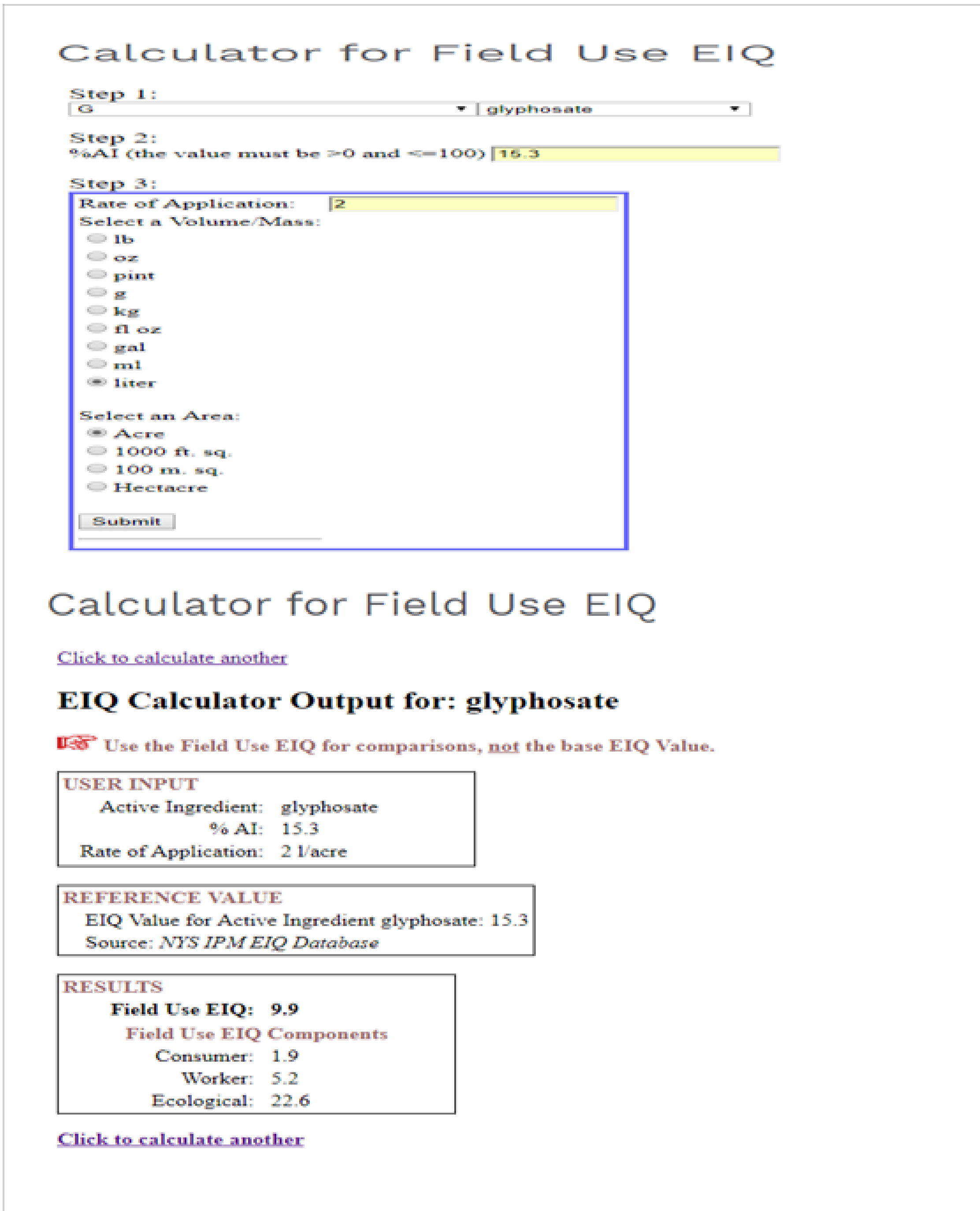
	Unmatched sample	Matched sample
Variable	Coefficient	Coefficient
Gender	-0.018 (0.149)	-0.015 (0.149)
Age	-0.006 (0.004)	-0.006 (0.004)
Education	0.025* (0.013)	0.021 (0.013)
Extension	0.678*** (0.131)	0.673*** (0.131)
Offarm	-0.252** (0.124)	-0.247** (0.124)
Fbo memb	0.050 (0.176)	0.038 (0.178)
Weatherinfo	0.135** (0.060)	0.131** (0.061)
Vulnerable	0.655**(0.232)	0.592**(0.211)
Household size	0.022 (0.022)	0.021 (0.023)
Credit-const	0.112 (0.128)	0.107 (0.129)
Tenure type	0.273** (0.128)	0.269** (0.128)
Machinery	0.492*** (0.179)	0.478*** (0.180)
Sample size	476	466
Logliklihood	-272.24	-271.82

*, ** and *** refers 10%, 5% and 1% significant levels, respectively. Values in parentheses are standard errors while those in square brackets refer to p-values.



PM refers to pooled matched sample. The TE estimates from DEA
AMS refers to adopters matched sample; NMS denotes non-adopters matched sample.

Figure 5.A1: Distribution of Matched sample DEA efficiency scores



Source: https://nysipm.cornell.edu/eiq/calculator-field-use-eiq

Figure 5.A2: Calculator for Field Use EIQ

Chapter 6

Conclusions and Policy Implications

The increasing concern about climate change, land degradation and the need for adoption of climate-smart agricultural practices for sustainable agriculture, have led to increasing support among the global community for mainstreaming CSA and SLM as part of efforts to achieve the sustainable development goals (SDG's). CSA seeks to contribute to the achievement of the SDG's by integrating the three dimensions of sustainable development (economic, social and environmental) in order to overcome the challenges of food insecurity and climate change impacts.

In particular, CSA is gaining significance as a sustainable agricultural system in SSA, with a lot of activities and promotion programs by local government and international agencies, as well as and civil society organizations. To our knowledge, this is the first study that has empirically examined the prospects of climate-smart agriculture from the perspectives of farm level economic performance and risk exposure, food and nutrition security and household poverty impacts. Firstly, the study contributes to the literature by employing recent advancements in the impact assessment literature to empirically identify location specific information on adoptable climate-smart practices, as well as implications of adoption on farm performance and risk exposure. Secondly, the study is the first to explicitly relate adoption of climate-smart agricultural practices to household dietary diversity scores (HDDS) and household food insecurity access scores (HFIAS). This is essential for climate-smart agriculture policy mainstreaming for the identification of the Nationally Determined Contributions

(NDC's)[50] in Ghana as part of global efforts to enhance mitigation and adaptation to climate change. Given that different diets drive different production systems, implementation of climate-smart agronomic practices, could influence farm performance, as well as food and nutrition security.

In addition, the study examined the role of SLM in farm efficiency, as well as environmental inefficiency with reference to use of glyphosate-based herbicides among food crop farmers. The study further estimated the effects of SLM adoption intensity on household welfare using poverty indicators. This study found that, climate-smart agriculture has a role to play towards attaining the adaptation to climate change, the Sustainable Development Goals (SDGs), food and nutrition security, as well as poverty reduction and environmental sustainability. In the subsections that follow, an overview of the empirical and analytical methods, summary of results and policy implications of the study are outlined.

6.1 Overview of empirical methods

The study employed various empirical strategies to arrive at results in the different chapters, including endogenous switching regression (ESR), Multinomial endogenous switching regressions (MESR) or BFG, multivalued treatment effects (mTE), dose-response functions (DRF), propensity score matching (PSM), Quantile treatment effects and Poisson regressions, bias-corrected stochastic production frontier (SPF) models and data envelopment approaches (DEA), as well as fractional regression models (FRM). Among these models, the ESR, MESR and bias-corrected SPF models address the issues of sample selectivity bias due to both observed and unobserved factors. The PSM addresses selection bias due to only observed factors.

[50] Nationally Determined Contributions (NDCs) - is a concept according to which countries that signed up to the Paris Convention are required to develop national climate protection goals, communicate internationally and regularly update their post-2020 climate actions (https://unfccc.int/process/the-paris-agreement/nationally-determined-contributions/ndc-registry#eq-5).

The MERS model was used in chapter 2 to estimate the impact of multiple adoption of climate-smart agricultural practices on crop yields and risk exposure (variance and skewness). The MESR is more appropriate to use when estimating the effect of a multinomial endogenous variable (i. e., multiple adoption of crop choice and soil and water conservation strategies) on continuous outcome variables such as yield and risk exposure.

In chapter 3, the study employed the ESR to estimate the impact of adoption of climate-smart practices on food and nutrition security outcomes (i.e. farm revenues, household dietary diversity scores, and household food and insecurity access scores). This model is appropriate to use when estimating the impact of a binary endogenous treatment variable on a continuous outcome variable. The quantile treatment effect regression approach was used in this chapter to account for heterogeneity at different quantiles of food and nutrition security outcomes. In addition, the treatment effects Poisson was employed as robustness check while treating the dietary diversity scores as count outcome variables.

In chapter 4 the study employed the mTE and DRF to estimate the impact of adoption intensity on poverty outcomes (per capita consumption expenditure, poverty headcount, poverty gap and poverty gap-squared). The mTE and DRF are more appropriate to use when estimating the impact of a multivalued continuous endogenous treatment variable on either continuous or binary outcome variables.

In chapter 5, both bias-corrected SPF and DEA approaches were employed to estimate technical efficiency, as well as environmental inefficiency among farm households. The bias-corrected SPF is employed when there is the need to address sample selectivity bias due to unobservable factors in stochastic production frontier models. The PMS was also employed in this particular study to address selection bias caused by observed factors. The DEA was employed to derive both efficiency scores and slacks of inputs, particularly herbicides (the potentially environmentally detrimental input in the model). The fractional regression models were then employed to assess the determinants of technical efficiency and environmental inefficiency since efficiency scores retrieved from the DEA model can be treated as fractional response variables.

6.2 Summary of results

The empirical results in chapter 2 showed that farmers' adoption of crop choice and soil and water conservation resulted in higher crop yields and minimal exposure to production risks. The largest adoption impact on yields came from joint adoption with more than 20% increase in crop yields, although the individual adoption impacts were also positive, 12.6% for crop choice and 11.6% for soil and water conservation measures, respectively. This is an indication of complementarity or the synergistic effects of crop choices and soil and water conservation strategies. This particular finding emphasizes the package adoption approach in order to optimize the synergies inherent in various climate-smart practices. The results in this chapter also showed that climate anomalies (both temperature and rainfall) positively influenced farmers' decisions to adopt climate-smart practices. Furthermore, the findings revealed that education of the household head, extension access and weather information influenced the likelihood of adopting these strategies.

The empirical results in chapter 3 showed that adoption of climate-smart practices had positive and significant impact on food and nutrition security outcomes. Adoption led to an increase in farm revenues by 12.4%, household dietary diversity scores by 15% and a reduction in food insecurity access scores by 35%. We also found that the impact of adoption differed across quantiles and agro-ecological zones. Adoption impacts on farm revenues in the 0.1 and 0.25 quantiles were 37% and 38% respectively, but the impact reduced to 14% in the 0.75 quantile. Also, in terms of farm revenues, the highest percentage yield effects of adoption were in the Guinea Savannah agro-ecological zone (13.4%). Other variables that were found to be associated with farm revenues were coefficient of variation of rainfall, plot level factors and the use of herbicides. In addition, the results showed that participation in off-farm work and being a female household head were found to be positively associated with household dietary diversity scores.

The results in chapter 4 showed that increasing intensity of adoption of SLM led to improved per capita consumption expenditure (PCE), reduced poverty headcount and poverty gap among farm households. The ATE of moving from non-adoption to low intensity adoption was 24% with respect to per capita consumption. Furthermore, there was a reduction in the poverty headcount from 10.6% to 22.6% as farmers moved from non-adoption to low intensity (expenditure on manure only) and high intensity (expenditure on both manure and bunds), respectively. The findings also revealed that the ATE of moving from non-adoption to low intensity was 30% across all quantiles, but this increased to 53%, 70% and 64% in the 0.25, 0.5 and 0.75 quantiles of PCE respectively, if we consider high intensity adopters versus non-adopters. In addition, the results of the DRF's showed that treatment effect of intensity of adoption on per capita consumption and poverty outcomes is nonlinear, peaking at 60-70% of adoption intensity level (dose).

The findings in chapter 5 showed that adoption of SLM technology had a positive and statistically significant effect on technical efficiency among farmers, although the impact of adoption decreased in the matched sample in both the level and statistical power of the meta-technical efficiency (MTE). In particular, in the matched sample, adoption of SLM technology resulted in an increase of MTE by 7.5% among adopters in the bias-corrected SPF. The results also showed that adoption led to higher expected farm revenues (8.5% increase in the matched sample). However, the results from the DEA model showed that adopters of SLM had excess environmental impact quotient (slacks) (57%) compared to non-adopters (26%) which could have adverse environmental consequences. The results of the fractional regression model showed that access to credit and extension services positively and significantly influenced farmers' technical efficiency levels, while environmental inefficiency was also influenced by adoption status and longevity of land usufruct right (land tenure security).

6.3 Policy implications

The findings from this study indicated that adoption of individual, as well as combination of climate-smart strategies can result in increases in yield and reduction in farmers' exposure to downside risk by lowering the probability of crop failure, while climate anomaly, access to climate information, education and extension influenced farmers' decisions to adopt individual and combinations of climate-smart strategies. Thus, government in collaboration with other development partners could step up efforts to ease adoption difficulties of farmers to enable them adapt to climate change.

To the extent that the access to credit and climate information appeared to be important factors facilitating farmers' adoption of crop choice and soil water conservation strategies, policies focusing on improving farmers' access to credit and enhancing the development of rural infrastructure such as irrigation system and meteorological services, would enhance adoption of climate-smart agriculture. In addition, given that effective adoption of climate-smart strategies requires some knowledge and skills, improvements in farmer education and access to extension services should be among the measures government can employ to enhance adoption of climate-smart agriculture.

The findings also revealed that adoption of climate-smart practices had positive and significant impact on food and nutrition security outcomes. The impact of adoption differed across quantiles and agro-ecological zones, with the effects of adoption generally higher for the poorer farm households, whose dietary diversity scores fell within lower quantiles. The implication is that adoption of climate-smart practices tend to benefit poor farmers through higher relative food and nutrition outcomes and reduction in food and nutrition insecurity. Thus, facilitating adoption of climate-smart agriculture can be an effective measure for poverty alleviation and rural development. Promotion of climate-smart agriculture can be employed to facilitate domestic efforts towards achieving the United Nations Sustainable Development Goals; to end hunger, achieve food and nutrition security, as well as promote sustainable development.

SLM adoption also positively influenced technical efficiency and farm revenues among farmers. The study also found that adoption of SLM at high intensity levels tended to positively affect per capita consumption at the middle and upper quantiles than at the lower quantiles, which implies a potential adoption gap that could be attributed to the constraints faced by farmers (e.g. tenure security, unpredictable climate or access to credit, etc.). This finding implies that farmers are not necessarily able to choose the SLM intensity level or specific practice(s) that they consider to be most effective or most desirable in economic terms. There exist substantial gaps between what farmers would want to do, and what they are practically able to accomplish. Thus, farmers may end up implementing only up to intensity levels or practices that they consider feasible, given their economic circumstances and endowments or constraints. Such adoption gaps can deny low intensity adopters of SLM from obtaining the optimum benefits associated with adoption based on recommended practice. Since education has positive influence on adoption at different intensity levels, improving education access, as well as extension services will facilitate effective adoption of SLM practices, which could enhance the poverty-alleviation. Thus, if government is to address the root causes of land degradation and manage adaptation to climate change in Ghana in a more sustainable manner, then these broader economic factors and drivers of farmers' land management decisions should be considered as routine part of SLM and climate-smart agriculture research, planning and implementation. Intensive education on the use of herbicides associated with certain SLM practices such as zero-tillage, will help reduce inefficiencies associated with herbicide use among farmers. This will promote environmental efficiency and sustainable crop production systems.

Appendices

Appendix A: Questionnaire

Christian-Albrechts University of Kiel, Germany

Institute of Food Economics and Consumption Studies

Climate change implications for smallholder agriculture and adaptation in Northern Ghana

This questionnaire is purposely for field survey on Climate change and variability Kindly note that all information provided is for research purposes only and shall be kept strictly confidential. Thank you for participating in this interview.

Survey Identification

Questionnaire number --

Name of enumerator --
Date of interview --
Time started --

General information
Region -------------------- District/ Community ----------------------------
Agro-ecological zone ---------------------- Name of village/town -------------------------
Language for the interview ----------------------
Section A: Socio-demographic characteristics
A/1 name of farmer.. Tel/ Address...
A/2 relationship with the household head...
A/3 age of the farmer ----------------------- A/4 level of education ....(years)
A/5 gender......... (1) Male (0) female A/6 ethnic group................. A/7 religion..................
A/8 status in the community .... (1) Chief (2) member (3) migrant (4) other (specify)
A/9 family type...................... (1) nuclear (2) extended (3) other (specify)
A/10 family type............... (1) polygamous (2) monogamous (3) other specify
A/11 size of the household (number of persons under your care) ----------------------

A/12 please complete the table below on the age composition of the household members

Children (less than 18 years)		Youths (18 - 30 years)		Adult 30 - 60 years)		Aged (above 60 years)		family farm workers		family non- farm workers	
Male	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female

A/13 Occupation: Please state the occupation(s) you are engaged in

Primary occupation	1.
Secondary Occupation	2.
Other occupations	3.

A/14 which farmer-based organization (s) have you worked with and for how long and the kind of relationship?

Institutions **How long (in years)** **Type of relationship (multiple response allowed)**

1………………………...……[…………………] ……/………/……/……../…../……../……

2………………………...……[…………………] ……/………/……/……../…../……../……

3………………………...……[…………………] ……/………/……/……../…../……../……

***Codes types of working relations**: 1. Ploughing services 2. Input credit (seeds, fertilizer, herbicides, etc.) 3. Cash credit 4. Provision of farm equipment 5. Sale of farm produce 6. Extension services. 7. Other (specify). ………………………..*

Section B: Perception and awareness of local climate and subjective assessment

B/1 How do you feel about the trend of the following climatic conditions in the last 20 years in your area?

	Climate variable	**Perception**			
(a)	Amount of rainfall	Increasing [ ]	Decreasing [ ]	No change [ ]	I don't know [ ]
(b)	Temperature	Increasing [ ]	Decreasing [ ]	No change [ ]	I don't know [ ]

B/2 Household Subjective rainfall satisfaction

	Subjective rainfall satisfaction	Yes = 1	No = 0
a	Did the rainfall come on time?		
b	Was there enough rain on your fields at the **beginning of the rainy** seasons?		
c	Was there enough rain on your fields **during the growing** seasons?		
d	Did the **rains stop on time** on your fields?		
e	Did it **rain during the harvest** periods?		

Rainfall Variability Question

B/3 How was the rainfall condition this year? 1 [ ] Good 2. [ ] Normal 3. [ ] Bad

B/4. For this locality, when is a rainfall condition referred as bad season/ year?

1. [ ] When the rain comes very late,
2. [ ] When the rain stops very early,
3. [ ] When there is long dry spell between during planting *(April/May & July)*,
4. [ ] When the annual rainfall is very low,
5. [ ] When the annual rainfall is very high.

B/5. Subjective probability (past ten years)

Between the periods 2005 and 2015, how many years were Good, Normal and Bad? ……………………….

Rainfall Condition	Number of Years	Which year is a typical example of the condition?
1. Good		
2. Normal		
3. Bad		
Total	10	

B/6. Subjective probability (next ten years): What is your expectation of rainfall for the coming 10 years 2015 to 2025, how many years will you expect to be *Good*, *Normal* and *Bad*?

Rainfall Condition	Number of Years
1. Good	
2. Normal	
3. Bad	
Total	10

Please indicate the *level of vulnerability* of your crop to climate variability and change

Vulnerability	**Level of vulnerability**		
	Not vulnerable at all (1)	Moderately vulnerable (2)	Highly vulnerable (3)
B/7 Based on experience and observation how do you feel about the level of susceptibility of your crop farming to experience climatic problems you indicated?			
	Not harmful at all (1)	Moderately harmful (2)	extremely harmful (3)
B/8 Based on experience and observation how do you feel about the level of harm/damage that your crops could face/currently exposed to due to the climatic problems you indicated?			

B/9 What is the distance to the nearest source of drinking water for the household? …………………… km

B/10 What is the nearest source of water for your livestock? ………………………….. …………km

Section C: Adaptation strategies

C/1. Do you take measures to adapt to the changing weather/climate? 1. Yes [ ] 2. No [ ]

C/2. Which of the following methods in agricultural sector have you used before to respond to climate change/variability?

	Adaptation strategy	Yes =1	No = 0	Plot size
Irrigation and water strategies				
a	Watering crops during drought/dry spells			
b	Practicing irrigation during the dry season			
c	Rain water harvesting for crop production			
d	Other ……………………………………………………………….			
Crop choice and changing plating date				
a	Using early maturing /drought resistant varieties			
b	Changing planting date			
c	Changing crops			
d	Stopping crop production			
e	Other ………………………………………………………………			
Soil conservation strategies				
a	Cover cropping			
b	Crop rotation			
c	Application of manure (FYM, Compost, etc)			
d	Erosion control measures (stone bonds, terracing, etc)			
e	Other …………………………………………………….			

[Extent of use: 1 = <20% of farm, 2 = 21-40%, 3 = 41-60%, 4 =61-80%, 5 = >80% of cultivated land]

C/3. Which adaptation method/s did you use or still use?

	Adaptation strategies	Yes =1	No = 0	Plot size
Irrigation and water strategies				
a	Watering crops during drought			
b	Practicing irrigation during the dry season			
c	Rain water harvesting for crop production			
d	Other …………………………………………………………….			
Crop choice and changing plating date				
a	Using modern varieties/drought resistant varieties			
b	Changing planting date			
c	Changing crops			
d	Stopping crop production			
e	Other ……………………………………………………………			
Soil conservation strategies				
a	Cover cropping			
b	Crop rotation			
c	Application of manure (FYM, Compost, etc)			
d	Erosion control measures (stone bonds, terracing, etc)			
e	Other ……………………………………………………….			

[Extent of use: 1 = <20% of farm, 2 = 21-40%, 3 = 41-60%, 4 =61-80%, 5 = >80% of cultivated land]

C/4. How do you rate the effectiveness of the different adaptation strategies in helping to reduce farming problems associated with climate change/variability? [*Please tick/ circle the appropriate response*]

Adaptation strategies		Highly Ineffective (1)	Ineffective (2)	Can't tell (3)	Effective (4)	Highly effective (5)
Irrigation and water strategies						
a	Watering crops during drought	1	2	3	4	5
b	Practicing irrigation during the dry season	1	2	3	4	5
c	Rain water harvesting for crop production	1	2	3	4	5
d	Other ………………………….	1	2	3	4	5
Crop choice and changing plating date						
a	Using modern varieties/drought resistant varieties	1	2	3		5
b	Changing planting date	1	2	3	4	5
c	Changing crops	1	2	3	4	5
d	Stopping crop production	1	2	3	4	5
e	Other …………………………	1		3	4	5
Soil conservation strategies						
a	Cover cropping	1	2	3	4	5
b	Crop rotation	1	2	3	4	5
c	Application of manure (FYM, Compost, etc)	1	2	3	4	5
d	Erosion control measures (stone/soil bunds, terracing, etc)	1	2	3	4	5
e	Other ……………………………	1	2	3	4	5

State of implementation of adaptation measures

C/5. What is the status of the implementation of the following measures on your farm/plot? *[code: 1 = Not implemented, 0 = Not implemented]*

	Activity	Status of Implementation	Year first implemented
(a)	Changing planting dates		
(b)	Staggering of planting of crops		
(c)	Using different crop varieties		
(d)	Use of drought resistant varieties		
(e)	Increased soil/water conservation techniques		

(f)	Water harvesting		
(g)	Diversifying into non-farming activities		
(h)	Increased use of irrigation		
(i)	Planting trees		
(j)	Increased use of fertilizer		
(k)	Other ……………………………..		

Adaptation Constraints

C/6 complete the table below on the constraints you face in your adaptation operations (table 2)

	Yes/No	If yes, *please rank*	Comment
Adaptation Constraints			
Small land size			
Poor property rights (ownership) on land			
Poor Quality of seed			
lack of drought resist varieties			
High cost of DR Varieties			
Inadequate training/demonstrations			
Limited access to markets			
Lack of technical skills			
Irrigation Water management at plot level			
Difficult to access water/no irrigation facility			
Difficult to manage water			
High cost of water fees			
High cost of irrigation accessories			
Credit			
Non- availability of credit			
High interest rate charges on credit			
Delays in acquiring credit			
Difficult to repay credit			
Extension services			
Unavailability of extension services			
Lack of effectiveness			
Long distance to the extension workers			
Climate/weather information			
Unpredictable weather			
Lack of access to information about right time to sow			
Lack of access to information about right time to harvest			
Lack of information about Drought resistant/ early maturing varieties			
Others			

Yes = 1, No = 0,   Ranking codes: 1=High; 2= Medium; 3= Low; 0= Not exist
NB: Use code 99 where farmer(s) knows nothing on the characteristic referred to (99= don't know)

Section D: Land holding, Irrigation and farming related activities
D/1 Please indicate the crop you cultivate, share of land and the purpose of crops cultivated by completing the following table

Crop	Variety	Share of total land Area	Purpose	remarks
Maize				
Rice				
Millet				
Sorghum				

Groundnut				
Cowpea/beans				
Yam/cassava				
Vegetables (pepper, tomato, etc.)				
Other crops: specify				
Etc.				
Total*		10		

[Purpose: 1 = food, 2 = sale, 3= both]

[Variety: 1 = local variety. 2 = high yielding variety, 3 = drought resistant variety, 4 = Don't know]

*total: total share of land area out of ten (10).

D/2 Please indicate the annual output of crops and the corresponding plot sizes over the past 5 years in the following table:

	Crop production in Bags/kg														
NO	Year	Maize		Rice		Millet/ sorghum		G'nut		Cassava/ yam		Other crop ……………		Total plots no.	Total plot size ha
		Plot size/ ha	Yield / kg	Plot size /ha	Yield / kg	Plot size /ha	Yield / kg	Plot size ha	Yield / kg	Plot size /ha	Yield / kg	Plot size/ ha	Yield/ kg		
1	2011														
2	2012														
3	2013														
4	2014														
5	2015														

D/3 How large is your farm land (acres)? …………………………………..

D/4 How many plots of farm land do you have ? …………………………

D/5 How did you acquire the farm land? (1) owner [>> D/10] (2) Inheritance (3) purchase (4) tenant (5) others (specify)

D/6 If tenant, what type of tenancy arrangement do you operate? .... (1) fixed rent *[>>D/7]* (2) share cropping *[>>D/8]* (3) other (specify) *[>>D/9]*…………………………………………………..

D/7 If fixed rent, what is the duration of tenure? .... (years)

D/8 If share cropping, what are the terms this rent? ....

D/9 Please provide other additional information about the tenancy arrangement (if any)..............................
....

D/10 if land owner; do you sometimes lease out part of your land? 1 yes [ ] 2 No [ ]

D/11 If yes, what size of your land is currently under lease/rented out? -------------------------- (ha)

D/12 do you keep some part of your land under fallow? 1 yes [ ] 2 No [ ]

D/13 if yes to "D/12", for how long? .... (years). Size of land under fallow ………… ha.

D/14 The relative slope of the land is 1 [ ] Plain 2. [ ] gentle slope 3. [ ] Hilly

D/15. The relative fertility of the farmland is 1. [ ] Fertile 2. [ ] Moderately fertile 3. [ ] Less fertile 4. [ ] Infertile

D/16. Does the household practice irrigation? 1. [ ] Yes 2. [ ] No *(>> D/15)*

D/17 If yes to D/16, how many plots of your farmland is covered by irrigation? ---------------------- ha

D/18. If yes to Q/16, how many hectares of your farmland is covered by irrigation? ------------------ ha

D/19 What is the nearest source of water for irrigation (if any)? ……………………………………… km

Section E: Labour use

E/1What type of labour do you use on your farm (1) family (2) Hired labour (3) Both (4) others (specify).........

E/2 How many members of your household work on your farm...

E/3 How many of your household do not work on your farm............................... why?................................…

E/4 Did you use family labour on your farm in 2015? .... 1. Yes [ ] 2 No [ ]

E/5 If yes, to "E/4" for which operation (s)...

E/6 For how many days/ weeks/months did you engage family labour? …………………………………

E/7 Do you use hired labour? 1. Yes [ ] 2. No [ ]

E/8 If yes to "E/7", in which year did you start using hired labour on your farm..

E/9 How often do you use hired labour? 1. Always 2. Sometimes 3. Rarely
E/10 Did you employ hired labour in 2015? .... 1. Yes [ ] 2. No [ ]
E/11. If yes to E/10, for which operation (s) ....
E/12 If yes to E/10, how many people did you hire? ...., for how many days? ....
E/13 what was the wage rate per day during 2015 season in this community?...
E/14 was the wage rate same for male and female? ------------------------- (1) yes (2) no
E/15 if no to E/14, what was the wage rate for a female worker during 2015 season? ---------------------------------
E/16 Do you face labour shortage during farming season? 1. Yes 2. No
E/17 If yes to "E/16" in which months (during which operations) do you experience the labour shortage most?
……………………………

Section F: Livestock and assets ownership
F/1 Please provide information on ownership of livestock in the table below

		Cattle	Sheep	Goat	pigs	chicken	guinea fowls	Others
a	What types of animals do you own? (tick)							
b	On average how many do you have now?							
c	On average how many did you sell/kill last year							
d	How many more have you acquired this year?							
e	Do you seek for veterinary services for them? (1=yes, 2=no)							

F/2: Please provide information about change in your stock of your livestock over the past 5 years in the following table:

NO	Year	Cattle	sheep	Goats	Poultry (fowls, guinea fowls, etc)	pigs	Other (state)
1	2011						
2	2012						
3	2013						
4	2014						
5	2015						

F/ 3 Please complete the table below on the **asset owned by your household** (table 3)

	Item/Asset	Is the asset available?		if yes, please state the number available	year of purchase	cost of purchase	Price if you were to sell it now. GHS
		Yes =1	No = 2				
a	Cutlass						
b	Hoe						
c	Knapsack						
d	Irrigation pump/kit						
e	Radio						
f	Mobile phone						
g	Television						
h	Bicycle						
i	Motorcycle						
j	Car/Moto-King/kia						
k	Bullock/Donkey						
l	Tractor						
m	Mechanized sheller						
n	House						
o	Other …………….						

Section G: Income, Cash and Credit sourcing

G/1. Indicate the income source(s) of the household (you mention/**tick** more than one if necessary)

[ ] 1. Crop sale [ ] 2. Livestock sale [ ] 3. Non-farm activities (state ……………….)

[ ] 4. Aid from relatives/friends [ ] 5. Other (state ……………………………………….)

G/2. Which is the major source of the Household income from the sources you indicated above in question G/1

[ ] 1. Crop sale [ ] 2. Livestock sale [ ] 3. Non-farm activities (state …………….)

[ ] 4. Aid from relatives/friends [ ] 5. Other (state …………………………………….)

G/3. Please indicate the annual income you earn from the following sources:

	Source of income	Amount/GHS
a	Annual income from sale of farm produce/crops	
b	Annual income from sale of livestock	
c	Annual income from non-farm activities	
d	Gifts and remittances	
e	Other, NGO/Gov't	

G/4 what is the average monthly cash income of your household from farming (crops and livestock)

(1)<100 GHS (2) 101 – 300 GHS (3) 301 -500 GHS (4) 501 - 1,000 GHS (5) > 1,000 GHS

G/5 what is the average monthly cash income of your household from non-farming including other business, donations, gifts and remittances?

(1)<100 GHS (2) 101 – 300 GHS (3) 301 -500 GHS (4) 501 - 1,000 GHS (5) > 1,000 GHS

G/6 If you suddenly need money where do you turn to?...

G/7 What is the average amount of money you can get from this source?..

G/8 Do you source credit to finance your farm operations?.. 1. [ ] yes 2. [ ] no

G/9 If no, please state the reasons for not sourcing credit? ....

G/10 If yes to G/8, please indicate name of credit gency...

G/11 Mention other sources of finance for your farm operations ....

G/12 Did you source credit for your farm business in the 2015 farming season? -------- (1) yes (2) no

G/13 Are you aware of other farming credit sources in your locality? ----- 1 [ ] yes 2 [ ] no

G/14 if yes to G/13, please name them...

G/15 Have you sourced credit from them before?.........1 [ ] Yes 2 [ ] No. *[if no go to G/18]*

G/16 if "yes", do you still source credit from them and why?...

G/17 has your loan application ever been rejected? -------- (1) yes (2) no

G/18 Did you buy any input on credit during the 2015 season? -------- (1) yes (2) no.

G/19 If yes list the inputs ....

G/20 If yes, what were the terms of the credit? 1. [ ] repay in cash 2 [ ] repay with farm produce 3 [ ] repay with cash and farm produce 4 [ ] other (specify) --------------------------------

G/21 Did you repay with interest................... 1 [ ] yes 2 [ ] no

G/22 If yes what was the interest rate? ....(% p.a.)

G/23 What was the average repayment period? ....months

G/24 Please provide your credit history in the table below (if any)

Source of credit	Year	Amount (GHS)	Interest rate	Purpose	Repayment Duration	Number of instalments	instalment amount

Section H: Produce Marketing and Farm revenues

H/1 kindly provide information on how you market your farm produce (for 2015 season) in the table below

Type of produce	please tick as appropriate	farm gate	Market	processed	Group/co-operative sale	middlemen
1.	Quantity sold in kg					
	price/kg					
2.	Quantity sold in kg					
	price/kg					
3.	Quantity sold in kg					
	price/kg					
4.	Quantity sold in kg					
	price/kg					
5.	Quantity sold in kg					
	price/kg					
6.	Quantity sold in kg					
	price/kg					
7.	Quantity sold in kg					
	price/kg					

H/2 do you have written contract with your buyer(s)? (1) yes (2) no
H/3 if yes, for how long? ------------------------------ (years)
H/4 how does the buyer support you? 1 [ ] supply of seeds 2 [ ] provision of training

3 [ ] provision of credit service in kind or cash 4 [ ] any other please specify ---------------------

Section J: Extension, Membership in social organizations, information access and others

J/1 kindly provide information about extension visits in the table below

	Public	Private	NGO
extension visit (yes =1, no = 0)			
frequency of visit*			
Meeting place**			
Distance extension office from meeting point (km)			

**(1) weekly (2) monthly (3) once in 6 months (4) once in a year (5) Never*

*** (1) your farm (2) your house (3) farmers field school (4) others, specify*

J/2 Have you ever visited any extension office? --- (1) yes (2) no.
J/3 If yes to K/2, specify the purpose of the visit ------------------------------------
J/4 which of the following is the major source of information for your farming operations? (1) TV (2) Radio (3) news paper (4) extension agents (6) fellow farmers (7) farmers' organisation others;
please specify _ _ _ _ _ _ _ _ _
J/5 Are you or any member of this household members of social organizations (eg. Co-operatives, youth group, FBO's, etc.)? 1. [ ] yes 2. [ ] No
J/6 If your answer to question (J/5) is yes, mention the total number of organizations the household is a member. -
----
J/7 How many relatives do you have the group you belong to? --------------------------------------
J/8 How many of your neighbours do you know who belong to an association? --------------------------
J/9 Do you receive weather /climate information on regular basis? 1. [ ] Yes 2. [ ] Yes
J/10 From who do you receive climate information most of the time? 1. [ ] Radio/TV 2. SMS
3. [ ] Extension agent 4. [ ] Neighbours 5 [ ] Social organizations 6 [ ] other ………………

Section K: risk, vulnerability and Household food and nutrition security status

K/1 In the past 10 years has your household been affected by any of the following climatic conditions? [*Please indicate with a tick*]

	Climatic condition	**Yes**
a	Drought	
b	Flood	
c	Shortage of rainfall	
d	Failure in the timing of rain	
e	Excessive rainfall	
f	Other …………………….	

K/2 Have you ever encountered crop failure (in the past ten years)? 1. Yes [ ] 2. No [ ]
K/3 If yes, how many years (seasons) has it happened to you in the past 10 years? ……………………….
K/4 What was the reason reason(s) for the crop failure?
……………………………………………………………..
……
K/5 The average amount of grain consumption of the household in bowls/kg/Olonka is ---------------
K/6. For how many months does your own farm production currently last to meet the food requirements of the family? 1. [ ] ≤3 months 2. [ ] 4-6 months 3. [ ] 7-9 months 4. [ ] 10-11 months 5. [ ] ≥ 12 months.
K/7. If your answer to question K/6 is from **1 to 4**, what is the major reason for your inability to meet the annual food requirements of the household? ---
K/8 Do you currently receive food aid (financial support, eg LEAP[51]) from government/NGO's?
1 [ ] Yes 2. [ ] No
K/9. If yes to k/8, indicate how many years you have been receiving the aid ……………… years

Section L: Household Food Insecurity Access Scale (HFIAS) Measurement Tool

L/1 Please answer the following questions in your capacity as the person responsible for food provision/preparation in the household in the past 4 weeks/one month.

NO	QUESTION	RESPONSE OPTIONS	CODE*
1.	In the past four weeks, **did you worry** that your household would **not have enough food**?	0 = No (skip to Q2) 1=Yes	
1.a	How often did this happen?		….|___|
2.	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 Q3) 1=Yes	….|___|
2.a	How often did this happen?		….|___|
3.	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 Q4) 1 = Yes	….|___|
3.a	How often did this happen?		….|___|
4.	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 Q5) 1 = Yes	….|___|
4.a	How often did this happen?		| |
5.	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 Q6) 1 = Yes	….| |
5.a	How often did this happen?		….| |

[51] The Ghana Livelihood Empowerment against Poverty. (LEAP) cash transfer programme is the Government of Ghana's programme, targeting extremely poor households with elderly, disabled or Orphans and Vulnerable.

6.	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 Q7) 1 = Yes	….|___|
6.a	How often did this happen?		
7.	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 Q8) 1 = Yes	….|___|
7.a	How often did this happen?		….|___|
8.	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 Q9) 1 = Yes	….|___|
8.a	How often did this happen?		.|___|
9.	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, 1 = Yes	….|___|
9.a	How often did this happen?		….|___|

** [Please use the Code 1 = Rarely (once or twice in the past four weeks), 2 = Sometimes (three to ten times in the past four weeks), 3 = Often (more than ten times in the past four weeks)]*

Section M: Household Dietary Diversity (HDDS)

Please describe the foods (meals and snacks) that you ate or drank yesterday during the day and night, whether at home or outside the home. Start with the first food or drink eaten in the morning. *[Please refer to list of foods attached]*

	Questions	Coding [0 = No, 1 = yes]
1	Any bread, porridge, rice, TZ, Banku, Kenkey, Noodles, biscuits, or any other foods made from millet, sorghum, maize, rice, wheat, or *[any other locally available grain]?*	A [….]
2	Any yams, cassava, Konkonte, potatoes, Cocoyam, or any other foods made from roots or tubers?	B [.....]
3	Any vegetables; eg Ayoyo, Kontomere, cabbage, etc	C […]
4	Any fruits? Eg. Orange, Mango, bananas, etc	D […]
5	Any beef, pork, sheep/lamb, goat, rabbit wild game, chicken, duck, or other birds, liver, kidney, heart, or other organ meats?	E [……]
6	Any eggs?	F […..]
7	Any fresh or dried fish or shellfish?	G [.....]
8	Any foods made from beans, eg. "Red-red", G'nuts, etc.?	H [….]
9	Any cheese, yogurt, milk or other milk products?	I […]
10	Any foods made with oil, fat, or butter?	J [……]
11	Any sugar or honey?	K […]
12	Any other foods, such as condiments, coffee, tea?	L [……]
Total	Sum (A + B + C + D + E + F + G + H + I + J + K + L)	…………………..

Section N: Farm Expenses

Please indicate the costs and expenses incurred over the past 12 months for the production of crops. During this period, has any of the following been used on any of the holdings?

CROP COSTS	CODE	N/1 Did you spend anything in cash and/or in kind on ……… in the past 12 months?	N/2 How much was spent in cash & in kind on ….. during the past 12	N/3 What was the source of …. ? Private Sector...1 Cooperative ….2 MoFA………..3 NGOs………..4	N/4 Was …. obtainable in this community any time during the year when you needed it?

		Yes….1 No…..2 (>> N/3)	months? Value/GHS	Other (specify).5	Yes….1 No…..2
Fertilizer (inorganic)					
Organic fertilizer					
Insecticides/Pesticides					
Weedicides/herbicides					
Purchased seed, seedlings, etc.					
Irrigation					
Hired labour					
Renting animals (Donkeys/Bullocks)/tractor services					
Hiring equipment					
Other crop costs …….					
Total cost					

Section O: Household Expenditure

Please indicate how much the household spent on food and non-food items in the past 4 weeks?

	Item	Amount GHS		Item	Amount GHS
O/1	**Food expenditure**		**O/2**	**Non-food expenditures**	
a	Cereals and bread, Starchy staples		a	Housing, utilities/ fuels	
b	Meat: live, fresh, frozen, processed		b	Health - - medical products	
c	Fish, Milk and milk products, Eggs		c	Communications - - postal and telecommunication services	
d	Oil and fats		d	Education related	
e	Fruits, fresh or canned, Vegetables including potatoes and other tuber vegetables		e	Social/cultural events	
f	Sugar, jam, honey, syrups, chocolate and confectionery				
g	Condiments and spices: pepper, ginger etc.				
h	Pulses and nuts				
i	Non-alcoholic and Alcoholic beverages				

Appendix B: Curriculum Vitae

Name: ISSAHAKU, Gazali

Place of Birth: Ghana (Sekyedumasi)

Nationality: Ghanaian

Contact Address: University of Kiel, Institute of Food Economics and Consumption Studies, Germany.

Email: gissahaku@food-econ.unikiel.de or issahakugazali01@gmail.com

Telephone: + 49 (0) 431880 3240 Fax: 49 (0) 431880 7308/5017, Mobile: +4915218997742

Academic and Professional Qualifications

2015-2018	PhD student at the Department of Food Economics and Consumption Studies, University of Kiel, Kiel, Germany
2006-2010	MPhil (Agricultural Economics) at University of Cape Coast, Cape Coast , Ghana
2002-2003	Education (Post-Grad. Certificate) at University of Education, Winneba, Ghana
1994-1999	B.Sc. at University of Cape Coast, Cape Coast, Ghana
1991-1993	SSSCE at Ghana Secondary School, Tamale, Ghana

Awards: DAAD Scholarship for Doctoral Studies at the University of Kiel; Germany.

International Exposure

Presentation of a paper at the 2017 Annual Conference of The Agricultural & Applied Economics Association (AAEA), Chicago, Illinois, USA.

Work Experience

Lecturer at University for Development Studies, FACS-CCFS (2013 to 2015)
Lecturer. Teaching, Research and Community Outreach, Department Exam co-ordinator
Assistant Lecturer at Ho Polytechnic, Ghana (2012 to May 2013)
Teacher and Head of Science Department at Eguafo-Abrem Senior High School, Elmina, Ghana (November 2006 to 2012)
Teacher and Head of Agric. Science Department at Sekyedumase Senior High School (2001 to October 2006).

Publications

Issahaku G. and Abdulai, A. (2019) Can farm households improve food and nutrition security through adoption of climate-smart practices? *Applied Economic Perspectives and Policy* (forthcoming)

Issahaku G. and Abdul-Rahaman, A. (2018). Sustainable land management practices, off-farm work participation and vulnerability among farmers in Ghana: Is there a nexus?, *International Soil and Water Conservation Research*, Available at

https://doi.org/10.1016/j.iswcr.2018.10.002.

Issahaku, G. and Abdulai, A. **(2017).** Adaptation to Climate Change and its Influence on Household Welfare in Ghana, Conference *Paper presented at the Agricultural & Applied Economics Association's 2017 AAEA Annual Meeting, Chicago, Illinois, July 30-August 1, 2017*. https://ageconsearch.umn.edu/record/259938/files/Abstracts

***Language Proficiency*:** English, Arabic, Deutsch, Dagbani and Ashanti-Twi
Computer Competencies: Stata, R-Studio, LIMDEP, Ox, SPSS
Hobbies: Reading, Farming, Research.

Referees

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