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# Factors Influencing Adoption of Conservation Agriculture in the Democratic Republic of the Congo

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Factors Influencing Adoption of Conservation Agriculture in the
Democratic Republic of the Congo

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by

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**Abstract**

The agricultural sector in the Democratic Republic of the Congo (DRC) is still struggling to cope with its post-independence political and structural instability. From 1961 to 2000, the DRC experienced a decrease of 34% and 37% in daily caloric intake and protein intake, respectively. The DRC's agriculture sector, led by women (who are the core of subsistence farming), is now being targeted as a potential pathway out of poverty through sustainable development programs. Empowering farmers to increase productivity by educating them to use conservation agriculture (CA), a more sustainable alternative to the traditional slash-and-burn agricultural practice, could contribute to reducing vulnerability, alleviate food insecurity, and fight poverty while being ecologically sustainable. This study assesses the impact of the "Improving Agricultural Productivity through No-Tillage Agriculture" program in the DRC from 2009 to 2012. This program targeted vulnerable women who were victims in some capacity of the Congolese War. Training on the sustainable CA practice was provided to 8,290 farmers in the Maniema province of the DRC. The program goal was to increase agricultural productivity and sustainability through CA adoption by improving crop yields and soil management and decreasing deforestation caused by slash-and-burn.

Findings suggest that the location of the farm (being in the savannah or forest), training, having accessed to credit, belonging to a farmers' group, and being a vulnerable female, all drove adoption to varying degrees and directions. Vulnerable women, the target for this project, were found to be less likely to adopt CA. From this study's findings, targeting vulnerable women who are part of a farmers' group may increase the number of vulnerable women who would adopt CA in the future. The results of this study provide future CA projects with important information on what the drivers of adoption are and what the perceived benefits of adoption by adopters. From

these two important pieces of information, future research and CA projects in the DRC can more precisely focus on specific groups of producers based on location, gender, and other social characteristics to both increase adoption of CA and market the specific benefits producers are looking for more efficiently.

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## Introduction

The agricultural sector in the Democratic Republic of the Congo (DRC) is still struggling to cope with post-independence political and structural instability. Agricultural output fell between 1970 and 1980 due to *zaïrianisation*, a policy implemented by president Mobutu's government which nationalized all private companies, including those in the agricultural sector, in the DRC. Tollens (2003) found that between 1961 and 2000, the DRC experienced increasing malnutrition. Agricultural output and food security continued to decline with an economic crisis in the 1990s when the DRC faced what Akitoby and Cinyabuguma (2004) call "the grip of an unprecedented circle of hyperinflation, currency depreciation, increasing dollarization and financial disintermediation, declining savings, deteriorating economic infrastructure, and broad-based output decline" (p.7). The economic collapse was only compounded during the war between 1996 and 2006 (Tollens, 2004; Smoes, 2012). DRC citizens and the agricultural community are still struggling to rebuild after an almost 20-year conflict that brought violence, insecurity, displacement, political upheaval (the Famine Early Warning Systems Network [FEWSNET[1]], 2015), and increased poverty and food insecurity. During the DRC civil conflicts from 1996 to 2006, agricultural tools and inputs were both expensive and difficult to obtain. As such, instead of investing in making existing agricultural land more fertile, agricultural communities practiced "slash-and-burn" agricultural practices, whereby destroying forests to harvest the nutrients of virgin soils. Women, the backbone of the agriculture sector in the DRC, were the largest victims of the civil unrest through increased work responsibilities, domestic violence, rape, and being widowed and left with the responsibility of caring for entire families. Currently, there is a

[1] FEWSNET is a leading provider of early warning and analysis on acute food insecurity. Created in 1985 by the US Agency for International Development (USAID) after devastating famines in East and West Africa, FEWS NET provides objective, evidence-based analysis to help government decision-makers and relief agencies plan for and respond to humanitarian crises. Find more at http://fews.net/.

conscious movement by the Government of the DRC (GoDRC) to empower women in the agricultural sector throughout the DRC. Empowering women farmers to increase productivity by educating them to use conservation agriculture (CA), a more sustainable alternative to slash-and-burn, could contribute to reducing vulnerability, alleviate food insecurity, and fight poverty while being ecologically sustainable. Educating women in CA could help reduce some burdens that years of civil unrest have caused for women in the agricultural communities of the DRC. First, it would allow for the reduction of labor, in that women would not have the arduous task of plowing or clearing the field (slash-and-burn) to plant new crops. Second, by staying closer to their communities, CA would reduce the chance a woman would encounter domestic violence or potentially be raped. Lastly, by reducing slash-and-burn agriculture and introducing CA, agricultural yields and subsequent profits could increase. Rebuilding the agricultural sector in the DRC will be complicated and time consuming but must be holistic in nature to ensure a sustainable (environmental, social, and economic) future. Programs that educate women in CA practices in the DRC have the ability to make positive social, ecological, and economic changes.

In 2013, the World Bank stated that the DRC had the potential to have rapid and sustained economic growth, reduce poverty, and improve its human development indicators (World Bank, 2013). However, today, the country is still low on the human development index, ranking 176$^{th}$ out of 188 countries (United Nations Development Program [UNDP], 2016) and, despite its abundance of natural resources, is consistently ranked among the poorest countries in the world. In 2016, the Central Bank of the DRC (officially known as “Banque Centrale de la république démocratique du Congo” [BCC]), reported that within the primary sector (agricultural, minerals, and natural resource production and extraction), which accounted for 37% of the country’s GDP, agriculture contributed 18.5%, while the mining sector accounted for 17.8% (BCC, 2017). The agricultural industry in the DRC is often classified into two sectors: a ‘traditional’ and a ‘modern’ sector (Smoes, 2012). The traditional agriculture sector consists mainly of subsistence and smallholders’ farmers, relies mostly on rain-fed agriculture, and provides 80% of the DRC food supply despite its relatively low yields. The modern sector, which uses industrial practices, is typically for the high-value export crops of sugarcane, coffee, cocoa, palm oil, cinchona, and rubber (Smoes, 2012). Smoes’s description of the DRC agricultural sectors is supported by FEWSNET (2015), which describes the agricultural sector in the DRC to be mostly informal and “driven by small-scale activities.” The DRC’s 2013–2014 demographic health survey (DHS) indicated that agriculture is the principal employment activity in the country, specifically in rural areas where it employs 70% of the population (Ministry of Planning [MINPLAN], Ministry of Health [MSP] & ICF International, 2014).

Agriculture in the DRC consists of many players, including large- and small-scale producers, cash and staple crop production, and foreign direct investment. Of all the participants in the agricultural community, the DRC Ministry of Agriculture (MINAGR) (2010) considers women as the most important contributors due to their primary roles in agricultural production and commitment to food security at both the household and community levels. In 2014, the DHS reported that agriculture is the primary occupation for 58% of all women in the DRC, with this percentage increasing to 66% for women between 45 and 49 years old who have more than five children. In the rural areas, the same report found that 77% of women are involved in agriculture. The majority of DRC women are self-employed, and they earn 63% of their in-kind and cash revenue from agriculture compared to 17% for non-farming activities (MINPLAN et al., 2014). The MINAGR (2010) recognized that women are also among the first victims of the country’s long past of political and social instability. In 2012, Herderschee, Kaiser, and Mukoko reported that women in the DRC were “disadvantaged relative to men,” a situation that was only intensified by civil conflicts, despite some recent progress to reduce that inequality. A 2014 report by the United States Agency for International Development (USAID) found that women face many types of discrimination, exploitation, and exclusion in their communities throughout the DRC (USAID, 2014). Such inequalities, combined with weak healthcare and education systems and inadequate economic rights, lead the DRC to earn a gender inequality index score of 0.663, which ranks the country 153$^{rd}$ out of 157 countries (UNDP 2016 Human Development Report). According to the DHS, the proportion of uneducated women is approximately twice as high as men (MINPLAN et al., 2014). Rural women in the DRC are exposed to higher levels of poverty and food insecurity and are more likely to fall victim to the DRC’s ongoing civil strife.

The poverty level in the DRC has been exacerbated by the ten years of civil discord. From 1996 to 2006, the country faced what Reyntjens (2009) calls “the Great African War,” which directly/indirectly involved 13 African nations, the DRC national army, and multiple national and foreign militias and rebel groups. This war initially aimed to overthrow president Mobutu, who had ruled for 32 years. The country’s development efforts have been stifled by conflicts, which became sporadic after 2006 and resulted in the continuing political instability which still undermines most development projects today. USAID determined that more than 17 years of conflict in the eastern DRC, an area including the provinces of Maniema, South and North Kivu, and the former provinces of Katanga and Orientale, has led to the depletion of much of the area’s resources and misled the country’s development plan (USAID, 2014). Otchia (2014), asserted that the agriculture sector in DRC suffers from a lack of “development strategies,” combined with the consequences of conflict that has led to widespread food insecurity in many parts of the country. Otchia (2014) considers that the GoDRC has “abandoned” the agriculture sector. Throughout all the civil conflicts and political instability since 1996, there has been one constant in the DRC: food insecurity. Tollens (2003) claimed that, in the DRC, food insecurity is the consequence of poverty brought on by civil conflict. From 1961 to 2000, the DRC experienced a decrease of 34% in daily caloric intake and 37% in daily protein intake (Tollens, 2003). These large decreases in caloric and protein intakes are a combination of civil and political unrest as well as a lack of investment in agricultural productivity enhancements. Compounding matters, since the early 2000s, the DRC has one of the world's highest internal displacement due to the aforementioned civil conflicts (Akakpo, Randriamamonjy, & Ulimwengu, 2014; NRC & IDMC, 2017). Due to the large number of people displaced in one of many agroecological zones not similar to their homes, agricultural productivity has diminished to the point of food insecurity in many parts of the DRC. The African Development Bank (AfDB) (2013) stated that the armed violence which led to widespread internal displacement was one of the primary drivers of increased food insecurity throughout the DRC. As of February 2018, it was estimated there are approximately 4.6 million people experiencing food insecurity, 2 million children who are acutely malnourished, and 4.5 million people were internally displaced in the DRC (United Nations Office for the Coordination of Humanitarian Affairs [OCHA], 2018), which is nearly 6% of total DRC population. The largest sector of the agricultural workforce in the DRC, women, are also some of the most vulnerable members, due to large communal displacements and sexual violence in and around conflict zones, host communities, and refugee camps (MINPLAN & International Monetary Fund [IMF], 2013; USAID, 2014). To help women who have been affected by displacement and/or the ongoing civil strife, the GoDRC and donors have included women empowerment among their key program strategies, integrated gender sensitivity as a cross-cutting theme, and required their implementing partners, recipients, and/or contractors on the ground to comply with those aspects (USAID, 2014; MINAGR, 2013; AfDB, 2013; World Bank, 2013).

In the DRC, like in most low-income countries, agriculture is one of the primary sources of employment and revenue. Improving agriculture, the backbone of the most African economies, can be the catalyst for poverty reduction and can improve livelihoods across the entire continent (Gates, 2015). For the DRC specifically, improving agricultural productivity and incomes also has the potential of reducing the vulnerability of the poorest of the poor. Vulnerable youth in the DRC have historically been predisposed to join armed groups or to leave villages for illegal mining opportunities which mutually fuel civil conflicts keeping the country in the poverty cycle. Herderschee et al. (2012) state that improving agricultural productivity is one of the best ways to combat the DRC's extreme poverty. The World Bank stated in 2013 that the DRC has not yet intensively used its agriculture potential to enhance its citizens' livelihoods and increase food security. The World Bank views the "over 80 million ha of fertile and arable land" (p.8) as an opportunity for large production of commodities such as maize, palm oil, soybean, and sugarcane but the area planted to these crops is small and not irrigated, despite water resources, (World Bank, 2013) due to a lack of knowledge and infrastructure. In the DRC, the agricultural sector, compared to other sectors including mining, has the potential to employ the largest numbers of new workers and, generate income and value added, while improving vulnerable people's lives (Tollens, 2004).

Agricultural productivity decreased by 60% in the DRC from 1960 to 2006 because of political instability and farmers abandoning production due to civil strife (MINPLAN, 2013). The post-independence crisis between 1960 and 1965 was indicative of periods of conflicts between the president, the prime minister and the parliament, rebellions supported by mining companies, the assassination of Patrice Lumumba, and the subsequent coup that brought Mobutu to power.

Since 1960, agricultural productivity has become stagnant, which has affected most of households' subsistence system throughout the country (MINPLAN & IMF, 2013). A 2013 World Bank study found that the weakening of the agriculture extension system throughout the DRC impeded the dissemination of the best management practices, leading to reduced agricultural productivity, low income, and increased food insecurity (World Bank, 2013). Smoes (2012) compiled the reasons for what he views as the major weaknesses of the agriculture sector of the DRC. The list includes the absence of finance/credit, underinvestment in agricultural research and development, obsolete agriculture practices and materials, bad infrastructure, an absence of well-structured farmers' entities, a weak and corrupted fiscal system, low investment, land issues, bad governance, and lack of high quality data. From Smoes' list, the lack of proper and adapted agriculture practices, materials, and infrastructures coupled with the absence of an effective extension service has led to low agricultural productivity. Slash-and-burn agriculture, a common farming practice in the DRC which consists of slashing the vegetation and burning their residues to create new fertile farmland, is still widely implemented in the DRC today. Slash-and-burn has detrimental effects on land, accentuates deforestation (United Nations Environment Program [UNEP], 2011), and also contributes to the degradation of aquatic ecosystems and biodiversity (National Institute of Agricultural Extension Management [MANAGE], 2016). A 2009 Catholic Relief Services (CRS) study found that in the province of Maniema, slash-and-burn agriculture makes women more vulnerable, as it continuously forces them to walk further from their village to the farm which increases their workloads and inherently exposes them to an increased possibility of rape.

Given the high incidences of food insecurity and the fact that increased agricultural productivity has the potential to reduce poverty, the GoDRC has begun to focus on investing in the agricultural sector. During the design of the "DRC's National Agriculture Investment Plan under the Comprehensive Africa Agriculture Development Programme (CAADP)," officially known under the French acronym "PNIA", in 2013, the GoDRC chose to focus on the enhancement of agricultural productivity in a sustainable manner, taking into consideration the environmental stress from slash-and-burn agriculture and the pivotal role in which women play in productive agriculture (MINAGR, 2013). The GoDRC should invest in the implementation of CA in an effort to enhance environmental sustainability and increase producer welfare, both from an economic and social perspective. "CA is defined as a management system based on three interlinked principles which are applied in a mutually reinforcing manner: (i) continuous no or minimum physical soil mechanic disturbance, (ii) maintenance of permanent soil mulch cover, and (iii) crop diversification in space and time" (Kassam, Mkomwa, & Friedrich, 2017).

As an innovative farming practice, CA was introduced in the DRC and piloted in 2009 in the Maniema province by CRS and its partners through a two-million-dollar Howard G. Buffet Foundation (HGBF) funded program named "*Kulima Pasipo Kutipula Udongo*: Improving Agricultural Productivity through No-Tillage Agriculture in Maniema Province," also known as the "NTA project." CA was promoted by the NTA project as a potential solution to the issue of slash-and-burn agriculture and its negative externalities on women farmers and the ecosystem throughout central and eastern DRC. One of the founding principles of CA in the DRC is to eliminate slash-and-burn agriculture, which has many positive externalities, but in the case of DRC, two externalities are the primary drivers of adoption. First, the reduction of slash-and-burn can reduce the agricultural work burden on women, as they do not have to continuously travel further distances to cultivate fertile land. Second, by reducing the distance women have to travel to farm it also reduces their chances of being put in vulnerable situations which are a byproduct of the ongoing conflicts in central and eastern DRC. In a holistic sense, CA is recognized as a viable concept for sustainable agriculture due to its potential comprehensive benefits in economic, environmental, and social aspects of sustainability (Derpsch, 2007).

In 2018 the United Nations Food and Agriculture Organization (FAO) stated that CA has the potential to improve production efficiency, expand agronomic soil productivity, and increase the environmental and social benefits that could protect soil with the possibility to make agriculture more sustainable. The economic benefits of CA are valued in terms of farmers' time and labor saved as compared to traditional slash-and-burn practices common in the DRC (CRS, 2012, 2015). CRS (2015) found that farmers who adopted CA in Maniema spent 100%–200% less time weeding their plots relative to those who did not implement CA. The reduction of weeding is a direct result of fewer weeds attributed to a thick layer of mulch covering the ground (a practice encouraged in CA in the DRC). Another economic benefit is the potential of enhanced yields (Lalani, Dorward, Kassam, & Dambiro, 2017; CA Group at Cornell University, 2015). According to the FAO (2015), the agronomic benefits of CA are mainly soil structure improvement and an increase in organic matter, which ultimately results in more fertile land. As a result, water and nutrients are used more efficiently and can potentially preserve the soil while also increasing farm production (FAO, 2015). Increased fertility with organic matter can both increase revenue (through higher yields) and decrease costs (reducing the need for inorganic fertilizer). The environmental benefits, mostly resulting from mulching and the reduction of deforestation attributed to slash-and-burn, are soil protection against erosion and carbon sequestration, which makes CA perceived as a climate-smart agriculture practice (Mkomwa, Kassam, Friedrich, & Shula, 2017). Covering the soil with mulch contributes to water infiltration and increases organic matter (FAO, 2015; CA Group at Cornell University, 2015). Together, these benefits can provide CA adopters the opportunity to improve economic, social, and environmental sustainability at the farm level. In a country like the DRC, where most of the population is involved in agriculture (and the majority of agricultural actors are women), it would seem logical to analyze any practice that has the potential to reduce strenuous work such as tillage and multiple weeding while preserving farm soils, reducing deforestation, and reducing yield variability for staple crops such as cassava, rice, and maize. Furthermore, CA has the real possibility of improving the livelihoods of women by allowing them to cultivate land closer to their villages, thereby reducing the threat of domestic violence when traveling long distances.

*Research objectives*

This study uses primary data collected in 2015 by Catholic Relief Services (CRS) for the ex-post evaluation study of the NTA project. The project was implemented from 2009 to 2012 and aimed to improve small-scale farmers' food security and natural resource base through CA training. The training sessions were led by NTA project extension agents using Kiswahili visual handouts and were implemented on demonstration sites located on community farms for groups of less than 30 farmers (CRS, 2009). On the demonstration sites, CRS (2012, 2015) exposed farmers to two plots: one with CA and the other with conventional local agricultural practices. Cassava, rice, maize, peanuts, and cowpeas (the primary crops of the area) were found on all the demonstration plots (CRS, 2012). As a group, farmers at each location learned, shared, and discussed with peers and extension agents; welcomed other farmers of their community, during field days, to visit and learn their experience; and were asked to apply the lessons on individual and group plots (CRS, 2012, 2015). The NTA project specifically targeted single women displaced or widowed by the Congolese war in Kabambare, Kailo, and Kasongo territories of the Maniema province. Vulnerable women were targeted to both reduce their workload and reduce the probability of domestic violence from having to travel far from their villages to farm. Training on sustainable conservation agricultural (CA) practices was provided to 8,290 farmers in the Maniema province of the DRC. The CRS' ex-post evaluation study did a random stratified sampling selection of 225 willing and voluntary households from seven and four villages, respectively, from Kailo and Kasongo territories, in the area of implementation of the NTA project (CRS, 2015).

Not all farmers adopted CA after training because they perceived mulching and sowing in the mulch to be too challenging, especially in the heavily forested part of Maniema (CRS, 2012, 2015). The NTA project management team took a year, starting in September 2009, combining training with awareness campaigns while they interacted with local farmers asking them to test the full CA package within their communities (CRS, 2012, 2015). From learning by seeing, the CA training turned to learning by doing, and three years after NTA project closure in 2012, CRS reported 71% CA adoption in Kailo and Kasongo. The present study chose to focus on those aspects that were close to the goal of the NTA project that targeted women farmers' vulnerability in a post-conflict context. However, the results are still applicable to many rural contexts in the DRC and in Sub-Saharan Africa where CA is being promoted.

The objective of this study was first to estimate the factors that drove adoption of CA in the DRC via the NTA project. This study set out to explore how female adoption compared to male adoption rates, given the project was targeted at vulnerable female farmers. Further, this research wanted to determine what/if any benefits farmers derived through the adoption of the CA practices. Because human capital can be transferred, the research also aimed to estimate the perceived benefits to producers who may have adopted CA but did not receive formal training from CRS and to compare those to the perceived benefits of farmers who actually received formal training, that is, to capture if there were any spillover effects of the formal training.

The study is the first one of its kind for the DRC because CRS has been the pioneer of CA in the country. Its relevance for agricultural research and development goes from policy design to implementation, takes into consideration the important role of gender within DRC agriculture, and fits in the current themes of sustainability and climate change. In a poor, post-conflict country continuing to struggle with food insecurity and malnutrition such as the DRC, this study provides important information to policy makers, NGOs and conservationists about why people adopt CA and what the perceived benefits are for those who do.

## Literature review

*Factors driving CA adoption*

Knowler and Bradshaw (2007) grouped the factors driving CA adoption into four categories: "Farmer and farm household characteristics, farm biophysical characteristics, farm financial/management characteristics, and exogenous factors" (p.33). Malawi, South Africa, Swaziland, Tanzania, and Zimbabwe are the selected countries where CA is already adopted as confirmed by FAO (2018) and where this review focused on studies which were less than five years old that explored CA adoption in smallholders' farmer communities. In these five countries, CA was introduced and promoted between 1998 and 2008 by national governments, research centers, and non-government organizations to enhance smallholders' farmers' crop productivity in response to drought and soil erosion (Kassam, Friedrich, Shaxson, & Pretty, 2009; Mamkwe, 2013; Mavunganidze, Madakadze, Mutenje, & Nyamangara, 2013; Chisenga, 2015; Mlenga & Maseko, 2015; Ntshangase, Muroyiwa, & Sibanda, 2018).

Mamkwe (2013) showed that in Tanzania gender, income, and land ownership were the primary drivers of CA adoption. Male farmers were more likely to adopt CA than female, farmers with high income were more likely to adopt CA than farmers with low income, and farmers who own land were more likely to adopt CA than those renting land or using community land (Mamkwe, 2013). In Malawi, Swaziland, South Africa and Zimbabwe, age, education, and extension positively influenced CA adoption; specific drivers were gender and wealth for Swaziland, a positive view of CA for South Africa, and labor, use of animal traction, and farm size for Zimbabwe (Mavunganidze et al., 2013; Chisenga, 2015; Mlenga & Maseko, 2015; Ntshangase et al., 2018). In addition, in Malawi, Chisenga (2015) showed that CA adoption, especially for women farmers, is driven by the availability of farm labor, access to CA training, farm size, access to farm inputs, and farmers' group membership, while adoption is impeded by wrong CA understanding, lack of extension support and financial rights, and farm smallness. The dissimilitude in CA adoption drivers between Malawi, South Africa, Swaziland, Tanzania, and Zimbabwe supports the Knowler and Bradshaw's (2007) conclusion to customize the study of CA adoption drivers to the location due to condition disparities, a view shared by Thierfelder, Bunderson, and Mupangwa (2015) and stated by Corbeels et al. (2014) as "the need to tailor CA interventions to the end users" (p.166). Total CA adoption is a process which unfolds in steps as farmers typically adopt aspects of new innovations before adopting the entire package (Prager and Lionberger, cited by Posthumus et al., 2011). Liu and Huang (2013) found that there are specific factors related to the farm, the farmer, the technology, and institutions that play a role in the adoption of soil conservation practices.

*Benefits of CA*

Even though Giller, Witter, Corbeels, and Tittonell (2009) stated studies' findings about the benefits of CA for smallholders' farmers in Africa are conflicting, and Brouder and Gomez-Mcpherson (2014) advised not to rush to concluding about better yields from CA, the majority of results from reviewing the literature for this study shows that benefits are location- and agroecological-based, and they seem to outnumber disadvantages. Unanimity seems to appear in studies conducted to date saying that benefits of CA take time to be witnessed and demonstrating that CA is a response to climate change and farmers' vulnerability, CA reduces GHG emissions, and CA provides better ecosystem functioning and services (Kassam et al., 2009; Derpsch, Friedrich, Kassam, & Hongwen, 2010). The benefit of CA would be "particularly important" for regions affected by the drought in Africa, as CA has the potential to hold subsurface moisture more efficiently (Palm, Blanco-Canqui, DeClerk, Gatere, & Grace, 2014). CA meets smallholders' farmers' need to spend less time on agricultural production (per unit of land) because it reduces intensive tasks such as tillage and weeding, and, as a result, more time is available to diversify their livelihoods (Friedrich & Kienzle, 2008).

Focusing on the impact of CA on food security, Mango, Siziba, and Makate (2017) demonstrated that CA did not change the food consumption score in Zimbabwe and Malawi due to a limited area of CA land and producers not being able to apply the correct CA techniques, but it had significantly improved the food consumption score in Mozambique. In Brazil, a FAO study which considered CA an improved cropland management technology reported an increase in average productivity and farm net income for maize, beans, bananas, and cassava in 2010 due to CA (Branca, McCarthy, Lipper, & Jolejole, 2011). A study in Mozambique explored the benefits of CA and found it provides better crop returns to smallholders' farmers, especially the poorest, when intercropping is also integrated (Lalani, Dorward, & Holloway, 2017). Numerous studies comparing conventional tillage to CA in South Africa showed better maize yields under CA (Sithole, Magwaza, & Mafongoya, 2016).

*CA in the DRC*

The literature is currently void on the drivers of adoption or the benefits subsequently thereafter for CA in the DRC. The factors hypothesized driving CA adoption in the DRC were chosen from the Knowler and Bradshaw list (2007) but also adapted to fit the gender context of the agriculture sector in the DRC. Unlike other studies on factors driving CA adoption in Africa, this research further explores the benefits of CA in the DRC. Furthermore, this study estimates the benefits, in terms of food security and income reliability, perceived by adopters of CA in DRC. Thus, this study is the first of its kind in that it uses primary data to both estimate the drivers and the benefits of CA adoption in the DRC.

## Research site and data

*Maniema province*

The research study took place in Kailo and Kasongo territories in the Maniema province in the DRC, where seven and four villages, respectively, were sampled (Figure 1 and Table 1). Maniema province has 132,250 square kilometers (51,062 sq. mi) and is located between 0° and 5° South latitude and 24° 30' and 28° 50' East longitude, a space that extends between the Lomami river in the west and the mountain ranges of Eastern DRC (Omasombo T. et al., 2011). This province has seven territories, Lubutu, Punia, Kailo (where Kindu, the provincial capital, is located), Pangi, Kibombo, Kasongo and Kabambare. Furthermore, the province has a population of 1,682,451 people in 2014, where 70% of the population is rural, and 60% and 65% of the women and men are involved in agriculture, respectively (Omasombo T. et al., 2011; MINPLAN et al., 2014). Maniema has a GINI coefficient of 0.34, less than the 0.4 national rate (MINPLAN et al., 2014).

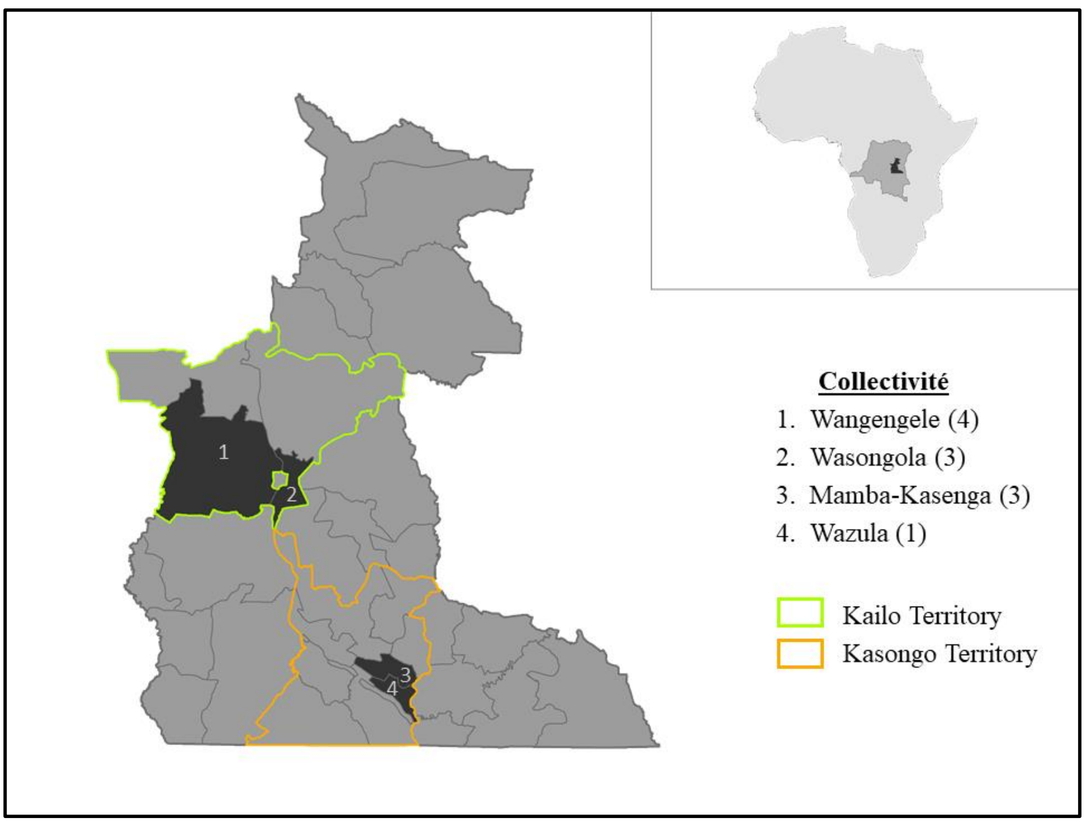


Figure 1. Map of Maniema province

MINPLAN et al. (2014) use the GINI coefficient here to illustrate population inequality in terms of the level of economic well-being. Maniema was slightly under the national GINI of 0.4. According to Omasombo T. et al. (2011), two thirds of Maniema province are classified as dense rainforest, and one third is a shrub savannah.

*Research data*

The data used for this study were collected in 2015 by Catholic Relief Services (CRS) for an ex-post evaluation study conducted three years after NTA project closure. CRS (2015) used a structured household survey questionnaire to interview farmers in Kailo and Kasongo territories, where the NTA project was implemented from 2009 to 2012. The household survey targeted both NTA project beneficiaries (participants) and non-beneficiaries (non-participants). Based on a population size of 5,800 farmers who participated in the NTA project in the two targeted territories, CRS utilized a random stratified sampling method to select 225 households for the interviews (CRS, 2015). Table 1 presents the breakdown of interviewees at village levels for the two territories.

Table 1. Number of farmers interviewed per village in 2015 by the Catholic Relief Services

| Territory | Village | Observations | |
|---|---|---|---|
| **Kailo (Forest)** | Enombe-Brigade | 7 | |
| | Enombe-Sakina | 18 | |
| | Lubangwana | 10 | |
| | Lubelenge | 18 | |
| | Nyoka | 33 | |
| | Kampala | 29 | |
| | Kimanga | 13 | |
| | | | **128** |
| **Kasongo (Savannah)** | Kauta | 43 | |
| | Lukongo | 15 | |
| | Kionga | 21 | |
| | Kamonga | 18 | |
| | | | **97** |

Source: CRS, 2015

From CRS' dataset, the information used for this study can be grouped into four categories:

- Geographical context. The research site has two agroecological zones (regions): the forest in Kailo territory and the savannah in Kasongo territory. Within each territory, the village in which each participant's farm is located is also taken into consideration. Enombe-Brigade, Enombe-Sakina, Lubangwana, Lubelenge, Nyoka, Kampala, and Kimanga are the villages of Kailo; and Kauta, Lukongo, Kionga, and Kamonga are the villages of Kasongo where interviews took place.

- Socioeconomic opportunities. This category includes farmers' access to credit, farmers' group membership, and farm size. CA adoption (did or did not adopt) and training (were trained formally or were not trained formally) also fall into this category.

- Demographic characteristics. The research used household size and age, literacy (literate/illiterate), and gender of the household head.

- Impact perception. This category assesses the benefits of CA adoption from farmers' perspective. The information used for this category includes farmers' apprehension about food security status (decrease, stagnation, or increase); reliability of income from CA (not reliable, less reliable, somehow reliable, or very reliable); and farmland under CA (decrease, stagnation, or increase) as a result of adopting CA.

For the purpose of this study, farmers were disaggregated in terms of CA adoption, CA training, and the two main agroecological zones, as illustrated in Table 2. Grouping the data between CA adopters and non-adopters indicate statistically significant differences ($p < 0.10$) between farm size, household size, proportions of farmers trained, living in the savannah, female non-married, members of farmers' groups, and those who had accessed credit (Table 2). Age and literacy of the household head for the two categories were found to be statistically the same.

Table 2. Farmers' characteristics based on CA adoption, training, and agroecological zones

| | Non-adopters (n=67) | Adopters (n=158) | Trained farmers (n=181) | Untrained farmers (n=44) | Forest region (n=128) | Savannah region (n=97) |
|---|---|---|---|---|---|---|
| Means [a] | | | | | | |
| *Farm size* | 0.725** (0.768) | 1.056 (1.731) | 0.997 (1.630) | 0.794 (0.895) | 1.033 (1.419) | 0.858 (1.636) |
| *Age* | 41.672 (11.181) | 43.804 (11.229) | 43.514 (11.118) | 41.750 (11.714) | 43.328 (10.012) | 42.959 (12.716) |
| *Household size* | 9.373*** (4.396) | 11.158 (4.388) | 11.094*** (4.392) | 8.705 (4.246) | 10.367 (4.563) | 10.969 (4.312) |
| Proportions (%) [b] | | | | | | |
| *Adopt* | – | – | 83.978*** (0.368) | 13.636 (0.347) | 64.844* (0.479) | 77.320 (0.421) |
| *Training* | 43.284*** (0.499) | 96.203 (0.192) | – | – | 85.256* (0.357) | 74.227 (0.440) |
| *Savannah* | 32.836* (0.473) | 47.468 (0.501) | 39.779* (0.491) | 56.818 (0.501) | – | – |
| *Literacy* | 86.567 (0.344) | 83.544 (0.372) | 83.425 (0.373) | 88.636 (0.321) | 87.500* (0.332) | 80.412 (0.399) |
| *Female non-married* | 17.910** (0.386) | 06.962 (0.255) | 09.945 (0.300) | 11.364 (0.321) | 14.844** (0.357) | 04.124 (0.200) |
| *Farmers' group* | 35.821*** (0.483) | 89.241 (0.311) | 85.083*** (0.357) | 25.000 (0.438) | 72.656 (0.447) | 74.227 (0.440) |
| *Accessed credit* | 11.940*** (0.327) | 63.924 (0.482) | 58.564*** (0.494) | 06.818 (0.255) | 42.188** (0.496) | 56.701 (0.498) |

**Note**:

- Significance codes '***' $p < 0.01$, '**' $p < 0.05$, '*' $p < 0.10$
- [a] T-test applied to assess differences. [b] Chi-square test to assess differences.

In terms of differences between trained and untrained farmers, statistical differences were found between household size, farmers who adopted CA, proportion of the sample living in the savannah, proportion of the sample who were members of farmers' groups and proportion of the sample who had accessed credit. Farm size, age and literacy of the household head, and non-married female farmers were found to be equivalent statistically between subsamples. Between farmers living in villages located in the savannah and those living in the forest, statistical differences are noted for those who adopted CA, who were trained, who were literate, who are female non-married, and those who had accessed credit.

*Data processing*

The software RStudio (RStudio Team, 2016) was used for data analysis and estimation. The computation using RStudio required the following packages: *Stargazer* (Hlavac, 2018) for descriptive statistics, *mass* (Venables & Ripley, 2002) for the regression models; and *erer* (Sun, 2016), and *oglmx* (Caroll, 2017) for the marginal effects.

**Model specifications**

*Modeling CA adoption*

(i) Explanatory variables

For this study, a CA adopter was defined as a farmer living in the research area and, applying the three CA principles (no-tillage, crop rotation, and mulching), whose farm was observed by the surveyor and determined to be in compliance with CA. The following drivers were hypothesized to explain CA adoption in the DRC.

*Age*

*Age* of the household head in years is a continuous (integer) variable. The variable *age* is hypothesized to affect CA adoption. In the DRC, where life expectancy is estimated around 60 (World Bank, 2018), 67.8% of the population is less than 25 years old (MINPLAN et al., 2014). Ntshangase et al. (2018) showed a positive influence of age on CA adoption in South Africa.

*Household size*

*Household size* is a continuous (integer) variable representing the household size, the total number of family members living in the farmer's home. Household size might provide a demographic influence on CA adoption. The average household size in the DRC is 5.3 (MINPLAN et al., 2014). Ntshangase et al. (2018) found that in South Africa, household size influences CA adoption as larger households adopt more. However, that does not necessarily mean more available labor. Moreover, for poor households, who represent a large group in Sub-Saharan Africa, CA tends to be an "attractive option" (Lalani et al, 2017, p.144).

*Farm size*

This variable is continuous and accounts for the farmer's total plot size used for farming. Studies have shown that farm size influence on CA adoption can be positive, negative, or neutral (Knowler & Bradshaw, 2007). In Lesotho, Malawi, and South Africa, for instance, it was found that farm size has a direct effect in CA adoption decision making (Bisangwa, 2013; Chisenga, 2015; Ntshangase et al., 2018). Table 2 indicates there are statistical differences in farm sizes between adopters and non-adopters. As such, this study added farm size in a regression framework to see if this is causation or correlation.

*Training*

*Training* is a dummy variable used to isolate the influence of the complete CA training provided by the NTA project. This variable takes the value 1 for farmers trained in CA and 0 for untrained farmers. The lack of proper CA knowledge is reported among the barriers to CA adoption (Giller et al., 2009; Kassam et al., 2009; Derpsch, 2007; Friedrich et al., 2010). In the agriculture sector, farmers mostly have access to knowledge through the extension service, which is not necessarily the case in the DRC, where non-government agriculture programs promoted CA.

*Savannah*

*Savannah* is a dummy variable used to test for location (agroecological zone) impact of CA adoption in the DRC. This variable takes the value 1 for Kasongo territory, meaning the farm is located in the savannah, and 0 for Kailo territory, meaning the farm is located in the forest. Based on agroecological studies, Lee (2005) recommends a regional approach in promoting farming technologies such as CA because they are “location-specific” and address “niche-type constraints faced by farmers” (p.1327). Palm et al. (2014) also support Lee’s recommendation in a study showing the influence of CA on ecosystem services in Sub Saharan Africa and South Asia. Agroecological information types are linked to crop growth, development, and yield, and so would impact the spread of CA say Sithole, Magwaza, and Mafongoya (2016), who observed CA impact on maize yield in South Africa.

*Literacy*

*Literacy* is a dummy variable which takes the value 1 for literate farmers (farmers who can read and write) and 0 for an illiterate farmer. This variable’s coefficient will measure the influence of basic education on farmers’ adoption of CA. Farmers’ education may have a positive, negative, or neutral influence on CA adoption (Knowler & Bradshaw, 2007). In this study, literacy is used as a proxy for education. In the DRC, 15% of women compared to 4% of men have no formal education (MINPLAN et al., 2014). Studies have shown a positive influence of women’s education on food security (Penders and Staatz (2001), Smith and Haddad (2002), and Webb and Lapping (2002) cited by Napoli, 2011).

*Female non-married*

*Female non-married* is a dummy variable taking the value 1 for a female, non-married farmer, and 0 for any other farmer. This variable was defined to comply with the NTA project goal, to help vulnerable women, and also to cross-check this CRS targeting approach influence on CA adoption. Fifty-one percent of NTA project participants were women, and 30% were widows (CRS, 2015). According to CRS (2015), the "single women and widower" pointed to labor-saving as their key incentive to adopt CA. Agriculture is the main activity for six out of ten women in the province of Maniema in the DRC (MINPLAN et al., 2014). Women in Maniema province have been weakened by war and poverty, and low agriculture productivity worsens their plight (CRS, 2009). As such, this variable is one of the cornerstones of the study, in that it first looks if the NTA project had the desired outcome of targeting and, ultimately, assisting women, and second if there was a gender component to adoption.

*Farmers' group*

*Farmers' group* is a dummy variable taking the value 1 for farmers who are members of a farmers' group, and 0 for farmers not in a farmers' group. In Malawi, membership in a farmers' group has been reported as a driver of CA adoption (Chisenga, 2015). Bisangwa (2013) argues that CA has "advantages that increase social capital through farmer[s'] groups," when listing his benefits of CA adoption in Lesotho. According to Silici (2009), "social interactions within a group and among this and other groups" increase farmers' knowledge and access to innovative information, and, so affected CA adoption in Lesotho. In the DRC, where the government extension service does not work well, the farmers' group approach is considered an alternative. Forming farmers' groups as entry points in Maniema's communities was chosen by the NTA project to reach the "poorest farmers" at low cost and to prepare them for collective marketing, as CA was expected to increase their crop production.

*Accessed credit*

*Accessed credit* is a dummy variable which takes the value 1 if the farmer had accessed credit and 0 for the farmers who had not accessed credit. An important delineation needs to be made between those who had "access to credit" and those who "accessed credit". The dataset used in this study only asked participants if they "accessed credit", and did not denote those who may have "access to credit" but were either turned down or did not apply for it. Access to credit is cited as a constraint and/or a determinant to CA adoption (Giller et al., 2009; Giller et al., 2011; Bisangwa, 2013; Chisenga, 2015; Thierfelder et al., 2015; Ntshangase et al., 2018). Increasing access to formal and informal credit sources could help farmers surmount short-run liquidity constraints which may be brought on by CA adoption (Lee, 2005).

Table 3 summarizes the explanatory variables used in the study with a brief description for each with their expected impact based on previous literature.

Table 3. Explanatory variables, description, and expected outcome.

| **Variable** | **Description and Measurement type** | **Variable type** | **Expected outcome (+/-)** |
|---|---|---|---|
| *Age* | Age of head of the household (years) | continuous | +/– |
| *Household size* | Farmer's household size (number of people) | integer | + |
| *Farm size* | Farmer's land size (in hectare) | continuous | +/– |
| *Training* | Training received on CA; Dummy, = 1 if the farmer was trained in CA, = 0 if the farmer was not trained in CA | categorical | + |
| *Savannah* | Agroecological zone where the farm is located; Dummy, = 1 means in the savannah (Kasongo), = 0 means in the forest (Kailo) | categorical | +/– |

Table 4. Explanatory variables, description, and expected outcome (Cont.).

| Variable | Description and Measurement type | Variable type | Expected outcome (+/-) |
|---|---|---|---|
| *Literacy* | Farmer can read and write; Dummy, = 1 if the farmer is literate, = 0 if the farmer is not literate | categorical | +/– |
| *Female non-married* | Farmer is female and non-married/widow; Dummy, = 1 if the farmer is Female non-married, = 0 for any married farmer | categorical | + |
| *Farmers' group* | Farmers' group membership; Dummy, = 1 if the farmer is a farmers' group member, = 0 if the farmer is not a farmers' group member | categorical | + |
| *Accessed credit* | Farmers had accessed credit; Dummy, = 1 if the farmer had accessed credit, = 0 if he/she did not accessed credit | categorical | + |

(ii) Logit models

Studies focusing on factors influencing CA adoption have used different methods of analysis such as linear probability models, ordinary least squares, random effects, GLS, stepwise regression, the Cragg model, logit model, probit model, multinomial logit model, non-parametric chi-square test, and multiple classification analysis (Knowler & Bradshaw, 2007). Similar studies conducted on small farms between 2013 and 2018 used logit and probit models in Tanzania, South Africa, and Lesotho and multinomial logit models in Mozambique, Zimbabwe, and Zambia (Bisangwa, 2013; Mkamkwe, 2013; Mavunganidze et al., 2013; Grabowski, 2015; Mlenga & Maseko, 2015; Ntshangase et al., 2018).

For this study, CA adoption is considered as the choice made by a farmer to apply all three components of CA technology (no-tillage, crop rotation, and mulching) simultaneously. The farmer "faces a pair of choices" (p.721) and chooses one outcome, in this case, to adopt or not to adopt (Greene, 2012). The dependent variable, *adopt*, is a binary response. A logit model was used to explore how explanatory variables affect the probability of CA adoption occurrence (Mlenga &

Maseko, 2015). The probability for an individual farmer ($i$) adopting CA can be modeled as follows (Greene, 2012):

$$Prob\ (adopt_i = 1 \mid \mathbf{x}_i) \ = \ \frac{e^{(\mathbf{x}_i' \beta)}}{1 + \ e^{(\mathbf{x}_i' \beta)}} \ = \ F(\mathbf{x}_i, \beta) \qquad (1)$$

where $\mathbf{x}_i$ is a vector of the independent variables listed in Table 3 above, $\beta$ is the parameter vector reflecting the changes in $\mathbf{x}_i$ on the probability, and $F$ is the logistic function taking on values strictly between zero and one.

The marginal effect on the probability of adopting for a change in $d$, a binary independent variable, is given by (Greene, 2012):

$$Marginal\ effect = Prob\left[adopt_i = 1 \mid \bar{\mathbf{x}}_{(d)}, d = 1\right] - \ Prob\left[adopt_i = 1 \mid \bar{\mathbf{x}}_{(d)}, d = 0\right] \quad (2)$$

where $\bar{\mathbf{x}}_{(d)}$ denotes the sample means of all the other variables in the model. This implies that the marginal effects are evaluated with all other independent variables set at their sample means. The formula for the marginal effect on the probability of adopting for one-unit change in a continuous variable in $\mathbf{x}_i$, as given by Greene (2012, p.729), is

$$Marginal\ Effect = \frac{\partial F(\mathbf{x}_i, \beta)}{\partial \mathbf{x}_i} = \left[\frac{dF(\mathbf{x}_i' \beta)}{d(\mathbf{x}_i' \beta)}\right] \times \beta \qquad (3)$$

Also, knowing that for the logistic function $F$, $F(z) = e^z/(1+e^z)$ and the computation of its derivative gives $dF/dz = F(z)*(1 - F(z))$.

In this study's approach, the estimation of a variety of model specifications establishes the validity of the findings. Hence, four different versions of the full-sample model are estimated. In addition, while it would be ideal if the parameters, $\beta$, were constant across the entire sample, our *a priori* belief—backed up by empirical evidence shown shortly—is that the parameter vector, $\beta$, is not constant across all observations. Consequently, models using samples that are subsets of the full sample are estimated. Such a sorting gives more precise insights into farmers' behavior. These different perspectives looking at CA adoption lead to eight analytical models given below.

1. Full-sample – logit model (n = 225)

This model was specified to provide a baseline model without considering the geographical context. In most of the eight models, the vector $\mathbf{x}_i$ includes all variables except *savannah* and *villages* selected by the researchers, so that the most basic full-sample model can be written as

$$Prob\ (adopt_i = 1 \mid \mathbf{x}_i) = F\begin{pmatrix} \beta_0 + \beta_1\ age_i + \beta_2\ household\ size_i + \beta_3\ farm\ size_i \\ + \beta_4\ training_i + \beta_5\ literacy_i + \beta_6\ female\ non-married_i \\ + \beta_7\ farmers'group_i + \beta_8\ accessed\ credit_i \end{pmatrix} \quad (4)$$

2. Agroecological zone – logit model (n = 225)

This model was specified to illustrate farmers' behavior based on their agroecological zones in a research area, where either the farm is located in the savannah or in the forest. The conditions in the two zones are not the same, and zone likely impacts farming. The vector $\mathbf{x}_i$ in (1) here includes all variables in (4) plus a binary for zone, where the binary is one if the observation is from the savannah.

3. Village level – logit model (n = 225)

This model was specified to illustrate farmers' behavior allowing village-level differences. The geography of the research area shows that the selected villages are in four different *collectivités*, meaning four ethnic groups. This cultural-locational aspect may play a role in CA adoption. The vector $\mathbf{x}_i$ in (1) here includes all variables in (4) with ten additional binaries to designate the village where the observation was taken. Enombe-Brigade was the baseline village.

4. Savannah region – logit model (n = 97)

This model was specified to illustrate farmers' behavior only in the savannah. This model is specified as (4), but only data collected in the savannah (Kasongo territory) are utilized in estimation. The focus is to model the behavior of farmers in savannah conditions. By comparing the estimated coefficient from this model to models (5) to (7), this study determines if the slope coefficients vary in addition to the intercepts as in models (2) and (3).

5. Forest region – logit model (n = 128)

This model was specified to illustrate farmers' behavior only in the forest. This model is specified as (4), but only data collected in the forest (Kailo territory) are utilized in estimation. The focus is to model the behavior of farmers in the forest conditions.

6. Trained group – logit model (n= 181)

This model was specified to isolate farmers' behavior after being trained in CA by the NTA project. This model is similar to (4) but uses a subset of the sample, including only trained farmers.

7. Untrained group – logit model (n = 44)

This model was specified to isolate how untrained farmers behave. This model is, like (1), estimated using the subset of observations of untrained farmers. The vector $\mathbf{x}_i$ as given in (1) excludes the variables *female non-married* and *literacy*. It turned out that for untrained farmers, there is very little variability in the dependent variable *adopt* but also little variability in *literacy* and *female non-married*, indicating that, for untrained farmers, *literacy* and *female non-married* are not related to CA-adoption decisions.

8. Full-sample without training – logit model (n = 225)

This model was specified as (1) but omits *training*. The purpose was to determine if the parameters of other variables change when CA training received from the NTA project is omitted. The focus is to show how farmers' behavior on the entire research area is affected by training. Some variations would be expected in coefficient estimates from their counterparts in (4). So, this helps us understand the full impact of training both through its direct effect, $\beta_4$ , and its indirect effect via the changes in the other coefficients without *training*.

*Modeling the perceived benefits of CA*

This section focuses on farmers' perceptions of the benefits of CA. The modeling approach here is similar to econometric studies that explored agricultural technology adoption in West Africa. In Burkina Faso, Guinea and Sierra Leone, Adesina and Zinnah (1993), and Adesina and Baidu-Forson (1995) showed that the way farmers perceived improved varieties was an incentive to adopt them. Farmers' perceptions are subjective and, thereby, hard to explain how they are formed. Modeling the perceived benefits of CA for farmers in the province of Maniema is a practical attempt to learn and explain their individual behavior in this part of the DRC. From field experience, smallholders' farmers do not accept or believe in an innovation until they have benefited from it or seen how it benefits their peers.

(i) Explanatory variables

To measure the perceived benefits of CA in 2015, three years after the completion of the NTA project in the research area, *adopt* and *savannah* are the two targeted variables that explain the variation in farmers' perceptions of the various benefits of CA. The purpose here is to quantify how perceptions vary as a result of whether farmers adopted CA or not and/or whether agroecological conditions play alone or together with CA adoption a role in explaining farmers' behavior. In 2015, "improving food security, [an] increase in revenue, and payment of school fees" were reported by CRS as the key incentives for CA adoption. The dependent variables in the next paragraph were used to measure farmers' perception of CA benefits.

(ii) Dependent variables

*Reliability of income from CA*

The variable *reliability of income from CA* is a response to the question "Is the income obtained from CA reliable?" The respondent was required to respond if he or she thought his or her *income from CA* was 'not reliable at all,' 'less reliable,' 'somehow reliable,' or 'very reliable' in relation to not using CA. This structure restricted and ordered the answer making *reliability of income from CA* an ordinally ranked variable. A study by Thierfelder et al. (2015) in Southern Africa that explored smallholders' farmers' perceptions and CA showed that CA adoption leads to an increase in farmers' household income. The present study used farmers' perception of income reliability to assess the benefit of adopting CA.

*Land under CA*

The variable *land under CA* is a response to the question "Did the farmland area under CA increase after the end of the NTA project?" The respondent was required to choose if the farmland under CA has 'increased,' remained 'static,' or 'decreased.' This structure restricted and ordered the answer while making this variable ordinally ranked. *Land under CA* is described as the farmland on which CA is applied. It allows for an approximation of CA expansion on household farms from a smallholders' farmers' perspective. Ntshangase et al. (2018) noted a decrease in farm size due to CA adoption. This study aimed to check how the perception of CA expansion is related to CA adoption.

*Food security status*

The variable *food security status* is a response to the question "What is the current (2015) food security status compared to 2012?" The respondents were required to say if they thought their food security status has 'decreased,' 'stagnated,' or 'improved.' This response structure results in an ordinally ranked variable. Thierfelder et al. (2015) showed that CA adoption led to increases in farmers' household food security. The present study also used farmers' perception to assess the benefit of adopting CA on food security status.

Table 4 summarizes the list of dependent variables with a brief description for each, and their hypothesized outcomes as a result of CA adoption based on existing literature.

Table 5. Explained variables, description, and hypothesized outcome.

| **Variable** | **Description and Measurement type** | **Variable type** | **CA influence (+/-)** |
|---|---|---|---|
| *Reliability of income from CA* | Farmers' perception of reliability of income gained from the farm due to CA (1 = not reliable at all, 2 = less reliable, 3 = somehow reliable, 4 = very reliable) | categorical | + |
| *Land under CA* | Farmer's perception of CA expansion on the farmer's land (1 = decreased, 2 = static 3 = increased) | categorical | +/– |
| *Food security status* | Farmer's perception of his own food security status due to CA (1 = decreased, 2 = stagnated, 3 = improved) | categorical | + |

(iii) Ordered logit models

To explain perception levels as a function of adoption and region, an ordered logit model is appropriate for the three variables in Table 4. According to Greene (2012), with an ordered logit model someone "reveals the strength of [his/her] preference with respect to a single outcome" (p.800).

The probability for an individual farmer ($i$) to select alternative $j$ in 1, 2, …, $j$ – 1 can be modeled as following Cameron and Trivedi (2005):

$$Prob\ (y_i = j \mid \mathbf{x}_i) = Prob\left(\alpha_{j-1} < y_i^* \le \alpha_j\right) = F\left(\alpha_j - \mathbf{x}_i'\beta\right) - F\left(\alpha_{j-1} - \mathbf{x}_i'\beta\right) \quad (5)$$

where $y$ represents one of the dependent variables: *reliability of income from CA*, *land under CA*, or *food security status;* and $y$* an index model with single latent variable representing the starting point ($y_i^* = \mathbf{x}_i'\beta + u_i$). Given $j$ alternatives for a particular $y$, the $\alpha_j$ are the thresholds between alternatives, $\mathbf{x}_i$ is a vector holding the regressors (*adopt* and *savannah)*, and $F$ is a logistic function $F(z) = e^z/(1+e^z)$.

The marginal effects for the expression (5) are given by (Cameron & Trivedi, 2005):

$$Marginal\ effect = \{F'\left(\alpha_{j-1} - \mathbf{x}_i'\beta\right) - F'\left(\alpha_j - \mathbf{x}_i'\beta\right)\}\,\beta \qquad (6)$$

where $F'$ denotes the derivative of $F$ and is interpreted as the change in the probability of selecting alternative $j$ as $\mathbf{x}_i$ increased one unit. Also, $F\left(\alpha_J - \mathbf{x}_i'\beta\right) = 1$ and $F\left(\alpha_0 - \mathbf{x}_i'\beta\right) = 0$, where $J$ denotes the highest alternative of the dependent variable.

Based on equation (5), five models of the three different perspectives (all research area, agroecological zones, and training) examined the impact of CA adoption on each of the dependent variables. The five analytical models are:

9. Full-sample – ordered logit model (n = 225)

This model estimates the influence of CA adoption and the agroecological context on the benefits perceived by farmers in terms of reliable income, CA farmland expansion, and food security at household level for the entire pooled dataset. Each of the explained variables (*reliability of income from CA*, *land under CA*, and *food security status*) is regressed on *adopt* and *savannah*.

10. Savannah region – ordered logit model (n = 97)

This model isolates the influence of CA adoption only in the savannah region on the benefits perceived by farmers in terms of reliable income, CA farmland expansion, and food security. Each of the explained variables (*reliability of income from CA*, *land under CA*, and *food security status*) is regressed on *adopt*. This model estimates the perceived benefits of CA adoption in Kasongo territory.

11. Forest region – ordered logit model (n = 128)

This model isolates the influence of CA adoption only in the forest region on the benefits perceived by farmers in terms of reliable income, CA farmland expansion, and food security. Each of the explained variables (*reliability of income from CA*, *land under CA*, and *food security status*) is regressed on *adopt*. This model estimates the perceived benefits of CA adoption in Kailo territory.

12. Trained – ordered logit model (n = 181)

This model illustrates the influence of CA adoption and the agroecological context on the benefits perceived by CA trained farmers in terms of reliable income, CA farmland expansion, and food security. Each of the explained variables (*reliability of income from CA*, *land under CA*, and *food security status*) is regressed on *adopt* and *savannah*. These models estimate the perceived benefits of CA adoption for trained farmers.

13. Untrained – ordered logit model (n = 44)

This model illustrates the influence of CA adoption and the agroecological context on the benefits perceived by CA untrained (those who did not go through formal CA training) farmers in terms of reliable income, CA farmland expansion, and food security. Each of the explained variables (*reliability of income from CA*, *land under CA*, and *food security status*) is regressed on *adopt* and *savannah*. This model estimates perceived benefits of CA adoption only for untrained farmers.

## Results & discussion

*CA adoption*

(i) Model results description

The characteristics and perspectives of survey participants from which CA adoption was examined are presented in Table 2. Table 2 provides comparisons between CA adopters and non-adopters, trained and untrained farmers, and survey participants located in the forest and savannah. This study went beyond the simple correlation of factors driving adoption by modeling the relationship CA adoption has with the each of the variables listed in Table 2 using regression analysis (binary regression or logistic models). In all logistic (logit) models, the logit link is used as opposed to the probit link for ease of computation of marginal effects. There were two major drivers for the logit modeling of factors that influence CA adoption: the impact of geographical location and the impact of CA training. First, the geographical location led to estimating CA adoption in the logit framework by segmenting the overall sample in four different ways (models (2) to (5)) in Table A.1 in Appendix. Alternative specifications of how CA training impacts the adoption of CA are located in models (6), (7), and (8) in Table A.1.

*Full-sample model*

The full-sample (pooling all regions into one) regression model (model (1)) in Table A.1 is the baseline model for CA adoption. Model (1) estimates CA adoption for the entire training area while the alternative seven models differ from it in distinct ways. Model (1) had the lowest Akaike Information Criterion (AIC) when the Stepwise backward analysis was used to select within the CRS database (2015) the most significant factors to use for this study.[2] With an AIC = 166, model (1) is "preferred" (Cameron & Trivedi, 2005) to model (8) with AIC = 186. This suggests a better model fit when *training* is included as a predictor. Model (1) has a better fit based

[2] A list of variables used in the stepwise process are located in Table A.2 in appendix.

on its lower AIC value. With model (1), *farmers' group*, *training*, *accessed credit*, and *female non-married* are highly statistically significant ($p < 0.01$) and as such are likely strong drivers of CA adoption. The influence of these four factors is positive for the first three factors and surprisingly negative for *female non-married*. *Age*, *farm size*, *household size*, and *literacy* are statistically insignificant ($p > 0.10$) in model (1).

*Agroecological zones model*

The agroecological zone regression model (model (2)) in Table A.1 adds the predictor *savannah*, essentially testing if there are statistical differences in CA adoption between the two agroecological zones. The AIC for model (2) is 155, indicating a better prediction of CA adoption than model (1). With model (2), *savannah*, *accessed credit*, *farmers' group*, *training*, and *female non-married* are highly significant ($p < 0.01$) on CA adoption. The influence of these factors is positive, except for *female non-married*, which has a negative influence on CA adoption. For model (2), *age*, *farm size*, *household size*, and *literacy* are statistically insignificant. Given the statistical significance ($p < 0.01$) of the *savannah* variable in Table A.1, model (2) indicates that each region (forest and savannah) may need to be modeled separately.

*Village level model*

Model (3) on Table A.1 is built from model (1) with the inclusion of the locations of the 11 villages targeted in the research site. The AIC for model (3) is 158, which is inferior to model (2) but still statistically superior to model (1), with respect to estimating factors of CA adoption. This would indicate that, from a geographical context, it is statistically superior to use the agroecological zones level over the village level model, though this may be due to the large increase in number of parameters estimated. This also means there are unobserved parameters (explanatory variables not included in the model) that make adoption more attractive in the savannah. Furthermore, in model (3), *farm size* has a statistically significant influence ($p < 0.10$) on CA adoption but is not as strong as *accessed credit*, *farmers' group*, *training*, and *female non-married*, which have a highly significant influence ($p < 0.01$). The influence of *female non-married* and villages on CA adoption are negative. *Age*, *household size*, and *literacy* are not statistically significant ($p > 0.10$).

*Savannah and forest regions models*

Model (4), using only observations from participants located in the savannah, and model (5), using only those observations from participants located in the forest, in Table A.1 estimate, respectively, CA adoption in the savannah and forest independently. The set of factors used for model (1) is identical to those used on the subsets in models (4) and (5). Model (4) indicates that in the savannah only *training* (if the participant was formally trained in CA) is statistically significant ($p < 0.01$) on CA adoption, with the remaining variables being statistically insignificant ($p > 0.10$). Model (5) indicates that in the forest, *accessed credit*, *farmers' group*, *training*, and *female non-married* have a high significant influence ($p < 0.01$) on CA adoption. *Accessed credit*, *farmers' group*, and *training* have a positive influence; *female non-married* was found to be a deterrent to adoption. In model (5), *age*, *farm size*, *household size*, and *literacy* are not statistically significant ($p > 0.10$). Models (4) and (5) provide evidence of differing factors of CA adoption relevant to each (savannah and forest) regional location.

*Trained group, untrained group, and full-sample without training models*

The impact of CA training is approached by estimating models with only trained farmers (model (6)), untrained farmers (model (7)), and all participants regardless of training (model (8)). Models (1) to (5) have highlighted the robustness of *training* in influencing CA adoption positively. Model (6) indicates that for those farmers who had completed formal CA training, *accessed credit*, *farmers' group*, and *female non-married* are statistically ($p < 0.01$) influential on the adoption of CA, and only *female non-married* negatively ($p < 0.01$) affects adoption. For model (7), none of the explanatory variables were found to be statistically significant ($p > 0.10$). Furthermore, model (8) is model (1) with *training* removed. Model (8) indicates that *accessed credit*, *farmers' group*, and *female non-married* play a statistical role ($p < 0.01$) on CA adoption, and only *Female non-married* has a negative influence. In model (8), *age*, *farm size*, *household size*, and *literacy* are not statistically significant ($p > 0.10$). Model (8) shows how excluding *training* makes CA adoption modeling different, with an increased AIC compared to model (1), and model (6) and (7) make it clear that factors influencing CA adoption are not the same among trained and untrained farmers. CA adoption among trained farmers, as shown by model (6), is driven by having accessed credit, being in a farmers' group, and being a female non-married, while there is no any influence for untrained farmers (model (7)).

(ii) Interpreting the impact of factors influencing CA adoption

Table 5 presents the marginal effects for each logit model used to explain CA adoption.

<u>*Savannah*</u>

*Savannah* is highly significant ($p < 0.01$) in model (2). The coefficient given by model (2) in Table 5 for *savannah* implies a farmer located in the savannah is 26.5% more likely to adopt CA than farmers located in the forest, ceteris paribus. In Table 2, looking at farmer characteristics, there are more CA adopters in the savannah (77%) than the forest (65%). The chi-square test shows in Table 2 a significant difference ($p < 0.10$) between farmers adopting CA in the savannah versus those located in the forest. It is important to highlight here that in the forest, CA was applied on 5-10-years-old fallows that used the slash-and-burn practice, and not the virgin forest (CRS, 2012, 2015).

Table 6. Marginal effects of factors influencing CA adoption

| Dependent variable =1 if the farmer adopted CA | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | Full sample | Agroecological zone | Village level | Savannah region | Forest region | Trained group | Untrained group | Full sample without training |
| *Savannah* | – | 0.265*** (0.077) | – | – | – | – | – | – |
| *Enombe - Sakina* | – | – | -0.787*** (0.195) | – | – | – | – | – |
| *Kamonga* | – | – | -0.052 (0.301) | – | – | – | – | – |
| *Kampala* | – | – | -0.702* (0.296) | – | – | – | – | – |
| *Kauta* | – | – | -0.049 (0.271) | – | – | – | – | – |
| *Kimanga* | – | – | -0.832*** (0.144) | – | – | – | – | – |
| *Kionga* | – | – | -0.439 (0.547) | – | – | – | – | – |
| *Lubangwana* | – | – | -0.863*** (0.082) | – | – | – | – | – |
| *Lubelenge* | – | – | -0.655 . (0.337) | – | – | – | – | – |
| *Lukongo* | – | – | -0.620 (0.403) | – | – | – | – | – |
| *Nyoka* | – | – | -0.587 (0.386) | – | – | – | – | – |
| *Age* | 0.006 (0.004) | 0.004 (0.003) | 0.002 (0.003) | 0.001 (0.002) | 0.008 (0.006) | 0.002 (0.002) | 0.004 (0.004) | 0.004 (0.003) |
| *Farm size* | 0.050 (0.040) | 0.065 (0.041) | 0.068 . (0.038) | 0.032 (0.040) | 0.124 (0.077) | 0.038 (0.030) | 0.0007 (0.057) | 0.042 (0.029) |
| *Accessed credit* | 0.260*** (0.072) | 0.197** (0.069) | 0.233** (0.078) | 0.107 (0.089) | 0.277* (0.109) | 0.166** (0.056) | 0.198 (0.287) | 0.317*** (0.064) |
| *Farmers' group* | 0.355*** (0.105) | 0.319** (0.107) | 0.360** (0.123) | 0.096 (0.106) | 0.422** (0.131) | 0.261* (0.110) | 0.157 (0.146) | 0.467*** (0.091) |
| *Household size* | -0.001 (0.009) | -0.002 (0.008) | -0.004 (0.007) | -0.007 (0.009) | 0.003 (0.014) | -0.002 (0.005) | 0.008 (0.011) | 0.005 (0.008) |
| *Female non-married* | -0.414** (0.154) | -0.299 . (0.161) | -0.388* (0.189) | -0.048 (0.169) | -0.416* (0.164) | -0.283 . (0.149) | – | -0.346* (0.154) |
| *Literacy* | -0.097 (0.075) | -0.046 (0.076) | -0.074 (0.057) | 0.142 (0.164) | -0.210 . (0.115) | -0.063 . (0.036) | – | -0.110 . (0.065) |
| *Training* | 0.516*** (0.119) | 0.671*** (0.112) | 0.745*** (0.120) | 0.521* (0.2659) | 0.690*** (0.112) | – | – | – |

**Note**:
- Significance codes '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
- The marginal effects in this table derived from regression models in Table A1. (see Appendix)

Based on Knowler and Bradshaw's (2007) listing of "factors affecting significantly" CA adoption, the variable *savannah* would be included in the farm biophysical characteristics group. An agroecological zone is an area of similar conditions in terms of temperature, soil characteristics, and rainfall, factors listed by Knowler and Bradshaw (2007). The forest part of Maniema province has an average annual rainfall of 1,600 mm and sandy-clay fertile soils while the savannah has an average annual rainfall of 1,500 mm and moderately fertile soils consisting of more sand than clay (FEWSNET, 2016). The results of this study show that agroecological conditions likely play a role in CA adoption. In 2012, CRS reported that lower CA adoption in the forest may have been due to the "existence of minerals and mining livelihood opportunities, insignificant reduction in weeding labor where bush-fires are rampant, and inadequate skills and effort to manage the vegetation during the first year of NTA project" (p.11). Beyond mining, the forest also offers more livelihood options in terms of "hunting and wild food gathering" than the savannah (FEWSNET, 2016). That said, there also may be some other exogenous factors playing a role in CA adoption in the savannah and forest. Nevertheless, the current result has clearly demonstrated that CA is more likely in the savannah than forest.

*Villages*

*Villages* represents unobserved differences among villages. The 11 villages of the research area are *Enombe – Brigade, Enombe – Sakina, Kampala, Kimanga, Lubangwana, Lubelenge,* and *Nyoka* in the forest and *Kamonga, Kauta, Kionga,* and *Lukongo* in the savannah. Figure 1 shows that the 11 villages fall into four ethnic groups areas: Wangengele, Wasongola, Mamba – Kasenga, and Wazula. *Enombe – Brigade* is the baseline village. *Enombe – Brigade* and *Kionga* have the highest CA adoption rate (86%). Two key lessons emerge from exploring the village level in model (3) as presented in Table 5. First, there is no statistical significance ($p > 0.10$) for all villages in the savannah region (Kasongo territory) relative to the baseline village. Second, for the villages in the forest (Kailo territory), the CA adoption differs amongst villages. While the village *Nyoka* is not statistically different ($p > 0.10$) compared to *Enombe – Brigade*, Table 5 illustrates that CA adoption is 86% less likely to occur in *Lubangwana*, 83% less in *Kimanga*, 79% less in *Enombe – Sakina*, 70% less in *Kampala*, and 66% less in *Lubelenge* compared to *Enombe – Brigade*. To interpret this, the five villages in the forest tend to be less likely to adopt CA relative to the baseline village. The inclusion of these villages made the intercept in model (3) statistically insignificant and illustrated that there are significant differences among the unobserved factors among villages. Because there are four different ethnic groups in the research area, it seemed evident that the models should include village dummies which act as a proxy for ethnicities. It happens that the location of CA farms in three out of four villages of Wangengele people and two out of three villages of the Wasongola people negatively influence CA adoption, while in the villages of Wazula and Mamba-Kasenga ethnic groups, location is not significant. Model (3) foregrounds the influence of ethnicity on CA adoption, as there must be specific unobserved factors for each location. CA is received differently by ethnic groups and this also expresses how farmers are connected to their beliefs. The sociologic context has the potential to absorb and customize factors influencing CA adoption. There may be some specific cultural and resources-access factors that played a role in Maniema province.

CRS (2015), who did not use regression modeling but rather a Chi-square analysis, reported that there was no relationship between village and CA adoption. CRS' statement appears to be in contradiction with this study's findings. In the forest of Maniema province, artisanal mining is one of the "coping strategies for poor households" (p.54) reported by FEWSNET (2016). That said, the proximity of villages to mining sites together with other unknown exogenous factors can possibly bring differences among villages and contribute to influence CA adoption at the village level.

*Age*

As shown in Table 5, *age* of the household head is robustly insignificant ($p > 0.10$) across all eight models. As such, *age* does not seem to affect CA adoption regardless of model specification. From Table 2, the means comparison between groups using t-tests also show that as a farmer characteristic, *age* of participants living in the savannah or forest, trained or untrained, CA adopters or not is just an insignificant factor.

Like with CRS results, this study shows that *age* does not influence CA adoption in the research area. This finding is consistent with Knowler and Bradshaw (2007) who showed that in many cases the influence of age on CA adoption is typically insignificant regardless of the method of analysis used. Looking at many chronic problems farmers still face in the DRC and their consequences, it could be that *age* is actually being proxied by other variables (single women farmers, member of farmers' group, etc.).

*Farm size*

With the exception of the village level model (model (3)), *farm size* is consistently insignificant ($p > 0.10$) across the other seven models. Model (3) in Table 5 indicates that a marginal increase (one hectare) in *farm size* will increase the probability of adoption by 6.8%. Model (3) highlights the variability of *farm size* across the villages in the research area. The average *farm size* for the 11 villages ranges from 0.53 to 1.65 hectares. Looking at descriptive statistics in Table 2 about farmers' characteristics, the results of t-tests demonstrate the presence of a statistical difference ($p < 0.05$) for *farm size* not between savannah and forest, or trained and untrained farmers, but rather between CA adopters and non-adopters. CA adopters' *farm size* is 30% larger than their non-adopters' counterparts.

*Farm size*, as a "farm specific factor" (Liu and Huang, 2013) has already been included by Knowler and Bradshaw (2007) in the "farm biophysical characteristics" group of factors driving CA adoption. According to the two last scholars (Knowler and Bradshaw) who explored CA adoption studies, *farm size* can have a positive, negative, or neutral influence on CA adoption. There is no clear pattern or delineation between large- and small-scale producers. Mavunganidze et al. (2013) found a positive influence of *farm size* on CA adoption by smallholders' farmers in Zimbabwe, while Ntshangase et al. (2018) demonstrated a negative influence with smallholders' farmers in South Africa. However, this study shows that in Maniema province, *farm size* has a positive influence on CA adoption only when village locations are included. This suggests more research may be needed at the village level to assess the influence of land-related drivers on adoption of CA.

*Accessed credit*

As shown in Table 5, *accessed credit* is robust and statistically significant ($p < 0.01$) across all models except model (4) (that estimates CA adoption for farmers in savannah region only) and model (7) (that estimates CA adoption for untrained farmers only), where it is not significant ($p > 0.10$). Model (1) in Table 5 indicates a farmer is 26% more likely to adopt CA if he/she has accessed credit. In the same Table 5, the positive influence of *accessed credit* is 19.7% in model (2), 23.3% in model (3), 27.7% in model (5), 18.1% in model (6), and 31.7% in model (8). Using a Chi-square test (Table 2), it appears that there is a statistically significant difference ($p < 0.05$) between CA adopters and non-adopters, trained and untrained farmers, and participants living in the forest versus those in the savannah for *accessed credit*. Almost 64% of CA adopters, 59% of farmers trained in CA, 42% farmers in the forest, and 57% farmers in the savannah had accessed credit.

Knowler and Bradshaw (2007) included *accessed credit* in the "farm financial/ management characteristic" group of factors influencing CA adoption. Ntshangase et al. (2018), Mamkwe (2013), Chisenga (2015), Bisangwa (2013) showed that limited access to credit reduced CA adoption by smallholders' farmers in South Africa, Tanzania, Malawi, and Lesotho, respectively. The findings of this study demonstrate the positive role of having accessed credit on CA adoption. CRS (2015) brought credit services into the research area with the Savings and Internal Lending's Communities (SILC) approach. SILC groups provided credit to smallholder farmers "to purchase farm supplies – seeds and tools – albeit in small proportions" (CRS, 2015, p.8). These results would suggest that improving financial options for poor farmers could be a good approach to support integration of CA in the Maniema communities in DRC.

*Farmers' group*

As illustrated in Table 5, *farmers' group* has a positive statistical significance ($p < 0.01$) on CA adoption across each model except model (4) (that estimates CA adoption for farmers in savannah region only) and model (7) (that estimates CA adoption for untrained farmers only) where it is not significant ($p > 0.10$). Model (1) in Table 5 indicates that a farmer is 35.5% more likely to adopt CA if he/she is a member of a farmers' group. Table 5 also indicates that being in a farmers' group increases the likelihood of adopting CA by 31.9% in model (2), 36.0% in model (3), 42.2% in model (5), 22.3% in model (6), and 46.7% in model (8). Furthermore, Chi-square test results in Table 2 display the significant difference ($p < 0.01$) between CA adopters and non-adopters and trained and untrained farmers. Eighty-nine percent of CA adopters and 85% of trained farmers are members of a *farmers' group*.

*Farmers' group* is similar to what Knowler and Bradshaw (2007) call "membership in [an] organization such as a producers' organization" and considered as an exogenous factor that positively influences CA adoption. For Chisenga (2015), in Malawi, *farmers' group* increased CA adoption by women. Chisenga (2015) recommended the formation of mixed groups and the use of farmers' groups by extension services as a channel to promote CA. Even though two of the eight models did not confirm the influence of farmers' group membership, in the savannah and among untrained farmers, the general consensus is that belonging to a farmers' group increases CA adoption. Ntshangase et al. (2018) had a similar finding in South Africa. Besides the social capital a farmers' group brings to smallholders' farmers' communities, it is also a strong platform for learning and information sharing where extension service is low.

<u>*Household size*</u>

*Household size* is robustly insignificant ($p > 0.10$) across all eight models in impact on CA adoption. These results are interesting, as it could be hypothesized that smaller households may be more likely to adopt CA since it is potentially labor saving. However, the t-test results in Table 2 about farmer's characteristics demonstrate that *household size* is statistically significant ($p < 0.01$) between CA adopters and non-adopters and trained versus untrained farmers but not between participants of the two agroecological zones (savannah and forest). CA adopters and trained farmers have larger (11 members) average household size than CA non-adopters and untrained farmers (9 members), respectively. This agrees with the CRS (2015) conclusion about CA adopters and legitimize the presence of the factor *household size* in this research on CA adoption.

Instead of *household size*, Knowler and Bradshaw (2007) modeled "family labor" and found it has positive influence on CA adoption. According to CRS (2015), in the research area, "the farm operations are usually done using family rather than hired labor" (p.17). So, a higher *household size* increases the potential labor resource. In Table 2, clustering the research participants, the statistical difference noted for *household size* implies CA adopters and trained farmers have potentially more labor than CA non-adopters and untrained farmers, respectively. Mango et al. (2017) observed similarity in household size between CA adopters and non-adopters in Zimbabwe, Malawi, and Mozambique. In Zimbabwe, where “family members are the main sources of labor in rural areas” (p.1644), among cotton farmers, CA adopters tend to have 6–10 members in their household (Mavunganidze et al., 2013), which is a little bit less than the 11 found in Maniema. In South Africa, Ntshangase et al. (2018) claimed that larger households influence CA adoption, but members need to be “economically active,” meaning they provide farm labor a view shared by Mamkwe (2013), who found that household size did not affect CA adoption in Tanzania. Finally, besides its lack of influence, household size remains an important factor to observe in modeling CA adoption not only because it is correlated with labor but also because it may lead to more research on how household active and non-active members affect CA adoption.

*Female non-married*

*Female non-married* has a robust and negative statistical significance ($p < 0.01$) influence on CA adoption across all models except model (4), where it is not statistically significant as presented in Table 5. Model (1) in Table 5 indicates a non-married female farmer is 41.4% less likely to adopt CA. Table 5 also says that a single woman farmer is 29.9% less likely to adopt CA in model (2), 38.8% in model (3), 41.6% in model (5), and 34.6% in model (8). Chi-square results in Table 2 also show that, as a farmer characteristic, *female non-married* is statistically different ($p < 0.05$) between CA adopters and non-adopters and farmers in the savannah versus the forest. Almost 18% of farmers who did not adopt CA are female non-married, and 15% female non-married live in the forest versus 4% in the savannah.

The CRS targeting strategy in the implementation of the NTA project was to prioritize “female headed households” (CRS, 2009, p.8) while giving particular attention to vulnerable women (widows, single-women, or separated/divorced due to consequences of DRC conflicts and poverty). *Female non-married* includes CRS-targeted vulnerable women farmers. In Maniema province, where 60% women are involved in agriculture as reported by the DHS (2014), the vulnerability of women is a result of many issues such as poverty, a weak healthcare system, low education, bad governance, and consequences of conflicts. While assessing gender roles within farmers’ communities in the NTA project targeted area, CRS (2009) highlighted two issues faced by women: “the volume of work allocated to women on a daily basis, and the weak involvement of women in decisions concerning the management of household resources” (p.4). With all this in mind, the finding that *female non-married* farmers are less likely to adopt CA can provide important information on how to possibly reprioritize their approach to getting vulnerable women to adopt CA. It appears that the current approach was not effective (relative to getting married females and men to adopt), and as such, a new strategy could be undertaken. In a CA adoption study, Mamkwe (2013) noted that, in Tanzania, “widows, divorcees and unmarried women have limited access to land.” The consequence of land shortage is a lower CA adoption by women farmers (Mamkwe, 2013). There must be gender challenges, customs, and beliefs that interact with CA adoption in farmers’ communities when a farmer happens to be *female non-married*. In Malawi, Ward, Bell, Droppelmann, and Benton (2018) reported how CA adoption is more likely to happen when there are more women than men in a farmer’s household. This supports including exogenous factors related to culture, gender, and land management in a region as drivers of CA in Sub-Saharan Africa.

*Literacy*

As shown in Table 5, *literacy* is robustly insignificant ($p > 0.10$) across all models. As a result of modeling (see Table A.1), that literacy does not appear to affect CA adoption. However, in Table 2 about farmers' characteristics, using Chi-square test, *literacy* is statistically different ($p < 0.10$) between participants located in the forest and those who are located in the savannah. Eighty-eight percent of farmers in the forest are literate versus 80% in the savannah. Between CA adopters and non-adopters or trained and untrained farmers, *literacy* is not significant ($p > 0.10$). CRS (2015) also reported that "there was no significant association between CA adopters and the level of education" (p.14).

Education and knowledge should play a positive role in the decision to adopt CA, but studies show not only positive but also negative and neutral influence on CA adoption (Knowler & Bradshaw, 2007). While in Lesotho, Malawi, South Africa, and Zimbabwe, education positively influences CA adoption (Bisangwa, 2013; Chisenga, 2015; Ntshangase et al., 2018; Mavunganidze et al.,2013), in Tanzania, it is insignificant (Mamkwe, 2013). The findings show that for a farmer in the research area, being able to read and write does not motivate him to adopt or not adopt CA. Perhaps the educated farmers in the forest are more interested in other livelihood opportunities and not farming. The number of literate farmers in the forest appears to be higher than the savannah, but farmers in the forest are less likely to adopt CA. Opportunities provided by the forest may have a certain relationship with farmers' education.

*Training*

If the producer had been formally trained (a dummy variable) was only included in models (1) to (5). As shown in Table 5, *training* is robust and statistically significant ($p < 0.01$) on CA adoption across all five models. Model (1) in Table 5 indicates that a farmer is 51.6% more likely to adopt CA if he/she has received CA training from the NTA project. Also in Table 5, the positive influence of *training* increases the likelihood of adoption of CA by 67.1% in model (2), 74.5% in model (3), 52.1% in model (4), and 69.0% in model (5). Table 2 also illustrates that *training* is not the same for CA adopters and non-adopters and the two agroecological zones. There are 17% more untrained than trained farmers, the majority of trained farmers live in the forest (85%), and 96% of CA adopters have been trained by the NTA project.

These results, with regard to *training*, are consistent with Bisangwa (2013) and Ntshangase et al. (2018), who demonstrated that CA training positively influenced CA adoption in Lesotho and South Africa, respectively. A similar result is also reported by Chisenga (2015), who claimed that, in Malawi, "access to farmer training on CA" has a positive influence on CA adoption. This research is case-specific as there are CA adopters who were not trained and CA non-adopters who were trained, but also, literacy does not matter for both trained and untrained farmers. This practically suggests there must be many lessons learned from NTA project field experience about promotion and education about CA.

*Benefits perceived from CA adoption*

"Farmers are consumers of the products of agricultural research, and their subjective preferences for characteristics of new agricultural technologies affect their adoption decisions" (Adesina & Baidu-Forson, 1995). For the smallholders' farmers in the Maniema province, CA is a new practice in their milieu. The first part of this research explored various factors influencing CA adoption. In this second part, this study estimates the perceived benefits of adopting CA. The research hypothesis is that the willingness to adopt CA is motivated by the way farmers perceive the benefits they derive from this technology. As a result of good perception about CA, there could be more room for CA dissemination in rural communities.

For the purpose of this study, ordered logit regression was used to model smallholders' farmers' perception. The perception of CA benefits was assessed looking at CA adoption, including the impact of geographical context, and the impact of CA training. Three kinds of benefits are modeled here: reliability of income, area under CA, and food security status. For each of these benefits, five ordered logit models are estimated. The full-sample ordered logit model (model (a)) uses all the observations (225) and has *adopt* and *savannah* as regressors. The forest ordered logit model (model (b)) and the savannah ordered logit model (model (c)) are two models, each with one regressor (*adopt*) and for which the observations are segmented based on agroecological zones, respectively, forest and savannah. The trained ordered logit model (model (d)) and the untrained ordered logit model (model (e)) each has two regressors (*adopt* and *savannah*), and the observations are segmented based on CA training into a subsample for trained farmers and a subsample for untrained farmers, respectively.

*Reliability of income from CA*

The marginal effects on how smallholders' farmers perceived income reliability as a CA benefit are presented in Table 6 below.

Model (a) in Table 6 shows clearly that agroecological context (being in the savannah or the forest) does not affect significantly ($p > 0.10$) farmers' perception of a reliable income as a result of applying CA. However, CA adoption significantly impacts these farmers' perception. The four levels of preferences for a reliable income from CA are highly significant ($p < 0.01$), with negative effect for the three lower levels ("not reliable," "less reliable," and "somehow reliable") and positive effect for the highest level ("very reliable"). Table 6 implies CA adopters' probability of perceiving very reliable income rises by 0.41 relative to non-adopters. Table 6 shows that CA adopters' probability of getting "somehow reliable," "less reliable," and "not reliable" income decreases, respectively, by 0.085, 0.102, and 0.223 compared to non-adopters. In terms of preference for a reliable income from CA, it appears that smallholders' farmers in the research area are really demanding. They perceive the decision to adopt CA despite the agroecological location as leading to a better income. For smallholders' farmers, obtaining a high income due to CA adoption should be a great incentive for the promotion and the dissemination of CA in the DRC.

Table 7. Marginal effects on reliability of income from CA.

| Dependent variable: Reliability of income from CA | | | | | |
|---|---|---|---|---|---|
| Models | | Not reliable at all | Less reliable | Somehow reliable | Very reliable |
| (a) Full sample | *Adopt* | -0.223***<br>(0.052) | -0.102***<br>(0.029) | -0.085**<br>(0.025) | 0.410***<br>(0.063) |
| | *Savannah* | -0.006<br>(0.027) | -0.004<br>(0.017) | -0.006<br>(0.024) | 0.016<br>(0.068) |
| (b) Forest region | *Adopt* | -0.196**<br>(0.060) | -0.078**<br>(0.029) | -0.095**<br>(0.033) | 0.368***<br>(0.080) |
| (c) Savannah region | *Adopt* | -0.289**<br>(0.092) | -0.146*<br>(0.060) | -0.055<br>(0.041) | 0.490***<br>(0.101) |
| (d) Trained farmers | *Adopt* | -0.008<br>(0.014) | -0.019<br>(0.031) | -0.037<br>(0.057) | 0.064<br>(0.101) |
| | *Savannah* | -0.012<br>(0.009) | -0.029<br>(0.021) | -0.062<br>(0.044) | 0.103<br>(0.072) |
| (e) Untrained farmers | *Adopt* | -0.332*<br>(0.162) | -0.015<br>(0.038) | 0.033<br>(0.032) | 0.314<br>(0.201) |
| | *Savannah* | -0.164<br>(0.149) | 0.015<br>(0.020) | 0.034<br>(0.035) | 0.115<br>(0.105) |

**Note**:

- Significance codes '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
- The marginal effects in this table derived from regression models in Table A3. (see Appendix)

Model (b) in Table 6 illustrates how, in the forest, CA adoption itself impacts farmers' perception of a reliable income. The four preference levels for a reliable income from CA are highly significant ($p < 0.01$), with negative effects for the three lower levels ("not reliable," "less reliable," and "somehow reliable") and a positive effect for the highest level ("very reliable"). Model (b) says CA adopters' probability of perceiving "very reliable" income rises by 0.37 relative to non-adopters. In the same table, model (b) shows CA adopters' probability of getting a "somehow reliable," "less reliable," and "not reliable" income decreases, respectively, by 0.095, 0.078, and 0.196 compared to non-adopters. The magnitude of smallholders' farmers' preferences for reliable income as they choose to adopt CA in model (b) is consistent with the results of model (a). This model makes it clear that farmers' preference in the forest focuses on the highest utility level.

Model (c) in Table 6 illustrates how in the savannah, CA adoption impacts farmers' perception of a reliable income as a result of applying CA. Three levels of preferences for a reliable income from CA are highly significant ($p < 0.01$), with negative effect on the two lower levels ("not reliable," and "less reliable") and positive effect for the highest level ("very reliable"). Model (c) says CA adopters' probability of perceiving "very reliable" income rises by 0.49 relative to non-adopters. In the same table, model (c) shows CA adopters' probability of getting "less reliable" and "not reliable" income decreases, respectively, by 0.146 and 0.289 compared to non-adopters. Having a "somehow reliable" income is insignificant. In terms of preference for a reliable income from CA, smallholders' farmers in the savannah show that they trust more in CA than their forest counterpart (see model (b)) and even more than the average farmer of the research area. Their choice for the best utility level must have been guided by a successful CA experience. Access to a high income by adopting CA adoption help encourage CA in the savannah.

Models (d) and (e) in Table 6 result from segmenting the sample dataset in a group of trained farmers and a group of untrained farmers, respectively. The two models provide little information on how both CA adoption and agroecological context affect farmers' perception of a reliable income as a result of applying CA. However, model (e) indicates CA adopters' probability of perceiving a "not reliable at all" income among untrained farmers decreases by 0.33 relative to non-adopters. This negative effect, however, favors the promotion of CA in the area, as it shows there are farmers, especially among the "untrained," who adopt CA even though they do not perceive a reliable income benefit. The negative influence among untrained farmers should draw CA promoters' attention to how CA training is being implemented. There is a need to assess locally and understand reasons behind untrained farmers' choice.

*Land under CA*

The marginal effects on how smallholders' farmers perceived the increase of farmland under CA as a CA benefit are presented in Table 7 below.

The way smallholders' farmers' perceptions about the *land under CA* was modeled appears not to illustrate any significance ($p > 0.10$) with models (a) to (d) in Table 7. However, model (e), which provided untrained farmers' perception, displays a statistical significance ($p < 0.10$), especially due to CA adoption. Model (e) in Table 7 says, among untrained farmers and despite their agroecological zone, CA adopters' probability of perceiving "increased" land under CA rises by 0.48 relative to non-adopters, and CA adopters' probability of perceiving "decreased" land under CA goes down by 0.30 relative to non-adopters. These results illustrate that untrained CA adopters implicitly admit applying CA on their farms. Untrained farmers' preference can also be interpreted as CA adoption is decreasing slash-and-burn practice, which would be potentially a socioenvironmental community benefit.

Table 8. Marginal effects on land under CA.

| Dependent variable: Land under CA | | | | |
|---|---|---|---|---|
| Models | | decreased | static | increased |
| (a) Full sample | *Adopt* | -0.091 (0.090) | 0.014 (0.023) | 0.077 (0.068) |
| | *Savannah* | -0.040 (0.064) | 0.003 (0.006) | 0.037 (0.060) |
| (b) Forest region | *Adopt* | -0.154 (0.105) | 0.037 (0.041) | 0.117 (0.070) |
| (c) Savannah region | *Adopt* | 0.076 (0.147) | 0.007 (0.033) | -0.083 (0.178) |
| (d) Trained farmers | *Adopt* | -0.081 (0.104) | 0.013 (0.025) | 0.067 (0.080) |
| | *Savannah* | -0.022 (0.069) | 0.002 (0.006) | 0.021 (0.063) |
| (e) Untrained farmers | *Adopt* | -0.297 · (0.155) | -0.186 (0.287) | 0.483 · (0.262) |
| | *Savannah* | -0.068 (0.158) | -0.036 (0.080) | 0.105 (0.221) |

**Note**:
- Significance codes '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
- The marginal effects in this table derived from regression models in Table A4. (see Appendix)

*Food security status*

The marginal effects on how smallholders' farmers perceived their food security status as a CA benefit are presented in Table 8 below.

Model (a) in Table 8 illustrates how both agroecological context (being in the savannah or the forest) and CA adoption impact smallholders' farmers perception of their own food security. The three ways respondents rated their food security is highly statistically significant ($p < 0.01$)

for CA adoption and statistically significant ($p < 0.05$) in the two agroecological zones. Model (a) in Table 8 says CA adopters' probability of perceiving "increased" food security status rises by 0.43 for those living in the savannah and 0.27 in the forest relative to non-adopters. However, the CA adopters' probability of perceiving "static" food security status decreases by 0.16 in the savannah and 0.09 in the forest, and "decreased" food security status decreases by 0.27 in the savannah and 0.18 in the forest. Farmers' preference levels of their food security status are motivated by CA adoption and agroecological context. In terms of impact, model (a) confirms CRS' (2015) claim about "improving food security" as a CA adoption incentive and even goes beyond that by providing an agroecological-based influence of CA. Behind CA adoption decisions, farmers show they want better food security.

Model (b) in Table 8 illustrates how in the forest CA adoption impacts farmers' perception of their own food security status as a result of applying CA. The three levels of the food security responses are statistically significant ($p < 0.10$). In Table 8, model (b) implies in the forest CA adopters' probability of perceiving "increased" food security status rises by 0.26 relative to non-adopters. However, the CA adopters' probability of perceiving "static" and "decreased" food security status decreases by 0.05 and 0.21, respectively. In the forest region of the research area, model (b) confirms that farmers believe that their decision to adopt CA leads to a better food security status.

Model (c) in Table 8 illustrates how CA adoption in the savannah impacts farmers' perception of their own food security status as a result of applying CA. The three levels of the food security responses are statistically significant ($p < 0.05$). In Table 8, model (c) implies CA adopters' probability of perceiving "increased" food security status in the savannah rises by 0.26 relative to non-adopters. However, the CA adopters' probability of perceiving "static" and “decreased” food security status decreases by 0.10 and 0.16, respectively. In the savannah region, model (c) confirms that farmers believe their decision to adopt CA leads to a better food security status. Farmers’ opinion about “increased” food security given by model (c) for the savannah is consistent with what model (b) says for the forest, with a slightly higher magnitude, and confirms the overall preference given by model (a).

Table 9. Marginal effects on food security status.

| Dependent variable: Food security status | | | | |
|---|---|---|---|---|
| Models | | decreased | static | increased |
| (a) Full sample | *Adopt* | -0.179***<br>(0.047) | -0.086**<br>(0.028) | 0.265***<br>(0.061) |
| | *Savannah* | -0.088*<br>(0.036) | -0.072*<br>(0.034) | 0.160*<br>(0.065) |
| (b) Forest region | *Adopt* | -0.205**<br>(0.067) | -0.051 ·<br>(0.031) | 0.256***<br>(0.069) |
| (c) Savannah region | *Adopt* | -0.158*<br>(0.076) | -0.099*<br>(0.042) | 0.257*<br>(0.108) |
| (d) Trained farmers | *Adopt* | -0.110 ·<br>(0.067) | -0.070*<br>(0.029) | 0.180*<br>(0.091) |
| | *Savannah* | -0.086*<br>(0.038) | -0.086*<br>(0.043) | 0.172*<br>(0.077) |
| (e) Untrained farmers | *Adopt* | -0.181<br>(0.112) | -0.063<br>(0.135) | 0.244<br>(0.225) |
| | Savannah | -0.240 ·<br>(0.130) | 0.033<br>(0.072) | 0.207*<br>(0.100) |

**Note**:
- Significance codes ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
- The marginal effects in this table derived from regression models in Table A5. (see Appendix)

Model (d) in Table 8 illustrates how trained farmers perceive their own food security status as a result of CA adoption in the two agroecological zones of the research area. The three ways respondents appreciated their food security is statistically significant ($p < 0.10$) for CA adoption and the two agroecological zones ($p < 0.05$). Model (d) in Table 8 says, among trained farmers, CA adopters' probability of perceiving "increased" food security status rises by 0.35 for those living in the savannah and 0.18 in the forest relative to non-adopters. However, the CA adopters' probability of perceiving "static" food security status for the same group of untrained farmers decreases by 0.16 in the savannah and 0.07 in the forest, and "decreased" food security status decreases by 0.20 in the savannah and 0.11 in the forest. Even though the coefficients in model (d) are lower than those in model (a), the main results are consistent and have the same pattern for both models. In order words, trained farmers in each of the two agroecological zones believe their food security gets better as they adopt CA.

Model (e) in Table 8 shows how untrained farmers perceive their own food security status as a result of CA adoption in the two agroecological zones of the research area. The three ways respondents perceive their food security is not significant at all ($p > 0.10$) for CA adoption, but there is a statistical significance ($p < 0.10$) for the two agroecological zones. In Table 8, Model (e) suggests that among untrained farmers living in the savannah, CA adopters' probability of perceiving "increased" food security status rises by 0.21 relative to non-adopters, while the probability of perceiving "decreased" food security status goes down by 0.24. It appears untrained farmers' food security preference is more guided by other factors, such as agroecological context, and less by CA adoption. However, model (e) confirms that untrained farmers in the savannah may also think that CA adoption contributes to a better food security status.

## Conclusion

The DRC's abundance of natural resources is not reflected in its people's well-being and the country's overall economic performance. Despite multiple challenges, both endogenous and exogenous, the agriculture sector in the DRC has the potential to make an economic difference both at the micro (household level) and macro (economy-wide level), and could be able to play a significant role in the country's growth and development. Poverty and food insecurity, which are not mutually exclusive but complementary issues, have been constant in the DRC since independence due to periods of civil and economic instability in a country where agriculture is the main activity for 70% people. Although women are at the forefront of agriculture in the DRC, they have faced heavy social and economic pressures. Given the effects of war and political instability, many women have lost husbands and now face the real danger of domestic and sexual violence as they have to travel further and further away from their villages to find fertile land. Furthermore, because of the long-standing practice of slash-and-burn agriculture, women who are now heading households must undertake large amounts of heavy labor practices to provide food for their families. These two factors (slash-and-burn and traveling far distances) are endogenous, as women must travel further to find new land to slash-and-burn and doing so leaves them more vulnerable to domestic violence as they must go further from their villages to farm.

In an effort to assist these vulnerable women, this study analyzed the innovative CA practice promoted by the CRS' NTA project in the province of Maniema in the DRC. The NTA project set out to teach the community to practice CA, which could reduce the need for slash-and-burn and enhance the use of fallows and old farmlands, as doing so could ensure women can farm close to their homes. Thus, CA could reduce both labor requirements as well as situations where women are made more vulnerable by having to travel long distances to provide food for their families. This study explored CA adoption in smallholder farmers' communities, while focusing on vulnerable women involved in the agriculture sector. To do this, this study used actual data from CRS to estimate the drivers of adoption of CA and the benefits obtained by those who adopted. The models included factors related to spatial differences, being a member of a farmers' group, having accessed credit, and if the farmer was formally trained in CA.

After a selection process that involved stepwise regression analysis, a total of ten variables were chosen from the CRS dataset to estimate the drivers of adoption. The ten variables (factors) are agroecological zones (savannah and forest), villages (Enombe – Brigade, Enombe – Sakina, Kamonga, Kampala, Kauta, Kimanga, Kionga, Lubangwana, Lubelenge, Lukongo, and Nyoka), age, farm size, accessed credit, farmers' group, household size, female non-married, literacy, and training. Binary logit models were estimated to explore the relationship of these factors with CA adoption. The results of modeling CA adoption eight different ways looking at the full sample, agroecological and location context, and the impact of training provided by the CRS' project suggested that the fact of being in the savannah or in the forest, accessing credit, being member of a farmers' group, and receiving training had a positive influence on CA adoption, while being a female non-married farmer or living in certain villages had a negative influence on CA adoption. These five variables are the key factors that drove adoption of CA in the territories of Kasongo and Kailo in the province of Maniema, and there is a village-level influence that makes results more specific. The other factors—age, household size, farm size, and literacy—did not show a statistical influence but kept their important place in modeling because of their variability among CA adopters and non-adopters, trained and untrained farmers, and farmers living in the savannah versus the forest for three of them (household size, farm size and literacy).

This study focused on vulnerable women farmers, CRS' targeted group in the implementation of the NTA project. A close look at the criteria of vulnerability among women farmers led this study to group the most vulnerable subgroups of widows, single mothers, and divorced under "female non-married." The factor "female non-married" reduces the probability of adopting CA. In other words, female, non-married farmers tend to reject CA as shown by the results of CA adoption modeling. CRS could use these results as a stepping stone for future projects. These results are not to say that the project failed at reaching and helping vulnerable women, only that they were less likely to adopt CA than less-vulnerable women. From this study's findings, targeting vulnerable women who are part of a farmers' group or who also have accessed credit may increase the number of vulnerable women who would adopt CA in the future. Future studies may want to assess the challenges surrounding women farmers' vulnerability with regards to local customs and traditions. It is likely cultural aspects (such as customs and local beliefs), lack of opportunities, poverty, and other DRC internal issues may have affected farmers differently and were more disruptive for female non-married farmers.

This study approached the exploration of CA benefits in terms of farmers' perception of specific gains that resulted from CA. Farmers' perception is subjective and, in the area of agricultural technologies, it has been studied by Adesina and Zinnah (1993) and Adesina and Baidu-Forson (1995) in West Africa, amongst others. Maniema smallholders' farmers' perception was approached as a categorical but ordered response and used their view on income reliability, food security status, and CA farmland expansion. The results of ordered logit modeling suggest that farmers perceive CA adoption as strongly playing a positive role on their income reliability. Similarly, the adoption of CA led to an increased perception of farmers' food security. Finally, it appeared that untrained farmers chose to adopt CA even though they do not positively appreciate

CA adoption influence on their income reliability and food security. These findings show farmers' subjective views on income reliability and food security need to be included in a modeling process that explores farmers' incentives to adopt CA.

This study has isolated factors that drive CA adoption in the DRC and presented the perceived benefits of those who adopted CA. CA as a solution to improving crop productivity is new to the DRC, but as climate-smart agriculture practice, it could help mitigate climate change via a reduction in slash-and-burn agricultural practices. This study is the first of its kind in that it uses primary CA field data from the DRC and provides policy-makers, donors, development agencies, and those who are designing and implementing agricultural enhancement programs in the rural DRC important information on the following:

- Targeting more specific vulnerable farmers may not yield a strong CA adoption response. Female, non-married farmers were less likely to adopt CA than male or married counterparts, although they were specifically targeted. However, since we do not know their adoption rate prior to the NTA project, we cannot say with any certainty how effective the program truly was at increasing the adoption rate relative to males or married farmers.
- If adoption by vulnerable farmers is the goal, an alternative education and gender strategy may need to be explored. There is a need to explore more about challenges and opportunities of empowering women in agriculture from their cultural and contextual perspectives.
- Regions, in terms of agroecological zones, are different contexts. Future work may want to target specific agricultural zones as CA adoption varied with locations. Future

research should focus on more localized factors that influence CA adoption even within communities.

- Participation in farmers' groups was related to greater CA adoption, especially in the forest area, suggesting that great farmer cohesion could lead to more adoption.
- Those producers with accessed credit had a higher a CA adoption rate than those who did not. A CA program should plan to use accessing credit options to increase CA adoption in poor farmers' communities.
- Perceived reliable income and food security due to CA are key incentives to adopt CA. Farmers' decision to adopt seems to be motivated by a clear purpose for their well-being.

This work should be viewed as the first step to a more holistically sustainable agricultural approach to subsistence farming in the DRC. The results of this study provide future CA projects with important information on what the drivers of adoption are and what the perceived benefits of adoption are assumed to be. From these two important pieces of information, future research and CA projects can more precisely focus on specific groups of producers in the DRC based on location, gender, and other social characteristics to both increase adoption of CA and market the specific benefits producers are looking for more efficiently. This study is part of a large social and economic puzzle the DRC faces, but results from this study can start putting pieces of that puzzle together to help future problem solvers.

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## Appendix

Table A1. Logit models results for factors influencing CA adoption.

| Dependent variable =1 if the farmer adopted CA | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | Full sample | Agroecological zone | Village level | Savannah region | Forest region | Trained group | Untrained group | Full sample without training |
| *Savannah* | – | 2.007$^{***}$ | – | – | – | – | – | – |
| | | (0.677) | | | | | | |
| *Enombe - Sakina* | – | – | -4.256$^{**}$ | – | – | – | – | – |
| | | | (1.952) | | | | | |
| *Kamonga* | – | – | -0.402 | – | – | – | – | – |
| | | | (2.059) | | | | | |
| *Kampala* | – | – | -3.667$^{*}$ | – | – | – | – | – |
| | | | (1.950) | | | | | |
| *Kauta* | – | – | -0.390 | – | – | – | – | – |
| | | | (1.971) | | | | | |
| *Kimanga* | – | – | -4.833$^{**}$ | – | – | – | – | – |
| | | | (2.263) | | | | | |
| *Kionga* | – | – | -2.286 | – | – | – | – | – |
| | | | (2.328) | | | | | |
| *Lubangwana* | – | – | -5.597$^{**}$ | – | – | – | – | – |
| | | | (2.206) | | | | | |
| *Lubelenge* | – | – | -3.291$^{*}$ | – | – | – | – | – |
| | | | (1.959) | | | | | |
| *Lukongo* | – | – | -3.082 | – | – | – | – | – |
| | | | (2.155) | | | | | |
| *Nyoka* | – | – | -3.060 | – | – | – | – | – |
| | | | (1.984) | | | | | |
| *Age* | 0.034 | 0.030 | 0.019 | 0.023 | 0.038 | 0.027 | 0.047 | 0.027 |
| | (0.022) | (0.023) | (0.025) | (0.043) | (0.029) | (0.026) | (0.043) | (0.019) |
| *Land* | 0.305 | 0.461 | 0.587$^{*}$ | 0.687 | 0.573 | 0.464 | 0.007 | 0.263 |
| | (0.251) | (0.304) | (0.352) | (0.991) | (0.365) | (0.392) | 0.622) | (0.185) |
| *Accessed credit* | 1.604$^{***}$ | 1.411$^{***}$ | 1.973$^{***}$ | 1.890 | 1.360$^{**}$ | 1.716$^{***}$ | 1.384 | 1.997$^{***}$ |
| | (0.492) | (0.519) | (0.656) | (1.386) | (0.595) | (0.539) | (1.499) | (0.466) |
| *Farmers' group* | 1.796$^{***}$ | 1.794$^{***}$ | 2.217$^{***}$ | 1.454 | 1.852$^{***}$ | 1.891$^{***}$ | 1.312 | 2.349$^{***}$ |
| | (0.485) | (0.506) | (0.602) | (1.010) | (0.610) | (0.549) | (1.019) | (0.436) |
| *Household size* | -0.008 | -0.013 | -0.039 | -0.162 | 0.016 | -0.024 | 0.083 | 0.034 |
| | (0.057) | (0.057) | (0.063) | 0.143) | (0.065) | (0.066) | (0.120) | (0.051) |
| *Female non-married* | -1.905$^{***}$ | -1.536$^{**}$ | -2.081$^{**}$ | -0.757 | -1.778$^{**}$ | -1.925$^{***}$ | – | -1.629$^{**}$ |
| | (0.675) | (0.684) | (0.813) | (1.922) | (0.768) | (0.713) | | (0.647) |

Table A1. Logit models results for factors influencing CA adoption (Cont.).

| Dependent variable =1 if the farmer adopted CA | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | Full sample | Agroecological zone | Village level | Savannah region | Forest region | Trained group | Untrained group | Full sample without training |
| *Literate* | -0.678<br>(0.616) | -0.357<br>(0.633) | -0.783<br>(0.711) | 1.790<br>(1.502) | -1.194<br>(0.853) | -1.004<br>(0.704) | – | -0.813<br>(0.567) |
| *Training* | 2.463***<br>(0.563) | 3.449***<br>(0.727) | 4.121***<br>(0.962) | 4.221***<br>(1.385) | 3.553***<br>(1.182) | – | – | – |
| Constant | -3.640***<br>(1.203) | -5.201***<br>(1.410) | -1.556<br>(2.217) | -3.533<br>(2.320) | -5.295***<br>(1.889) | -0.663<br>(1.254) | -5.282**<br>(2.474) | -2.253**<br>(1.036) |
| Observations | 225 | 225 | 225 | 97 | 128 | 181 | 44 | 225 |
| Log Likelihood | -74.056 | -67.946 | -60.216 | -17.413 | -47.416 | -57.905 | -15.272 | -85.249 |
| Akaike Inf. Crit. | 166.113 | 155.892 | 158.432 | 52.826 | 112.832 | 131.809 | 42.545 | 186.498 |
| **Note:** | *p < 0.1; **p < 0.05; ***p < 0.01 | | | | | | | |

Table A2. List of variables selected from CRS dataset for stepwise analysis.

Variables

- Accessed credit
- Adequate contact with field agent
- Age
- Age squared
- Amount saved
- Aware of NTA project
- Distance to the nearest market
- Education
- Farm size
- Farm size squared
- Farmers' group membership
- Female non-married farmer
- Food security improved as primary benefit
- Food security status
- Frequency of meeting
- Frequency of selling farm products
- Frequency of SILC meetings Gender
- Group marketing
- Home improvement as primary benefit
- Household size
- Household source of income for farming
- Income Improved Benefit1
- Income reliable from NTA
- Land cultivated
- Land under CA
- Literate
- Ln Farm size
- NTA services
- Number of Boys
- Number of Chickens
- Number of Children
- Number of Girls
- Number of Goats
- Number of male adults
- Number of male elderly
- Number of meals par day 3 years after NTA project 2015
- Number of meals par day at the end of NTA project 2012
- Number of meals par day before NTA project 2009
- Number of meeting after NTA project closure
- Number of months of food insecurity 3 years after NTA project 2015
- Number of months of food insecurity at the end NTA project 2012
- Number of months of food insecurity before NTA project 2009
- Number of Sheep
- Participant
- Percentage of children
- Percentage of elderly
- Percentage of women
- Purchase asset as primary benefit
- Reduced workload
- School fees as primary benefit
- Similar project in the area
- Start business as primary benefit
- Storage loss
- Store products
- Trained
- Village
- Year of joining NTA project
- Yearly income average

Table A3. Ordered logit models results for reliability of income from CA.

| Dependent variable: Reliability of income from CA | | | | | |
|---|---|---|---|---|---|
| | (a) | (b) | (c) | (d) | (e) |
| | Full sample | Forest region | Savannah region | Trained group | Untrained group |
| *Adopt* | 1.741***<br>(0.305) | 1.548***<br>(0.375) | 2.144**<br>(0.532) | 0.284<br>(0.436) | 1.450*<br>(0.874) |
| *Savannah* | 0.067<br>(0.281) | – | – | 0.483<br>(0.345) | 0.664<br>(0.615) |
| AIC | 468.502 | 280.347 | 192.349 | 329.018 | 108.356 |
| Observations | 225 | 128 | 97 | 181 | 44 |

Table A4. Ordered logit models results for land under CA.

| Dependent variable: Land under CA | | | | | |
|---|---|---|---|---|---|
| | (a) | (b) | (c) | (d) | (e) |
| | Full sample | Forest region | Savannah region | Trained group | Untrained group |
| *Adopt* | 0.384<br>(0.367) | 0.640<br>(0.428) | -0.356<br>(0.738) | 0.336<br>(0.426) | 2.488*<br>(1.409) |
| *Savannah* | 0.174<br>(0.281) | – | – | 0.097<br>(0.296) | 0.544<br>(1.193) |
| AIC | 411.469 | 234.623 | 181.244 | 383.448 | 32.6012 |
| Observations | 184 | 105 | 79 | 171 | 13 |

Table A5. Ordered logit models results for food security status.

| Dependent variable: Food security status | | | | | |
|---|---|---|---|---|---|
| | (a) | (b) | (c) | (d) | (e) |
| | Full sample | Forest region | Savannah region | Trained group | Untrained group |
| *Adopt* | 1.111***<br>(0.278) | 1.167***<br>(0.354) | 1.058**<br>(0.456) | 0.730*<br>(0.382) | 1.130<br>(0.874) |
| *Savannah* | 0.646**<br>(0.267) | – | – | 0.701**<br>(0.325) | 1.181*<br>(0.619) |
| AIC | 451.254 | 269.796 | 185.346 | 359.521 | 97.7394 |
| Observations: | 225 | 128 | 97 | 181 | 44 |