ADOPTION AND ECONOMIC ASSESSMENT OF INTEGRATED *Striga* MANAGEMENT (ISM) TECHNOLOGIES FOR SMALLHOLDER MAIZE FARMERS IN NORTHERN NIGERIA

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DECLARATION 1 – PLAGARISM

I, Muhammad Bello Hassan, declare that:

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(Co-supervisor)

DECLARATION 2 – PUBLICATION MANUSCRIPTS

The following publications (submitted, in press, or under review) form part of the research presented in this thesis.

Publication 1 – Chapter 3 of the thesis

M.B. Hassan, L.J.S. Baiyegunhi & G.F. Ortmann (under review). Integrated *Striga* Management (ISM) Technologies Adoption and Diffusion: a case of smallholder maize farmers in Rural Nigeria. Submitted to *Technology in Society* (under review).

Publication 2 – Chapter 4 of the thesis

M.B. Hassan, L.J.S. Baiyegunhi, G.F. Ortmann & T. Abdoulaye 2016. Adoption of Integrated *Striga (Striga hermonthic*a) Management technologies in northern Nigeria. *Agrekon, 55(1-2):168-188.* (Published).

Publication 3 – Chapter 5 of the thesis

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Publication 4 – Chapter 6 of the thesis

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Publication 6 – Chapter 8 of the thesis

M.B. Hassan, L.J.S. Baiyegunhi & G.F. Ortmann. An assessment of Integrated *Striga* hermonthica Management and its economic benefit to maize farmers in northern Nigeria. Submitted to *Agro-ecology and Sustainable Food Systems* (under review).

Publication 7 – Chapter 8 of the thesis

M.B. Hassan, L.J.S. Baiyegunhi & G.F. Ortmann. *Striga* management through herbicide resistant maize and its contribution to farm productivity in northern Nigeria. Submitted to *Agricultural Systems* (under review).

The data analyses and discussion of empirical results of all of the above publications were conducted in their entirety by M.B. Hassan, with technical guidance from Dr Llyod Baiyegunhi, Prof. Gerald Ortmann and Dr Tahirou Abdoulaye. All tables and figures were produced by M.B. Hassan, unless otherwise referenced in the respective publications.

DEDICATION

This thesis is dedicated to the memory of my beloved late parents, Hassan and Khadija, whose love, care and morality inculcated in me will forever be remembered.

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ABSTRACT

The agricultural sector plays a crucial role in Nigeria. According to a recent report released by the Food and Agriculture organisation and the National Bureau of Statistics (NBS), the agriculture sector contributed only 20% to Nigeria's gross domestic product (GDP) in the year 2014. The sector remains critical to national food security, wealth creation, employment generation and above all poverty reduction, as over 70% of the workforce is engaged in the sector either directly or indirectly. However, the sector is being constrained by many factors. Significant among them are the infestation of the parasitic weed, *Striga*, drought, low soil nitrogen and climate change. Globally, the estimate of the land area affected and under threat by *Striga* spp. is about 44 million hectares (ha) of cultivable land. This weed impinges on the livelihoods of more than 100 million smallholder farmers. Striga mostly affects land planted with cereals, which lead to a substantial loss of cereal yield ranging between 10% and 100%, depending on crop and variety. Host plants severely affected are cowpea and cereals like rice and sugarcane. Cereal is usually the most severely damaged crops, followed by cowpea. The African Agricultural Technology Foundation (AATF) estimated that over 822,000 ha of maize farms in Nigeria is infested by *Striga*, which represents about 34% of the total farmland in Africa. *Striga* decreases maize productivity by 20% to 100%, sometimes leaving farmers with no harvest and little or no food. Based on the initial study output obtained in the Bauchi and Kano states, the major constraints plaguing maize and cowpea growing areas in the study region were identified to be *Striga*, stem borers, termites, storage insects, low and erratic rainfall, water logging, and low input. The majority of farmers (over 80%) in the surveyed states reported *Striga* as the most important constraint upon maize production. As a result of the intensity of *Striga*'s occurrence in northern Nigeria and its damaging effect on cereal and legume crops, the International Institute of Tropical Agriculture (IITA) commissioned and initiated an Integrated *Striga* Management in Africa (ISMA) project in collaboration with the Ahmadu Bello University (ABU), the Bayero University Kano (BUK), the Institute for Agricultural Research (IAR), the Kano State Agricultural and Rural Development Authority (KNARDA) and the Bauchi State Agricultural Development Programme (BSADP). The ISMA is an extension project being implemented in two states, Kano and Bauchi, with a lag period of four years, starting from 2011-2014. Specifically STR varieties and other *Striga* management technologies needed to be developed in order to curb with *Striga* problems. This action was essential considering the economic importance of cereal production, particularly maize, and the magnitude of investment made towards improving maize production such as doubling the maize project via the Federal Government and donor agencies in northern Nigeria. There is a need to understand why many farmers are not adopting the ISM technologies despite its suitability and ease of application. At this stage, there is also a lack of research on the prospect of adoption and the economic benefits of using ISM technologies in northern Nigeria. This study was, therefore, an attempt to address these knowledge gaps. Furthermore, it provided an opportunity to draft relevant policy and management implications to inform future strategies in the agricultural sector, particularly in maize production. The specific objectives of the study were (i) to identify the socioeconomic characteristics of maize-producing households and their perceptions of ISM technology attributes in the study area; (ii) to determine factors influencing farming households' potential adoption and intensity of adoption of ISM technologies in the study area; (iii) to estimate the potential impact of ISM technology adoption on livelihood improvement, income and food security of maize-farming households in the study area; and (iv) to assess the financial and economic profitability, and identify the constraints upon the adoption of ISM technologies at smallholder farm level in the study area.

The data used for this study were collected by means of a multi-stage sampling procedure from a cross-section of 643 respondents selected from 80 communities (353 adopters and 290 non-adopters from both project intervention areas (PIAs) and non-project intervention areas (NPIAs). The results revealed a significant overall adoption rate of 55% of the targeted population in the study area. The difference in performance in terms of adoption between PIAs and NPIAs was 11%. The results demonstrated the effectiveness of on-farm trial evaluations with farmers through organized field days. Thus, the scaling out of the technologies to NPIAs will help potential adopters to make more informed decisions in eliminating *Striga*. In addition to on-farm trials and field days, the improvement of public knowledge about ISM technologies can be achieved through mass public education and awareness programmes.

Results from the double hurdle regressions showed that the estimated coefficients of exogenous income and distance to extension office had a negative impact on adoption. Higher total farm income, polygamous households, past participation in on-farm trials, awareness of the technology, contact with extension agents and access to cash remittances had a positive impact and are the most significant factors likely to influence ISM technology adoption. Marital status, household size, farm size and access to cash remittances are the most significant factors influencing adoption intensity. Maize farmers in the study area, who adopted ISM technologies, were found to have obtained higher output than non-adopters, resulting in a positive and significant effect on their total farm income. Hence, policies targeted at increasing maize productivity through *Striga* management need to include ISM technologies as a potentially feasible option. This study recommends actions to improve farmers' access to financial services in order to increase their liquidity. Nevertheless, immediate action will be an improvement in farmers' access to extension services, as they have demonstrated to be a reliable source of information in rural areas. Results from the TE regression model indicated that adoption of ISM technologies played a positive role in enhancing farm productivity of rural households, with adopters producing about 47% higher maize output than that of non-adopters ($p<0.001$) after controlling for selection bias and endogeneity. Also, the result from the Foster-Greer-Thorbecke (FGT) index showed that adopters are not as poor in terms of household income per adult equivalent when compared to non-adopters. The result from the endogenous switching regression (ESR), which accounts for heterogeneity in the decision to adopt or not, indicated that ISM technologies have a positive effect on farmers' income, as measured by farm income levels per adult equivalent. It was also found that ISM adoption increased farming income by 66%, although the impact of technology on farming income was smaller for farm households who did adopt the technology than for those who did not adopt it. In the counterfactual situation, however, if non-adopters had adopted the technology, they would have gotten more benefit than adopters. It implies that the integrated approach to *Striga* management is beneficial to smallholder farmers and need to be scaled out to other areas prone to *Striga*. Results from the economic impact analysis also indicated that gross margins (GM), benefit-cost ratio (BCR), and net benefit per capita for the ISM technologies are all positive across all locations. Therefore, farmers can recover their costs and maintain a positive balance. The highest GMs made ISM technologies a viable, profitable, bankable and potential option for northern Nigeria which is prone to *Striga*. ISM technologies guarantee significantly higher yields than local practices. Thus, the long-term economic worth indicators showed that ISM technologies could lead to increased income and poverty reduction. Also, its net present value (NPV), BCR and net benefits per capita are attractive. ISM technologies, especially maize-legume rotation with STR maize and Imazapyr-resistant maize (IRM), should occupy a central role in the design of *Striga* eradication

campaign initiatives and sustainable management in maize fields. ISM technologies should therefore be prioritised, particularly in the *Striga*-infested areas of northern Nigeria.

In general, findings from the study proved the need to support the provision of extension services, on-farm trials and field demonstration to remote areas, as the results suggest that distance to the extension office do influence adoption of ISM technologies. In an effort to enhance farmers' access to ISM technologies, the public sector needs to take the lead in technology promotion and dissemination at the initial stages and create an enabling environment for effective participation of the private sector. Awareness campaigns for ISM technologies, combined with the improvement of appropriate access to these technologies and corresponding inputs, and accessible rural micro-finances at reasonable costs will offer the most likely policy mix to accelerate and expand the adoption of ISM technologies. While awareness of ISM technology is a major problem, it is clear that the availability of seed (for seed-based technologies) is a serious issue. Therefore, improvement in the Nigerian seed sector is required to boost adoption. High risk and fear of failure are related to farmers' risk aversion. All technologies requiring cash investment reflect a face of fear and risk constraint for most farmers.

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LIST OF ABBREVIATIONS AND ACRONYMS

AATF	: African Agricultural Technology Foundation
ABA	: abscisic acid
ABU	: Ahmadu Bello University
ADP	: Agricultural Development Programme
AE	: Adult equivalent
AM	: arbuscular mycorrhizal
ATA	: Presidential Initiatives Agricultural Transformation Agenda
ATE	: average treatment effect
ATET	: average treatment effect on the treated
ATT	: average total of treatment
BCR	: benefit-cost ratio
BOA	: Bank of Agriculture
BSADP	: Bauchi State Agricultural Development Programme
BUK	: Bayero University Kano
CDF	: cumulative distribution function
CIMMYT	: International Maize and Wheat Improvement Centre
DFID	: Department for International Development
DFRRI	: Directorate of Food Roads and Rural Infrastructure
DH	: Double-hurdle
DT	: Drought tolerant
ESR	: endogenous switching regression
FAO	: Food and Agriculture Organization
FAOSTAT	: Food and Agriculture Organization Statistics
FFS	: farmers' field schools
FGD	: focus group discussion
FGT	: Foster-Greer-Thorbecke
FIML	: full information maximum likelihood
GDP	: gross domestic product
GM	: gross margin
GPS	: Global Positioning System
GR	: gross revenue
HND	: Higher National Diploma
HYV	: high-yielding varieties
IAR	: Institute for Agricultural Research
IITA	: International Institute of Tropical Agriculture
IRM	: Imazapyr-resistant maize
IRR	: internal rate of return
ISC	: integrated *Striga* control

ISM	: Integrated *Striga* Management
ISMA	: Integrated *Striga* Management in Africa
JSS	: junior secondary school
KII	: key informant interviews
KNARDA	: Kano State Agricultural and Rural Development Authority
LGA	: local government area
MLE	: maximum likelihood estimator
MSM	: metsulfuron-resistant maize
₦	: Naira (Nigerian currency) symbol
NACB	: Nigerian Agricultural and Cooperative Bank
NALDA	: National Agricultural Land Development Authority
NARI	: National Agricultural Research Institute
NBS	: National Bureau of Statistics
NCE	: Nigerian Certificate in Education
NEPAD	: New Partnership for Africa's Development
NER	: National Economic Research
NERICA	: New Rice for Africa
NIP	: National Implementation Plan
NPB	: net present benefit
NPC	: National Planning Commission
NPC	: National Population Commission
NPIA	: non-project intervention area
NPV	: net present value
OFN	: Operation Feed the Nation
OND	: ordinary national diploma
OLS	: ordinary least squares
OPV	: open pollinated variety
PB	: partial budget
PIA	: project intervention area
PSM	: propensity score matching
SLF	: Sustainable Livelihood Framework
SSA	: sub-Saharan Africa
SSCE	: Senior Secondary Certificate of Education
TE	: treatment effect
TEST	: on-farm test
TETFUND	: Tertiary Education Trust Fund
TFP	: total factor productivity
TVC	: total variable cost
UNDP	: United Nations Development Program
UNSD	: United Nations Statistical Division

US$	: United State Dollar
USDA	: United States Department of Agriculture
VC	: variable cost
VIF	: variance inflation factor

CHAPTER 1
INTRODUCTION

1.1 Background

This chapter is divided into eight sections. After the introduction, the second section presents a general background of the thesis, focusing on agricultural development and production of staple foods (e.g., maize and beans) in Nigeria. The third section describes the problem statements of the study, including a brief description of the extent of *Striga* distribution, the economic damage associated with *Striga* infestation in Nigeria and the reason for conducting this study in brief. The fourth section discusses the research questions and objectives, while the fifth section describes the hypothesis testing. The sixth section describes the rationale for the study. The seventh section describes the policy relevance of the study and the last section describes the expected output of the study.

Nigeria, with a total land mass of 92.4 million hectares (ha), comprises 1.3 million ha of various water bodies and 91.1 million ha of land. The agricultural land area consists of about 83.6 million ha, comprising 33.8% arable land, 2.9% land permanently under crops, 13% forest or woods, 47.9% pasture and 2.4% irrigable land or *fadama* (NEPAD, 2004; Adetunji, 2006; FAO, 2009). Livestock and poultry production account for about 10% of the gross domestic product (GDP). Major crops include maize, rice, sorghum, millet, cowpeas, soybeans, cassava, yams, groundnut, cocoa, palm kernel, palm oil, sesame, cashew nuts, gum Arabic, kola nut, melon, plantains and rubber.

Agriculture remains the backbone of Nigeria's economic growth. It is composed of four sub-sectors: arable crops, forestry, livestock and fisheries. Like in other developing countries, particularly those in sub-Saharan Africa (SSA), the agricultural sector plays a major role in the development of the Nigerian economy. According to data released by the National Bureau of Statistics (NBS, 2013), the agricultural sector contributed 41% on average to Nigeria's GDP and employed around 70% of its total workforce during the 2001-2009 period. The contribution of the agricultural sector to Nigeria's GDP in 2013 was 20% and represents an area that embraces high prospects for diversifying the economy away from oil revenues (NBS, 2013). However, despite its growth potential, Nigeria's agricultural sector's contribution to the GDP has been on the decline from 41% in the last eight years (2001-2009), while it has only recorded about 30% of the growth in non-oil output (National Planning Commission, 2009). Despite the potential of the agricultural sector, Nigeria's cereal import ratio is at a very high 21.7%. While its continued significant stake in the GDP is an indicator of underdevelopment in the economy (because of weak expansion in the industrial sector), the significance of the agriculture sector to Nigeria's national development cannot be emphasised enough. Considering the Nigerian vision of becoming one of the 20 largest economies in the global arena by the year 2020, a strong, technology-enabled agricultural sector is necessary to grow its national output. The development of agriculture will help grow the industrial sector through the release of excess labour, thereby supporting the industrial expansion and raising foreign exchange earnings. Above all, making food available for the fast-growing population and making provision for gainful employment along the agricultural value chain may ultimately lead to wealth creation and, on a sustainable basis, bring about remarkable reduction in poverty. The agricultural sector can play a major role in the attainment of the nation's economic transformation blueprint, Vision 20:2020, namely "optimizing the key sources of economic growth to increase productivity and competitiveness, regarding growth in national output, and total factor productivity (TFP). Under the 1st National Implementation Plan (NIP), the policy thrust was on enhancing TFP (that is a reasonable increase in output per unit input) in the agricultural sector through the application and diffusion of technology and improvement in the knowledge base," (National Planning Commission, 2009).

Despite agricultural sector contribution to the GDP, the sector remains weak, which, according to records, is brought about by the mere increase in hectarage under cultivation rather than by efficient productivity gains. This situation does not differ from the finding of De Janvry *et al.* (2010) on agricultural production in SSA. Low input (seeds and fertiliser) characterises this inefficient agricultural production that results in:

- yields below the average African production system (World Bank, 2013);
- weak intersectoral linkages;
- aging farmers;
- an informal production that is not accompanied by efficiency; and
- poor marketing structure.

Governments have, at various times and stages, made all possible efforts through the formulation and implementation of various programmes and projects to improve the sector and come up with a feasible option to address some of the growth bottlenecks in the sector. These programmes and projects include Green Revolution, Operation Feed the Nation (OFN), National Agricultural Land Development Authority (NALDA) and National Food Security Programme (NFSP). Other agricultural programmes of government include National Accelerated Food Production Programmes, River Basin Development Authority, Agricultural Development Programme (ADP), Directorate of Food Road and Rural Infrastructures (DFRRI), Nigerian Agricultural and Cooperative Bank (NACB), now Bank of Agriculture (BOA), Presidential Initiatives Agricultural Transformation Agenda (ATA), etc. The agricultural sector is considered to be critical to the attainment of the nation's vision of boosting the vital sources of economic growth and development in order to increase productivity and competitiveness. However, among many others, the parasitic weed *Striga spp*. have become one of the major biotic constraints to grapple with in achieving the sector's goals. Other constraints include poor market demand and low market price for produce. The high cost of labour, inputs such as fertiliser, seeds, and agrochemicals, and transportation of farm produce to distant markets significantly reduce farmers' net income (African Fertilizer Summit, 2006; Amaza *et al.*, 2007; Hassan and Sanni, 2011; Mignouna *et al.*, 2013).

1.1.1 Importance of maize crop and *Striga*

Maize is a major staple food crop grown across many agro-ecological zones and production systems. It is consumed by diverse communities in different forms among different socio-cultural backgrounds in SSA. The place of maize in SSA as staple food can be compared to that of rice or wheat in Asia. Maize is grown on over 34 million hectares in Africa with a corresponding output of about 70 million tonnes, making it the highest among the cereals. Out of the 22 countries globally where maize constitutes the highest proportion of the diet in terms of calorie intake, 16 of those countries are in Africa. One fifth of the calories and protein consumed in West Africa are from maize (FAO, 2015). About 208 million people in SSA depend on maize as their source of food and well-being. In SSA, 200 millions hectares of cultivable land, more than 33 million hectares are occupied by maize (FAO, 2015). Nigeria produces more 43% of maize grown in West Africa (Kudi *et al.*, 2011).

According to the African Agricultural Technology Foundation (AATF (2006), and Woomer and Savala (2007), an estimated 823,000 ha of maize fields in Nigeria are infested by *Striga*, implying that about 34% of farmland in Africa is under *Striga* threat. Especially the rural communities among the smallholder farmers in northern Nigeria, are severely affected by *Striga* infestation, with reported yield losses of between 70% and 100% (Emechebe *et al.*, 2004; AATF, 2008a). Hence, there is an urgent need for effective control of these parasites to enhance higher yields.

In Nigeria, only three of the *Striga* species were found to be affecting crops: *Striga hermonthica* (sorghum, rice, millet and maize), *Striga aspera* (rice) and *Striga gesnerioides* (cowpea) (Dugje *et al.*, 2006). Across the different communities, *Striga* species are known as *wuta-wuta, kudiji, makasa or kanjamau* and may occur in the same field because of intercropping. Several years of research on *Striga* management have resulted in identifying some range of control technologies. Examples of these are *Striga*-tolerant and *Striga*-resistant varieties of maize (*Zea mays*), sorghum (*Sorghum bicolour*) and millet (*Pennisetum glaucum*), which proof to be an effective way of reducing *Striga* seed bank and damage (Kling *et al.*, 2000). Currently, many *Striga*-resistant maize varieties have been developed by IITA in collaboration with the National Agricultural Research Institutes (NARIs). They have also been approved and released after satisfying the release requirement by the National Variety Release Committee in Nigeria.

Striga strains, however, may show some resistance to *Striga*-resistant cereal varieties due to future evolutionary adaptation. The use of legume trap crops, which can stimulate the suicidal germination of *Striga* is another technology to help control *Striga*. Trap crops include varieties of cowpea (*Vigna unguiculata*), sesame (Sesamum *indicum*), soybean (*Glycine max*) and groundnut (*Arachis hypogaea*) (Hess and Dodo, 2004). Due to the poor soil condition on farms, the application of nitrogenous fertiliser to cereals on fields with low fertility can reduce crop damage caused by *Striga* (Joel *et al.*, 2007). Farmers have developed a range of mitigative measures on their own to control *Striga*. These include the use of manure or compost, hand-rogueing and incessant hoe-weeding (Emechebe *et al.*, 2004). However, none of these individual technologies can, on its own, provide adequate *Striga* management across the wide range of socioeconomic and biophysical environments. The majority of farmers in Africa have failed to manage *Striga* on cereals fields, even with various released *Striga* management technologies that have demonstrated to be successful on-farm and on-station. Hence, an integrated *Striga*-management (ISM) technology that is adjustable and healthy enough to meet the wide range of farming environments have been suggested (Chikoye *et al.*, 2006).

As a result of the intensity of *Striga* occurrence in northern Nigeria, the IITA initiated an Integrated approach to *Striga* management dubbed the Integrated *Striga* Management in Africa (ISMA) project. That is jointly implemented by Ahmadu Bello University (ABU), the Bayero University Kano (BUK), the Institute for Agricultural Research (IAR), the Kano State Agricultural and Rural Development Authority (KNARDA) and the Bauchi State Agricultural Development Programme (BSADP). The ISMA project was an extended project implemented in the two states (Kano and Bauchi) in northern Nigeria, with a project life cycle of four years, from 2011-2014. Its aim is to increase productivity, the income of households and food security. The project aimed to achieve these goals via project farmers delivering improved extended services to farmers participating in the project and to increase adoption, commercialisation and marketing of improved STR and suppressive varieties through a community seed-production approach.

Achieving affordable and sustainable *Striga* management for poor farmers in Nigeria through the ISMA project comprises two parts: the inception stage, followed by the impact study stage. During the inception stage, the IITA conducted a baseline study in areas that were to benefit from *Striga*-control interventions, by measuring the key economic and social indicators before implementing the major components of the project. The baseline study was specifically aimed at understanding the production systems; identifying maize varieties grown and farmers' preferences; determining constraints and opportunities; establishing *Striga* incidence and severity on the two crops; and, moreover, assessing yield levels (Mignouna *et al.*, 2013). After that, the ISM technology on-farm trials, which represents the impact study stage, began in the affected communities.

1.2 Problem statement

An estimated 70% of Nigeria's population are directly or indirectly engaged in agriculture and the poverty level is rising, with almost 100 million people living below $1 a day. Based on a recent survey of 20 million households across the country, 112,519 million Nigerians live in poverty (NBS, 2013). According to the record issued by the NBS, the northwest and northeast geo-political regions had the highest rates of poverty in the country in 2010, namely 77.7% and 76.3%, respectively. Co-incidentally, Kano and Bauchi fall within these geo-political zones where the *Striga* incidence is so severe.

Maize and cowpea (*Vigna unguiculata*) are two major staple food crops from cereals and legumes that are widely produced and consumed throughout Nigeria. They provide sources of income to smallholder households in rural areas. An estimated 90% of the country's maize is produced in the northern region, which is the most suitable and agriculturally productive region of the country. In Nigeria, for instance, maize and sorghum are the two primary crops that occupy about 40% of the total cultivable land. Nigeria accounts for about 43% of the maize production in West Africa (Smith *et al.*, 1997; Phillip *et al.*, 2009). Among the different income groups, maize forms an important source of both protein and calories among the poorer population of consumers, including HIV/AIDS-affected families, who cannot afford foods such as bread, milk or meat that are considered more expensive (Byerlee and Heisey, 1996; Byerlee and Eicher, 1997). About 3.5 million people in Nigeria are infected with HIV/AIDS, which makes out about 9% of the global infection (FAO, 2015). Therefore, maize production is considered significant for national food security and the socioeconomic stability and well-being of Nigeria. However, recurring droughts, insurgent activities (Boko Haram) and *Striga* infestation, among others, are continuous challenges for the production of these important crops in Nigeria, since they drastically reduce yields and livelihoods. The average maize yield in Nigeria was 2,000 kg/ha in 2012 (USDA, 2014), being far below the potential yield of 7,000 to 9,000kg/ha. Recent findings from the biophysical and baseline surveys in the Kano and Bauchi states reveal that the *Striga hermonthica* incidence in maize fields ranged from 0%-100% in the Kano state, and varied among communities and Local Government Areas (LGAs) (Ekeleme *et al.*, 2014). *Striga* incidence ranged from 63%-100% in 77% of the sampled communities. In the Bauchi state, the *Striga hermonthica* incidence in maize and sorghum fields was 100% in all the communities. *Striga gesnerioides* was prevalent in more than 95% in both of the states. The *Striga* incidence in Bauchi and Kano was negatively correlated with maize, sorghum and cowpea yields (Ekeleme *et al.*, 2014). Average households' maize yield was very low, ranging from 1,430 kg/ha (local variety) to 2,317 kg/ha (hybrid), compared to 4,000 and 9,000 kg/ha obtained in South Africa and the USA, respectively (Mignouna *et al.*, 2013; USDA, 2014). The cowpea yield in the study area ranged between 323 kg/ha to about 900 kg/ha where improved varieties were used (Mignouna *et al.*, 2013), with cowpea being an integral component of ISM technologies. The development, deployment and cultivation of *Striga*-control technologies and

Striga-tolerant maize (STM) varieties, therefore, have the potential of reducing vulnerability, food insecurity and damage to local markets associated with food aid.

Based on the recent output obtained from the ISM biophysical and baseline study in the Bauchi and Kano states, the finding revealed that the major constraints identified as plaguing cereal and legume production in the study region, include *Striga*, stemborer, termites, storage insects, low and erratic rainfall, water logging, and low input. The majority of the farmers (more than 80%) in the Bauchi and Kano states reported *Striga* as the most significant constraint to maize and cowpea production (Mignouna *et al*., 2013). *Striga* infestation of cereal crops has had a negative impact on the livelihoods of smallholder farmers in Africa. In order to tackle this problem and improve the livelihoods of millions of smallholder farmers in northern Nigeria, the IITA initiated a project in 2010, tagged as ISMA and funded by the Bill and Melinda Gates Foundation. The project adopts and intensively promotes proven integrated *Striga* control (ISC) strategies in targeted areas in northern Nigeria, with the active participation of farmers, communities, extension workers, policy makers and researchers.

The immediate past Minister of Agriculture, Akinwumi Adesina (Daily Times, 2013) stated that the maize 'Green Revolution' would transform the maize industry and make farming more profitable. His agricultural reforms would target the raising of Nigeria's annual maize production from the then 8 million tons to an annual 20 million tons. This revolution was part of the efforts to enhance food security, create jobs and, more importantly, cushion Nigeria from the effects of rising food prices. Increasing maize production and other crops would ensure food security and generate income and jobs, thereby alleviating the prevailing poverty condition. However, this could only be achieved if constraints to farmers' productivity, such as *Striga* infestation, were drastically reduced or completely eradicated. While ISM technologies may raise farm household productivity through the reduction of the *Striga* count, another constraint may arise, such as getting corresponding inputs like STR seeds, Imazapyr-resistant maize (IRM), bio-control inoculums and other socioeconomic and institutional factors. These factors are, however, beyond the control of farming households and make it more important to recognise the degree to which farmers' socioeconomic characteristics and other institutional and cultural constraints hinder farmers in adopting ISM technologies. Given the above scenarios, this study intends to provide answers to the following research questions:

i) What are the socioeconomic characteristics of maize-farming households and their perceptions of ISM technology attributes?
ii) What are the determinants of potential adoption and intensity of adoption of ISM technologies at farm level in the study area?
iii) What is the potential impact of ISM technology adoption on livelihood improvement, income and food security of maize farming households in the study area?
iv) What are the financial and economic benefits of ISM technologies in the study area?

1.3 Research objectives

The broad objective of the study is to assess farmers' perceptions, and identify the adoption determinants and potential impact of adoption of ISM technologies on income and food poverty among farming households in northern Nigeria. The specific objectives of this study are to:

i) identify the socioeconomic characteristics of the maize-producing household and their perceptions of ISM technology attributes in the study area;
ii) determine the factors influencing the potential adoption and intensity of adoption of ISM technologies by farming households in the study area;
iii) estimate the potential impact of ISM technology adoption on the livelihood improvement, income and food security of maize-farming households in the study area; and
iv) assess the financial and economic impact of ISM technologies in the study area.

1.4 Hypotheses

Given the objectives of the study, the hypotheses are presented as follows:

Hypothesis I: Households who adopted ISM technologies systematically do not have different characteristics to counterfactuals.

Hypothesis II: Households' socioeconomic circumstances have no significant influence on the potential and intensity of adoption of ISM technologies.

Hypothesis III: There is no statistical difference in the average farm income of households using ISM technologies and the counterfactual (local or farmer practice).

Hypothesis IV: There is no significant difference in the profitability of ISM technologies and the counterfactual.

1.5 Rationale behind the study

Serious efforts in providing high yield varieties (HYV) and environment-friendly technologies are required to achieve sustainable agricultural growth and development, which will bring about an improvement in rural household income and possibly translate into improving household well-being. According to Asfaw (2010) and Di Falco *et al.* (2011), it is, in respect of increasing economic and climatic variability, especially in the semi-arid tropical countries of Africa where cereal production is grossly affected. Improvement in the production of legumes, such as cowpea, Bambara nut, green gram, groundnut and soybean, presents an opportunity to draw back trends in productivity, food insecurity and poverty. Because legumes have the capacity to incorporate atmospheric nitrogen into the soils, they improve soil fertility and possibly even reduce the quantity of fertiliser required in future cropping seasons. Also, leguminous crop can promote a more comprehensive and innovative use of land, especially in areas where there is a paucity of land. It is also possible to grow it as a second crop under residual moisture, such as planting cowpea as a relay crop in a maize field. Furthermore, eating legumes can reduce malnutrition and enhance human health improvement, especially for the poor who cannot afford animal protein. Finally, the growing demand for legumes in both local and international markets (Simtowe *et al.*, 2011; Asfaw *et al.*, 2012b) can provide a source of income for smallholder farmers and earn the country foreign exchange (AATF, 2008b). Therefore, agricultural research and technological development are vital to enhance agricultural productivity, thereby increasing household income and reducing poverty among smallholder farmers. However, the assessment of the impact of these technologies on rural household income was limited by the lack of appropriate approaches. Most of the past studies by Ellis-Jones *et al.* (2004) and Mignouna *et al.* (2011b), had thus failed to move beyond calculating economic surplus, particularly to *Striga* management technologies and returns to research investment.

Despite all the research efforts by the IITA and the NARIs to developed some *Striga*-resistant maize, soybeans and cowpea for the past decade and released by the variety release committee. To date, *Striga* persists as a major challenge to the northern Nigerian farmers, despite the release of the developed STR maize, improved soybeans and cowpea varieties, and using the legumes for rotation in maize-based farming systems to the farming communities in Nigeria's Savannah. Limited assessment had been made to document the likelihood of farmers' adoption and profitability of adoption of these technologies in northern Nigeria. The demand for STR varieties of maize and cowpeas is, however, likely to increase if varieties are designed to include end users' preferred traits. Technologies in focus for economic assessment are:

i) maize-legume (soybean, STR cowpea, groundnuts) rotation;

ii) maize-legume (soybean, STR cowpea, groundnuts) intercropping;

iii) STR maize monocrop; and

iv) IRM monocrop (the IRM consists of dressing the seed of the IRM with the Imazapyr herbicide). By the time the maize seed germinates, it has absorbed the herbicide used to dress it. During germination, the *Striga* is stimulated to germinate too and attaches to the maize root, whereby the *Striga* plant gets killed by the action of the herbicide before it causes damage to the maize plant. The herbicide that is not absorbed by the maize plant then diffuses into the soil and kills the *Striga* seeds that have not germinated (CIMMYT, 2004; AATF, 2006).

In reviews of adoption studies in developing countries (Feder and Umali, 1993; Adesina *et al.*, 2000; Mendola, 2007; Langyintuo and Mungoma, 2008; Bernard *et al.*, 2010; Awotide *et al.*, 2012; Arslan *et al.*, 2014). Many of these studies were found to have analysed the direct effects of farmers' personal assessment of agricultural technology characteristics on adoption decisions, however, none had analysed the direct effects of farmers' subjective assessment of ISM technologies. Therefore, this study was set out to examine this direct effect of farmers' personal assessment of agricultural technology characteristics on adoption decisions, and evaluate the potential impact of ISM technologies on the welfare of smallholder farmers in the rural areas. These effects were measured in terms of productivity and income, net present benefits (NPBs) and BCR in northern Nigeria.

1.6 Policy relevance

The goal of any food insecurity reduction strategy is to increase yield and revenue in order to improve the well-being of the client. Hence, understanding the factors influencing technology adoption, the intensity of adoption and the potential impact of technology adoption on farmers' welfare is of paramount importance for policies that aim to increase farmers' output, income and well-being to ensure the meaningfulness of target intervention (Adesina and Baidu-Forson, 1995; Alene and Manyong, 2007; Mignouna *et al.*, 2011a). This study also examined the income portfolios of farmers in the study area, which provided an in-depth understanding of the different farming activities that rural farmers in the *Striga*-infested areas were engaged in. Moreover, the study examined how farmers' socioeconomic characteristics affected their potential for and intensity of adoption.

1.7 Plan and structure of the study

This study contributes to the project databases through the analysis of cross-section survey data on production conditions, productivity impacts and adoption constraints. The analysis provided new insights into research and targeting activities, which can be used to maximise the adoption and resultant economic gains for poor and vulnerable households. The results will gradually inform and improve technology development and delivery activities, and contribute to the development of more relevant technologies, partnerships and institutional arrangements to, in turn, improve the transfer of *Striga*-control technologies. The study can also serve as a guide for the implementation of *Striga*-control measures in other areas of the sub-region, and Africa at large, which are constrained by *Striga*. Considering the economic importance of *Striga* and the quantum of grain loss due to *Striga* infestation, the study justifies the need for synergy between institutions in combating this pest and achieving a relative increase in the productivity of affected crops.

This dissertation is presented in ten chapters, including the introductory chapter. Chapter 2 discusses the literature review and presents key concepts and definitions. It provides an overview of the biotic plant parasite, *Striga*, and its economic importance in SSA. It also provides different technologies developed to manage *Striga* problems. Furthermore, the chapter provides theoretical and empirical evidence of the socioeconomic determinant of agricultural technologies, the intensity of adoption of these technologies, and the impact of its adoption on the welfare of farming households.

In Chapter 3, the socioeconomic characteristics of the farmers and their perceptions of ISM technologies, diffusion and adoption pathways in the study area are examined. Chapter 4 analyses the factors that influence ISM technologies among smallholder farmers and the factors that affect the intensity of ISM technology adoption. In Chapter 5, smallholder maize farmers' productivity impact of ISM technology adoption at farm level is determined by measuring maize productivity and household welfare, expressed in poverty gap, index and severity. The impact of ISM technologies on farm income (measured in per adult equivalent unit) is determined in Chapter 6, while Chapter 7 presents the economic analysis of ISM technologies and local practices in terms of financial and economic profitability. The results of two selected on-farm trial technologies are presented in Chapter 8 and Chapter 9, and the conclusion, some policy implications of the study findings, and measures for further research are presented in Chapter 10.

CHAPTER 2
LITERATURE REVIEW

2.1 Introduction

In this chapter, a review of relevant literature is undertaken as it relates to the agricultural significance of *Striga* and its parasitic nature on maize. A discussion on some of the emerging technologies for the effective control of *Striga* is also included. Furthermore, the chapter presents literature on the conceptualisation of technological adoption and factors that are associated with farmers' adoption behaviours. These behaviours focus on their socio-demographic characteristics, institutional factors and perceptions; on technology characteristics; and on risks and constraints to agricultural technology adoption. Literature on the factors influencing the intensity of agricultural technology adoption and the economic attributes of technology adoption is reviewed as well. Another focus in this chapter is the concept of technology adoption impact on household income, as well its economic profitability in the rural economy.

2.2 Economic importance of *Striga* and control management

This section reviews some of the significance of *Striga* parasites and its devastating effect to cereal production. It also reviews some of the *Striga*-control management that is currently available and their mode of action.

2.2.1 Agricultural significance of *Striga* and yield losses

Striga, commonly known as witchweed, is a parasite that adversely constrain the production of cereal crops such as millet, maize, rice and sorghum across many agro-climatic regions of SSA. *Striga* survives through absorbing nutrients and water from the host crop for its growth and survival (AATF, 2008a). It is very productive, with a single plant producing over 200,000 tiny, sticky seeds, which can remain dormant in the soil for longer than 20 years. *Striga* seeds can spread by the wind, water, humans, animals and farm implements (Gressel *et al.*, 2004; AATF, 2006). Their seeds can only germinate when they sense germination stimulants from a potential host crop, after which the parasite sucks nutrition from the host plant (De Groote *et al.*, 2008). *Striga* causes severe injury to its host crop before appearing on the surface of the soil, through the production of phytotoxins which are harmful to the host crop. When *Striga* attaches to the roots of the plant and extracts nutrients consisting of water and minerals, the plant appears like a 'witch' because of its retarded growth and withering (Diallo *et al.*, 2007). *Striga* has persistently reduced farmers' harvests for decades, leading to some farmers entirely abandoning maize cultivation (De Groot, 2007; Ejeta, 2007). According to Unicef (2015), about half of the population living in *Striga*-infested regions lives below the 1 US$ poverty line per day, and two-thirds of the countries in that region are classified as "weak" in the ranking of the human development index. Also, 40% of the girls and 30% of the boys in this region are not in school, resulting in the Sahelian region's literacy level being far below that of coastal West and Central Africa. Similarly, according to the Joint United Nations Programme on HIV/AIDS (UNAIDS, 2014), around 24.7 million people of the population living in the regions are also infected with HIV, thus depriving farming households of much-needed labour and leading to a further reduction in staple crop yields. The cost of labour and drudgery, particularly for women associated with weeding prolific weeds such as *Striga*, only compounds an already grave situation for poor farming households.

2.2.2 Current status of *Striga* problems worldwide

Currently, there is no reliable estimate of the total area affected by *Striga*, however, it is believed that, in 1991, about 16 million hectares of land were considered to be under threat of *Striga* in the West Asia region and Mediterranean (Sauerborn *et al.*, 1991). In Africa though, it is estimated that 44 million hectares are "endangered", with a total estimated loss of $US 2.9 billion revenue from maize, pearl millet and sorghum in 1991. The latest records suggest that 300 million farmers and 50 million hectares in Africa are affected by *Striga* spp., with a total loss of $US 7 billion (Ejeta, 2007). According to Ejeta (2007), *Striga hermonthica* is the most destructive among all *Striga* spp., affecting mostly staple crops grown in Africa. This *Striga* expands from tropical and northern subtropical regions of Kenya, Tanzania and Ethiopia in the east to Gambia in the west.

According to (IITA, 2013), farmers expect an average maize yield of 1.5 tons/ha in the Nyanza Province of Kenya where maize is grown without *Striga*, whereas the expected yield is about 700 kg/ha in fields with moderate infestation and only about 20% in areas with severe infestation. I the case of the Western Province of Kenya, the corresponding figures are 1.8 t/ha, 50% and 20% yields, respectively (IITA, 2013). With the introduction of the novel technology of Imazapyr-treated seed of herbicide-resistant maize, the estimated yield per hectare of farmers' field was double in those areas (De Groote *et al.*, 2008). Past reviews (Elzein and Kroschel, 2003), however, suggested the persistence of the problem and made no reference to its decreasing importance as a result of strong control management. In northern Ghana regions, it is estimated that about 70% *Striga*-infestation of all cereal fields do not suggest any over-all progress either.

However, to some extent, there is a little progress that indicate some reduction locally in the *Striga* problem. Reports from East Africa are favourable towards *Striga hermonthica* control applied by means of the *Desmodium* intercrop technique (Khan *et al.*, 2006a; Khan *et al.*, 2008a). This technique was estimated to be adopted by at least 7,000 farmers across Tanzania, Kenya and Uganda. Furthermore, the use of herbicide-treated maize seed (De Groote *et al.*, 2007), or a combination of the two approaches (Vanlauwe *et al.*, 2008) had also been fruitful. Farmers are using these two technologies and there seems to be a possibility of getting a remarkable result on farms that can afford them. Farmers using the push-pull (*Desmodium* cereal intercrop) technique are attaining twice the maize yields when compared with the farmer controls. The accrued benefit is mostly due to *Striga* control (Khan *et al.*, 2008b; Khan *et al.*, 2011).

2.2.3 *Striga* parasitism

Striga spp. is a plant parasite that limits cereal crop production in many parts of Asia and Africa. The gathering of signals exchanged between *Striga* and a majority of its hosts that lead to successful parasitism is an interesting biological relationship. Some chemical substances produced by host plants are signs required to induce the germination of *Striga* plant seeds and trigger connection organ formation. Even though the *Striga* can photosynthesize, once it appears above the ground, it relies on host plants for a substantial part of its carbon supply (Cechin and Press, 1994); (Pageau *et al.*, 1998). Apart from losing food and water to these parasites, host plants also suffer disorders like the symptoms of crops growing under drought, for example, the increased root:shoot ratios and leaf scorching (Rank *et al.*, 2004). The name *Striga* is derived from Latin which means 'witch,' and its English equivalent is witchweed, the name commonly used by many African communities. The nature of this witch-like appearance is not well understood but it may be the result of hormonal alarms that is principally in abscisic acid (ABA) (Taylor *et al.*, 1996), or poisons that are produced by the parasite (Rank *et al.*, 2004). The *Striga* problem is predominantly more severe in Africa, where the giant witchweed, *Striga hermonthica*, is extensively spread and cause great damage to cereal crops, when compared with other parts of the world. If *Striga* infestation reaches an extreme level, over a hundred *Striga* can attach to a single crop plant, each producing tens of thousands of seeds (Rich and Ejeta, 2008). *Striga* seeds are long-live and can render the field unproductive for future cereal production (Rich & Ejeta, 2008).

The *Striga* parasite can be managed through various genetic improvements of crop plants and cultural practices. Infestation of crop by *Striga* is less severe where soil fertility and water are optimal for host crop growth than where a field has a nutrient deficiency, principally of nitrogen (Joel *et al*., 2007; Rich & Ejeta, 2008). In much of Africa, optimum growing conditions of crops do not always occur. Although some outstanding *Striga* management choices exist, such as the application of high levels of nitrogenous fertilisers, herbicides and irrigation (Joel *et al.*, 2007), these options are beyond reach of many African smallholder farmers. Other options include:

- biocontrol technology options, such as inoculation of maize seed with *Fusarium* isolates (Zahran *et al.*, 2008);
- arbuscular mycorrhizal (AM) fungi (Lendzemo *et al.*, 2006); or
- agronomic suppression by intercropping cereals with allelopathic legumes (Mohamed *et al.*, 2007), which has also been proposed and is underway to being deployed.

Above all, the use of crop varieties with *Striga* resistance remains the most promising technology for African smallholder farmers. Incorporating various *Striga*-management options with better agronomic practices, such as cereal-legume rotation, will enhance the efficiency of *Striga* management and cost (Ejeta and Gressel, 2007).

2.2.4 Emerging technologies for effective *Striga* control

The thought of *Striga hermonthica* is known for its ability to develop resistance to treatment (Ejeta, 2007). Therefore, thoughtful piling of characters with resistance to deployed cultivars reduces the possibility of developing resistance breakdown. *Striga* races that are virulent would be less likely to emerge when multiple mutations to overcome host-resistant genes are required (Rubiales *et al.*, 2006). Reported to date, *Striga* resistance of maize appears to be recessive and qualitative in nature (Gethi *et al.*, 2005). For national and regional location deployment, integrating genetic-resistant maize with other control measures could be the best possible choice, both for the effectiveness of management, as well as for improving the robustness of resistance genes. Table 2.1 presents the current list of *Striga*-resistant maize varieties released by the National Variety Release Committee in Nigeria.

Table 2.1: *Striga*-tolerant and -resistant maize varieties developed and release in Nigeria

Variety name	Types of cultivars	Year of release	Adaptation zone
SAMMAZ11	*Striga*-tolerant and late maturing OPV	2001	Moist Savannas
SAMMAZ28	Extra-early *Striga*-tolerant OPV	2009	Sudan Savannas
SAMMAZ29	Extra-early *Striga*-tolerant OPV	2009	Sudan Savannas
SAMMAZ21	*Striga*-tolerant early maturing OPV	2009	Moist Savannas and Sudan Savannas
SAMMAZ27	Extra-drought and *Striga* tolerant OPV	2009	Moist Savannas and Sudan Savannas
SAMMAZ15	*Striga*-tolerant medium maturing OPV	2008	Moist Savannas
SAMMAZ16	*Striga*-resistant late maturing OPV	2009	Moist Savannas
Oba Super 7	*Striga*-resistant hybrid	2009	Moist Savannas
Oba Super 8	*Striga*-resistant hybrid	2009	Moist Savannas
SAMMAZ26	*Striga*-resistant OPV Medium-late	2009	moist Savannas
SAMMAZ32	*Striga*-tolerant and drought escaping, QPM OPV	2011	Guinea and Sudan Savannas
SAMMAZ33	*Striga*-tolerant and drought escaping, QPM OPV	2011	Guinea and Sudan Savannas
SAMMAZ35	*Striga*-tolerant OPV Early	2011	Guinea and Sudan Savannas
SAMMAZ37	*Striga* and drought resistant	2011	Savannah
SAMMAZ38	*Striga*-resistant and QPM OPV Extra-Early	2011	Guinea and Sudan Savannah
SAMMAZ40	*Striga*- and drought-resistant OPV Late	2013	South and North Savannas
SAMMAZ18	*Striga*-tolerant OPV Early	2009	South and North Savannas
SAMMAZ19	*Striga*-tolerant OPV Medium	2009	Moist Savannas
SAMMAZ20	*Striga*-tolerant OPV Early	2009	Guinea and Sudan Savannas
SAMMAZ21	Highly *Striga* tolerant	2009	Guinea and Sudan Savanna
Ife maize hybrid 5	Low soil nitrogen-tolerant, *Striga*-resistant Hybrid	2013	Moist Savannas
Ife maize hybrid 6	Low soil nitrogen-tolerant, *Striga*-resistant Hybrid	2013	Moist Savannas
P48W01	Resistant to *Striga*, tolerant to Metsulfuron methyl (MSM)	2014	South and North Savanna
PW8W03	Resistant to *Striga*, tolerant to Metsulfuron methyl (MSM)	2014	Savannas

Source: (IITA, 2015)

According to Ejeta and Gressel (2007), the use of herbicide as a seed-coating technology was deployed as a complement to *Striga* resistance in maize. In Tanzania and Kenya in East Africa, a mutation for herbicide resistance in maize as a *Striga*-control technology was used. Treatment of maize seed with the herbicide, Imidazolinone-resistant (IR) maize, mixing small quantities of

Imazapyr (<30 g/ha) to the maize seed has shown effective control of *Striga* during the early stages of *Striga* attachment to maize seedlings (Kanampiu *et al.*, 2003). The IRM technology was tested across multiple locations and seasons in many fields and the outcome was successful before BASF Agrochemical Company trademarked it as "*Striga*way" and deployed it into hybrid maize seed that was given to private seed companies for distribution to farmers. The second generation of the maize hybrid retains an introgressed pile of herbicide resistance from IRM, with natural STR genes from *Zea diploperennis* (Rich and Ejeta, 2008). Maize breeders like Dr Menkir at the IITA have developed such maize hybrid metsulfuron-resistant maize (MSM) for deployment in West Africa.

2.2.5 *Striga* inhibitions using *Desmodium intercropped*

Intercropping maize or sorghum with *Desmodium spp*. Greenleaf *D. intortum* (Mill.) and *D. uncinatum* (Jacq.) (Fabaceae) reduces the infestation of sorghum and maize *Striga hermonthica* (Del.) Benth. Moreover, intercropping maize with legume is correspondingly effective against *S. asiatica* (L.) Kuntze (Khan *et al.*, 2002). The technique not only increases maize yield but also fixes nitrogen that improves soil fertility, as well as reducing soil erosion (Khan *et al.*, 2006a). Further investigation of the mechanism by which *Striga* parasitism on maize was prevented by *Desmodium* was conducted (Khan *et al.*, 2006b). On-farm trials were conducted with maize intercropped with *D. uncinatum.* Nitrogen fertiliser was added to some fields and not to others, maize monocrop with with maize stover, with and without added nitrogenous fertiliser; and maize monocrop, with and without added nitrogenous fertiliser (Khan *et al.*, 2002). The results show that *Desmodium* can decrease *Striga* parasitism when under shaded ground imitated by stover covering and also through fixation of nitrogen. However, the significant reduction of *Striga* parasitism by *Desmodium* cannot be explained by these physical and soil fertility factors alone and, together with the contribution of other factors, it suggests an incremental effect by means of allelopathic mechanism.

In an experiment carried out in a field infested with *Striga*, intercropping maize and *Desmodium uncinatum* in Mbita high Point of Western Kenya. It was found that, after seven years, the *Striga* seed bank was drastically reduced with about 12 seeds per kg of soil. This is not like the maize-cereal intercrop or maize monocrop where the *Striga* seed bank was found to increase by about 800 seeds per kg of soil (Macías *et al.*, 2007). The maize *Desmodium* intercrop can only be practiced among smallholder farmers, where the *Desmodium* will remain in the field permanently and can be cut and fed to livestock, or even sold to generate some revenue. The *Desmodium* leaves are a good source of nitrogen when fed as forage to livestock, especially cattle under stall for dairy production. The nutritional content of the *Desmodium* forage resulted in a rise in the number of exotic, high-milk-yielding breed of cattle, which helped to enhance the nutritional status and increase the income of the farming population (Khan *et al*., 2008a).

2.2.6 Evidence of *Striga* resistance in improved maize

As reported by Rich and Ejeta (2008), resistance reactions manifesting in laboratory co-cultures in an inbred line of cultivated maize, ZD05, developed through an enduring breeding at the IITA (Amusan *et al.*, 2008). The inbred line was selected for *Striga hermonthica* resistance in the field, and has tropical maize germplasm as well as *Zea diploperennis* in its pedigree, as reported by (Menkir, 2006). In the field, *Striga* emergence had significantly reduced, but the fundamental mechanism of this resistance was uncharacterised. Laboratory observation of the early interactions of *Striga hermonthica* showed that ZD05 had fewer root divisions than the maize variety susceptible to *Striga* to which it was compared (Menkir, 2006). Additionally, it had lesser attachments than the susceptible inbred line, in spite of the equal amounts of pre-germinated *Striga* seeds positioned on both roots. The *Striga* attached to the resistant maize generally died on the resistant maize roots, rarely developing to the growth stages when it usually positions to susceptible maize. With these findings of typical resistant reactions found in cultivated *Z. mays*, the incorporation of strong *Striga*-resistant traits in the maize appears likely.

2.2.7 Success stories of *Striga* management

Reports from Africa and some parts of Asia confirm tremendous achievement in respect of *Striga* control. For example, research in Tanzania revealed some impact, where there has been encouraging adoption of green manuring technology by farmers who helps to control *Striga asiatica* in rice fields and also improve soil fertility (Parker and Riches, 1993; Parker, 2009). Also in the KwaZulu-Natal province of South Africa, the *Striga* problem was brought under control with the assistance of a government eradication campaign principally based on the use of herbicides, as reported by (Albert, 1999). Positive results were also recently obtained from Kenya and Tanzania where double the maize yield and a significant reduction in *Striga* seed bank proved IRM to be effective (Illa *et al.*, 2010; Mignouna *et al.*, 2011c). Another interesting result was reported from farmers in Western Kenya who adopted the push-pull technology to control *Striga* in their maize field. They found this technology very effective in reducing the *Striga* seed bank and increasing the maize yield (Amudavi *et al*., 2008; Mwangi, *et al.*, 2014).

2.3 Farmers' perceptions and adoption of new agricultural technology

Agricultural research and focus on development of new technologies that will enhance agricultural production and productivity may, with the anticipation of its adoption by farmers, likely improve their income. The accelerated adoption of some newly developed agricultural technologies in the advanced nations and some developing countries has greatly increased agricultural productivity, contributed to general economic growth, and reduced food poverty and insecurity (Bandiera and Rasul, 2006). The meaning and conceptualisation of improved agricultural technology adoption vary among professionals. In their study of agricultural technology adoption in developing countries, Feder et al. (1985) hypothesised agricultural technology adoption at two different levels, namely individual (farm-level) and aggregate adoption level. They define agricultural technology adoption as the amount to which new technology is adopted in long-run sustainability, that is, when the farmer has complete information and understanding about the newly introduced technology and its potential with regard to agricultural productivity. Professionals in this area define aggregate technology adoption and diffusion as the process by which improved agricultural technology is spreading within a particular agro-ecological region. According to them, aggregate technology adoption should be measured thoughout the entire population of farmers rather than individual farmers.

Farmers' perceptions of the characteristics of new agricultural technology are very significant factors that are likely to correlate with their demand for new agricultural technologies (Adesina and Baidu-Forson, 1995). The technologies may be, subjectively, evaluated differently by farmers, based on the cultural and technical aspects of technologies. Therefore, understanding farmers' perceptions of the technologies is important in the design and promotion of agricultural technologies (Uaiene *et al.*, 2009). Overall, farmers' perceptions of the new agricultural technologies and its characteristics are divided into three main categories, namely cost requirements, yield performance and risk.

Neill and Lee (2001) argue that farmers' decision to adopt new agricultural technologies can be influenced by their perceptions of the amount of money required for the initial investment, and the labour requirements they would have to allocate to manage the technology should they adopt it. Martel *et al.* (2000), in the case study they conducted on the marketing of dry beans in Honduras, argue that farmers use new agricultural technologies because they perceive it to likely reduce labour demand and other costs associated with its production. Loss reduction could also be achieved due to less risk, such as crop diseases and other biotic and abiotic constraints during production and post-harvesting. Furthermore, Martel *et al.* (2000) argued that farmers always compare a new bean variety to their popular local variety. There is that likelihood to adopt a new bean variety if it performs well under different environmental conditions such as drought, tolerance or resistance to pests and disease, and can enhance their economic productivity.

Feder, Just and Zilberman (1985) argue that yield performance (or the expected yield of new varieties) is one of the characteristics of improved varieties that affect farmers' technological adoption behaviours. Several empirical studies show that the adoption rate of improved varieties is high if they meet farmers' expectations. A new improved variety would be adopted at exceptionally high rates if it was technically and economically superior to local varieties. Improved varieties are technically superior if they produce a higher yield that that of traditional varieties. For example, farmers in Tanzania adopted an improved Pigeonpea variety because it gives them higher yield when compared to their local variety (Shiferaw *et al.,* 2008; Amare *et al.,* 2012). Also reported by Simtowe *et al.* (2011) that farmers in Ethiopia and Tanzania adopted maize/chickpea and maize/Pigeonpea technologies because it gives them more income and enhance their welfare. Moreover, Adesina and Baidu-Forson (1995) reported that farmers in Burkina Faso adopted a new variety of sorghum because higher yields were obtained as compared with the local variety that farmers planted in the past growing seasons. Similarly, Awotide *et al.* (2015) reported that farmers adopted improved cassava varieties in southern Nigeria because the economic benefit associated with the technology could not be compared with that of the local variety.

Adegbola and Gardebroek (2007), who studied the effect of information sources on technology adoption and modification in the Benin republic, reported that, apart from the yields benefit, direct cost and profit accompanied by improved maize technology were measured as well. Furthermore, adopters believe that seed characteristics that reduce risks, such as insects and disease infestation that can cause injuries during maize production either in the field or in the storage, can lead to increased farm revenue. In some circumstances, losses not only intensify the risk of food insecurity for farmers but could also lessen their farms' income if losses in yields are not adequately compensated for by complimentary price rises due to the shortage in domestic supply. In relation to risk, various researchers found that farmers consider environmental features when adopting a new technology, such as weather and climate change. Examples are drought-tolerant maize varieties, developed by the IITA in collaboration with International Maize and Wheat Improvement Centre (CIMMYT) for local tropical and sub-tropical climates such as dry-spell and soil-fertility conditions (Ramírez *et al.*, 2003; Di Falco and Bulte, 2013; FAO, 2015a).

The significance of commodity attribute perceptions has been of interest to scientists investigating adoption of agricultural technology among farmers. Anthropologist, extensionists and sociologists have played a significant role in this sense and have debated the use of qualitative approaches, of which farmers' subjective evaluation of improved technologies influence their adoption behaviour (Kivlin and Fliegel, 1967). Nevertheless, since most of the earlier works on technology adoption by researchers (O'Mara, 1980) were not able to have close observation on farmers' perceptions of technology, it was not quantitatively possible to directly subject the hypothesis to statistical testing that proves that perceptions of technology characteristics do determine farmers' adoption decision of a newly introduced technology. Instead, factors that affect farmers' access to information, for example extension service, education and media exposure, both in print and electronic, were used in economic models as factors influencing technology adoption decisions (Shakya and Flinn, 1985; Polson and Spencer, 1991; Mendola, 2007).

Scholars investigating consumer demand behaviour gathered enough evidence to prove that consumers have subjective preferences for product attributes and that their demand for such products is highly influenced by their perceptions of these attributes (Jones, 1989; Lin and Milon, 1993; Adesina and Baidu-Forson, 1995). For example, using the double-hurdle (DH) and Tobit models, Lin and Milton (1993) learned that commodity traits and consumers' safety perceptions of commodities were found to be significant in explaining consumers' decisions to consume, and the frequency of shellfish consumption in the USA. Similarly (Jones, 1989), the DH model adopted from Cragg's framework found that consumers' subjective perceptions also influenced cigarette-smoking decisions. Currently, only a few studies were found to have analysed the direct effects of farmers' subjective assessment of agricultural technology characteristics on their adoption decisions in Zambia, Nepal and Nigeria (Langyintuo and Mungoma, 2008; Ghimire and Huang, 2015).

Earlier studies have, however, attempted to determine technology attributes and the decision of farmers to adopt. Relatively little of the economics literature on variety adoption has treated the specific attribute of variety directly, e.g. (Baidu-Forson, 1999; Lusty and Smale, 2002). In their study of new rice adoption in Sierra Leone, Adesina and Zinnah (1993) reported that farmers' perceptions of the rice characteristics significantly affected their adoption decisions. Also, Adesina and Baidu-Forson (1995), in their study in Burkina Faso, found that farmers' perceptions of the technology characteristics of four varieties of sorghum were related to the probability of adoption and intensity of their cultivation. They also found that the quality of sorghum flour used for making paste, yield, the age of the farmer, performance under poor soil conditions, and farmers' participation in on-farm tests (TESTs) were statistically significant in explaining adoption decisions.

Similarly, (Oladele and Rantseo, 2010), in their study on perceived relevance of livestock technologies in Botswana, found that education level, herd size, income and distance to crushes were statistically significant determinants of perceived importance of livestock technology. All the variables mentioned were positively related to perceived significance, except distance to crushes – as the distance to crushes increased, the perceived relevance of livestock technologies decreased. Anim (2008) reported that, in South Africa, cattle farmers' age and herd size determined their willingness to pay for extension services. Kenneth *et al.* (2012) reported that farmers' perceptions of varietal attributes, disease and pests, and yield and agronomic attributes were associated positively with the likely adoption of most of the hybrid bananas in Uganda.

2.4 Determinants of technology adoption

The majority of people in sub-Saharan countries, about 675.5 million, live in the rural settlement and the majority of them are directly or indirectly engaged in agriculture for a living (FAO, 2015b). In the previous more than 50 years, an increase in crop production was driven largely by productivity that increases in yield per unit of land, and crop intensification. Development in agriculture is, however, not uniform across regions. For example, in Asia and North Africa, most of the growth in wheat and rice production was from the increase in grain yield, while the increase in land cultivation has led to maize production growth in SSA and Latin America (FAO, 2015b). Most of the world's poor lives in rural areas, particularly those in SSA, and the majority of them are engaged in agriculture. Therefore, research activities are planned to reduce the vulnerability of this rural poor towards improving their production practices in agriculture as a means of advancing their efficiency, productivity and, ultimately, their income (WDR, 2008; Parvan, 2012). Governments, NGOs, and agricultural extension and development workers have since identified that the success of any agricultural project partially depends on whether farmers adopt the newly introduced technologies. If they do, the question is whether those farmers adopt the offered technologies in an ideal combination and for the estimated time required to deliver the desired results (Roling, 1988).

For many years, many surveys and analyses were conducted by researchers across the world in an attempt to understand the agricultural technology diffusion patterns and adoption decisions of farmers among poor rural communities. These surveys help scientists to understand how these smallholder farmers and their communities decide on whether to adopt the introduced technologies or not. Researchers in this area can improve their agricultural research outreach to address the awareness concerns of targeted communities, and to understand the increase in the propensity that farmers are willing and able to participate and contribute to project activities located in their communities (Parvan, 2012).

In an attempt to establish the progression of adoption and diffusion of agricultural technology, investigators used mostly three methods of analyses in order to understand the factors that influence the adoption of new technology over time and space, namely cross-sectional, time-series and panel-data analyses, as indicated by (Besley and Case, 1993; Langyintuo and Mungoma, 2008; Samson *et al.*, 2012). Any of the three approaches involves the gathering and analysing of different kinds of cross-sectional data. Various methods are applied to explain a different aspect of the process involved in the adoption of agricultural technology. Most researchers extensively use time-series data to explain the rate of adoption and diffusion of agricultural technology varieties over time. However, analysis using time-series data does not explain the reasons that are fundamental to technology adoption. According to Besley and Case (1993), "cross-sectional data analyses are of two types: 'snapshot' and 'recall'." In summarising the two types, they described the snapshot as the relationship that associate farmers' socioeconomic characteristics with likelihoods of adopting new technologies, while the recall relates to farmers' attributes with the time at which adoption happened. The deficiencies of this data are the unrealistic assumption that is prerequisite to making the data applicable, principally assuming that the farmers' attributes do persist over time. On the other hand, panel data uses a collection of both cross-sectional and time-series data and is analysed to explain both the adoption decision and the socioeconomic factors that are associated with technology adoption. This methodological approach is rarely used because of the cumbersome nature of the data collection and handling.

Even though agricultural technology adoption is regarded as an important instrument to combat poverty among some of the developing countries in SSA (Bandiera and Rasul, 2006; Macharia *et al.*, 2012), its impact is slow across many of the SSA countries due to the low adoption rates of available technologies. For example, in 2014, Nigerian farmers applied an average of only 3.3 kg of nitrogen fertilizer in one hectare of cultivable land, which is too small when compared with the total average recorded for SSA farmers who applied an average of 13.8 kg per hectare. This is also insufficient when compared with the world average of 141.3 kg (FAO, 2015b; World, 2015). Similarly, on average Nigerian farmers applied only 0.8 kg of phosphate fertilizer per hectare when compared to African average of 5.9kg in 2014 (FAO, 2015a). Behind these low adoption rates, there are several theories and empirical justifications, which include:

- inadequate credit to purchase technologies and their relative perception of low economic benefits (Duflo *et al.*, 2008);
- limited access to labour and a lack of access to financial markets ((Ndjeunga and Bantilan, 2005; Langyintuo *et al.*, 2010; Teklewold *et al.*, 2013b);
- high transportation and transaction costs (Minten *et al.*, 2013; Mmbando *et al.*, 2015);
- a lack of awareness of new agricultural technologies, or their inaccessibility to it (Krishnan and Patnam, 2014);
- climatic variability, or price risks (Juma *et al.*, 2009; Dercon and Christiaensen, 2011; Asfaw *et al.*, 2014); and
- land tenure security (Denning *et al.*, 2009; Teklewold *et al.*, 2013b).

Most farmers are risks averse, particularly in respect of adoption of new technology, as reflected in previous studies (Antle, 1987; Kim and Chavas, 2003).

Farmers who are risk-averse are always careful when it comes to the adoption of new technologies and may persist using their local technology even though it yields very low productivity and profit, which may, consequently, drive them into perpetual poverty and food insecurity situations (Dercon & Christiaensen, 2011). Furthermore, the precautionary measures taken due to their risk aversion attitude and non-availability of coping incentives, such as informal and formal credit and the availability of agricultural insurance policy, may also preclude farmers from using capital investments that could yield a high income and likely drive them out of the vicious cycle of poverty.

Many studies have reported the consequences of risk and its subsequent effects on adoption of agricultural technologies (Groom *et al.*, 2008; Kassie *et al.*, 2011; Holden and Fischer, 2015). In the face of the number of studies on risk, different conclusions persist concerning the importance of identification of risk factors in encouraging decisions on adoption of agricultural technology. However, this may not only be connected to the operational differences across different regions of the world, but also to the complexity and dynamic forces associated with the process of technology adoption (Moser and Barrett, 2006). Most of the past studies on technology adoption made use of cross-sectional data and used econometric models that do not consider farmers' unobserved heterogeneity, which, if not checked, could lead to selectivity biased and inconsistent estimates. Current adoption studies have focused on either a particular technology such as improved fertilizer or seeds, green manuring, water and irrigation systems, or a bundle of technologies treated as a one-in-a-box form (Dorfman, 1996). However, farmers on their own go further to pool different technologies of their choice, many of whom derive the highest potential benefit from each of the technological components. The adoption decision looks more like a multivariate decision (considering more than one component simultaneously) than a univariate process (considering only one unit).

Most of the reported factors used among scholars to explain the inconsistency in agricultural technology adoption and its diffusion process are those reported by Akpan et al., (2012a), Asfaw *et al*. (2011; 2012a; 2014) Awotide *et al*. (2015), (Johannes *et al.*, 2010) and Tambo and Abdoulaye (2012). The explanatory variables differ in terms of their real-world applicability but conventionally among them are:

- farm size;

- human capital;
- labour availability;
- credit constraint;
- land tenure security;
- proximity to commodity markets;
- household asset ownership;
- risk associated with new technology and ability to bear the risk;
- farming experience of the farmer;
- age of the farmer;
- social capital and collective action.

Regarding relationships, these factors are not independent of themselves. For example, poor access to rural financial market reduces the accessibility to credit and poor access to credit increases the propensity to risk aversion of investment such as the adoption of new technology. Many poor farmers are risk averse and it decreases their ability to withstand risk, which is also related to higher poverty and, in turn, increases exposure to shocks. High poverty indices themselves are linked with smallholder farmers who cultivate smaller plots and, due to low levels of education, have poor allocative ability to manage change (Feder *et al.* 1985).

Many adoption studies show that each of these factors influence the agricultural technology adoption process. Trying to isolate one factor from another is challenging and may even be needless. The main objective of the review of adoption literature surveys is to show how each variable influences the adoption of agricultural technology.

2.4.1 Farm size

Among the most important variables considered when modelling adoption processes are farm size. The effect of farm size on adoption is not constant. It could be positive or negative, depending on the type of the technology deployed and the formal setting of the client community (Feder *et al.*, 1985), for example, deployment of a new upland rice seed variety or drip irrigation to communities that are known for growing maize and has the potential to grow rice. The initial cost outlay is often a big hurdle to adoption of this new agricultural technology among smallholder farmers. Therefore, spreading the high initial investment over larger farms could be the reason for the observed linear relationship between farm size and potential technology adoption (Diagne, 2006; Fufa and Hassan, 2006; Denning *et al.*, 2009; Teklewold *et al.*, 2013b; Arslan *et al.*, 2014). Farm size can also influence other factors, such as access to extension services and credit, because bigger farms can stand on their own as strong collateral value in order to access credi0 Large farms can also attract extension agents and aid agencies to conduct technology trials on them. On the other hand, these correlated factors may have an effect on the adoption decision and, therefore, failing to control them in the adoption models may have a tendency to bloat the relationship between farm size and the propensity to adopt new technology.

According to (Parvan, 2012) on the review of agricultural technology adoption "Neill and Lee (2001) in their study of maize-*mucuna* adoption in Honduras, reported farm size met the apriori expectation of a positive relationship with a propensity to adopt the agricultural technology". Also, Feder and Umali (1993) found that large-scale farmers adopt divisible and non-divisible technologies more rapidly than their smaller counterparts. The latter adopts the divisible technology more intensely and may finally adopt the lumpy technology. Similarly, in their study of fertiliser adoption among farmers in southern Nigeria, (Akpan *et al.*, 2012a) found that farm size significantly influenced adoption of fertiliser use. Bernard *et al.* (2010), in their study of certified maize seed technology adoption in Kenya, also learned that farmers with larger plots were more likely to adopt certified maize seed as compared with farmers with smaller plots of land. Therefore, farmers with bigger farms were more likely to adopt new technology and more likely to continue using it.

2.4.2 Human capital

Human capital comprises individual farmer attributes like age, gender, education and human health indicators. It is suggested that farmers with a higher level of education may possess a very good allocative ability and can adjust faster to variability in market and farm conditions (Feder *et al.*, 2003). Researchers investigating factors influencing farmers' adoption decision of new agricultural technologies across different locations (Amare *et al*., 2012, in Tanzania; Awotide *et al*., 2015; Fuglie and Kascak (2001), in the USA; Simtowe *et al*., 2010a, in Tanzania; Teklewold *et al*., 2013a, in Ethiopia), found that human capital, such as education and access to the extension, positively correlated with innovators and early adopters. Farmers with a higher level of education, such as a university degree or an equivalent thereof, are more likely to adopt new agricultural technology faster than farmers with only a high school or primary certificate, while laggards are mostly associated with lower education. Poor soil quality and new technology does not perform well on poorly managed fields. In assessing the adoption of agricultural technology among smallholder farmers, for example, improved seed adoption in Mozambique (Lopes (2010), and pigeonpea adoption in Tanzania (Amare *et al.* (2012), it was found that human capital features, such as education, access to information, improvements in education and health condition will raise the adoption of new agricultural technologies.

As with risk aversion, which, when persisting to continue aggravating the vicious cycle of poverty due to the increased vulnerability of poor households to smaller shocks, negative human development can likewise correlate highly with income and also reinforce unsound agricultural practices and aversion to the adoption of agricultural technology. Yamauchi *et al.* (2009) found that investment in human development, particularly education, decreases aftershock consequences. Yamauchi *et al.* (2009) also found that accumulation in human capital development before disasters surges resilience to the hostile effects of those shocks. The adverse human capital development indicators that are prevalent have already made the most vulnerable household less likely to adopt more income-generating technologies. They rather tend to adopt low capital investment technologies such as integrated *Striga* management (ISM). Mendola (2007) asserted that better targeting of smallholder and poor farmers might be the main driving force for taking full advantage of direct-effect poverty reduction, and it is under this consideration that new agricultural technology is designed to operate. Activities that are income-generating by their virtue such as land rehabilitation and conservation, and irrigation and drainage schemes will help farmers to generate more income and strong capital formation. Ultimately, these activities will reduce farmers' risk aversion to the level where most of the farmers will adopt the new agricultural technology, thereby creating a succession of progression and adoption. Furthermore, the adoption of improved agricultural technologies also depends on other considerations such as institutional factors. The deployment of improved agricultural technologies creates awareness and demand for information that are handy for decision-making. Agricultural extension services provide beneficial information about improved agricultural technologies to agencies and organisations that are saddled with the responsibility. However, access to such information sources can be crucial in the adoption process of those technologies (Johannes *et al.*, 2010). Many studies such as (Teklewold *et al.*, 2013a; Arslan *et al.*, 2014; Asfaw *et al.*, 2014) found education and extension contact to greatly influence adoption of various improved technologies.

2.4.3 Risk and uncertainty about technology

All decisions on adoption of new technology come with some element of individual risk, such as human predispositions to doubt in the beneficial outcomes from using the new techniques, physical risks that may arise due to weather variability such as rainfall, pest and disease incidences, and the access to critical inputs at the right time and in the right quantities (Feder, 1985). The observed nature of farmers' technology adoption in developing countries was also influenced by farmer's feelings about risk and their ability to bear risk and uncertainty associated with investment in new technology.

Poverty is the major factor that leaves farmers defenceless against food production shocks that ultimately lead to shocks in income of which they have little or are incapable to insure (Parvan, 2012). Thus, even significant future benefits may not seem profitable if the direct investment, and associated risks, are satisfactorily distorted (Mosley and Verschoor, 2005). Moreover, when farmers are of lower wealth status in society, their constraints to financial resources and production inputs will preclude them from being able to bear risk associated with the newly introduced technologies, even if they would otherwise prefer the riskier option. Virtually, resource constraints cause farmers to exclude themselves from trying the new production practice and technologies by the extent of risk they can afford, not to the amount of risk they prefer to accept (Mosley and Verschoor, 2005).

The first financial commitment of an improved technology discourages farmers from adopting the high-yielding practice and technologies that may likely bring them out of their vulnerability, which is the result of their preference for the traditional or local practice, yet deficient, farming techniques (Holden and Shiferaw, 2002). The adoption of new agricultural technologies is associated with great risks which has been an important influence in adoption decision-making (Parikh and Bernard, 1988; Shiyani *et al.*, 2002). However, because of the recently experienced drought in Malawi, the country found a government programme on input subsidies to principally influence the adoption of drought-tolerant (DT) maize among the most risk-averse farmers. Their risk aversion stimulated their adoption of the technology, because they found improved varieties to perform higher in terms of yield during the drought period of the 2011/2012 growing season when compared with local varieties (Holden and Fisher, 2015).

2.4.4 Family size and labour availability

With regard to labour-demand technologies, labour availability plays an important role in explaining agricultural technology adoption decisions. The availability of labour was found to be a significant factor that influenced the adoption of fertiliser in Malawi positively (Green and Ng'ong‘ola, 1993). Labour availability could influence the adoption of technology differently, depending on the labour endowment of the area targeted with the technology, that is, whether it has a net labour shortage or labour surplus. Labour availability contributes another dimension to agricultural technology adoption, as reported by different authors (Mittal and Kumar, 2000; Teklewold *et al.*, 2013b; Asfaw *et al.*, 2014) in India, Ethiopia and Malawi.

Another thought for consideration is whether the proposed technology is labour-intensive or labour-saving. A greater amount of labour supply is related to the adoption of technologies that is labour-intensive (Feder *et al.*, 1993), the inverse of which is also true. Lee (2005) reports that labour availability is related to household size, and labour availability significantly influences the adoption of soil conservation investments in Ethiopia and the Philippines (Welch, 1970; Shiferaw and Holden, 1998). Polson and Spencer (1991), investigating the adoption of high-yielding varieties (HYV) of cassava among subsistence farmers in Nigeria, found that family size, which is a proxy of labour availability, did not have a significant influence on adoption. This discrepancy was explained by (Polson and Spencer, 1991), by suggesting that subsistence farmers do not experience the same types of labour constraints as their well-off counterparts who are income-generating by status.

The influence of effect of family size on technology adoption can be ambiguous. It can hamper technology adoption where farmers are penniless and the meagre resources available are used to honour other family obligations (Asfaw *et al.*, 2012b), with little or no money left to purchase production inputs. Conversely, it can also be an inducement for the adoption of new agricultural technologies, where the larger proportion of farm output is needed to meet the consumption needs of the family, or additional family labour is needed for the farmer to adopt labour-intensive agricultural technology. (Kenneth *et al.*, 2012) found that family size significantly influenced the probability of adopting hybrid bananas in Uganda.

2.4.5 Credit limitations

As reported by Parvan (2012), credit accessibility on its own is a factor that directly or indirectly influences other factors related to agricultural technology adoption, such as:

- farm size, for example, farmers with larger farms can use it as a collateral to borrow money for production purposes, while those with smaller farm sizes cannot benefit ceteris paribus;
- human capital, for example, farmers who are more educated tends to be more informed about credit availability and can even look for a loan with moderate interest rates;
- land tenure, which is strongly related to credit worthiness, for example, farmers who own a parcel of land are more likely to have access to loans than their landless counterparts; and
- social capital and collective actions, for example, farmers in groups or associations are more likely to secure credit because they can cross-guarantee each other.

Credit considerations are of secondary importance because of its ambiguous and embedded interest rates which regulate the future value of financial capital, and when interest rates rise, moderate income can be generated immediately, which seems more appealing than even large future returns (Parvan, 2012). Rational farmers compare existing opportunities versus the stream of future income, and can therefore be expected to show sensitivity to other credit considerations and interest rates. Farmers living in areas with high interest rates are less likely to partake in any activity which can make them forgo their immediate cash returns for future returns (Parvan, 2012). López-Calva and Lustig (2010), in their study of Latin American countries, found credit accessibility from commercial banks and other credit providers not statistically significant at national level, however, it is statistically significant (1% level) in the southern region of Latin America, influencing the adoption of agricultural technologies. Simtowe *et al.* (2010b) found credit accessibility to be highly correlated to adoption of Pigeonpea technology in Tanzania. Credit access and belonging to social capital and collective action groups positively and significantly influences adoption of agricultural technologies across different regions of Africa such as Tanzania, Ethiopia and Nigeria (Amare *et al.*, 2012; Awotide *et al.*, 2015). In their study in

Ethiopia, (Dercon and Christiaensen, 2011) used historical rainfall distributions as the counterfactual to identify consumption risk. While monitoring the unobserved time-varying village and household characteristics, they found not only credit constraints exante to inhibit adoption, but also the possibility of low consumption that may follow when harvests fail, and this dampened the application of inorganic fertiliser. They attributed all of these factors to the absence of insurance, which can result in inefficiency in agricultural production options.

2.4.6 Land tenure

Land tenure is a big issue among smallholder farmers. As mentioned earlier, the uncertainty related to changing plots is, of course, an impediment to technology adoption. The poor and landless are the most vulnerable in communities, because the ones who do own land, own smaller plots and all of them use traditional methods of production, their output is smaller and they cannot afford to risk their marginal output. Because this group of farmers is poor, they can least afford risk and, as a result of their inherent risks-aversion, they remain in the vicious cycle of poverty. Some farmers who are both poor and landless mostly grow their crops on sharecropped or rented plots and, as such, their tenure rights are not secure. Farmland insecurity is also found to be associated with poverty, which reduces the propensity of vulnerable communities to adopt new agricultural technology that is considered risky and this, in turn, aggravate the land tenure risk cycle.

In their study of measuring the impact of land certification on investment and land tenure security, Deininger *et al.* (2008) found that land tenure security reduces the fear of land redistribution, in so doing revealed the uncertainty over land possession. They also found that there is a strong relationship between land tenure security and the increasingly likelihood to invest in water and soil conservation management, and that is more than twice the estimated number of spent on each management activity. Furthermore, they reported that increased land tenure security increases the probability to rent out land, which can lead to the tenant allocating more resources should the landlord not be willing to cultivate his or her plots (Deininger *et al.*, 2011). The same authors in a different article found the opposite outcomes, the reason being that sharecroppers will, in a growing season, receive only a little return from their small harvest because they have little or no incentives by investing more than the least required time, labour or cash (Deininger *et al*., 2008). For example, farms infested with *Striga* is known to be controlled with farmyard or organic manure. Landlords may re-allocate their plots to other farmers in the next cropping season and, because of this uncertainty of losing a plot in the next cropping, sharecroppers or renting tenants will not invest their resources in such plots. The same uncertainty applies to soil conservation activity where sharecroppers or tenants are afraid to invest in the land that they have no authority over. As reported by Asfaw *et al.* (2014), land tenure security significantly influences the adoption of strategies and investment, which reduces the demand for short-term inputs in the long run. Their findings indicate that production resources and farm output intensities are significantly lower on land tenants when compared to that of land owners. Therefore, land tenure insecurity will greatly reduce smallholder farmers' propensity to adopt new agricultural technology.

2.4.7 Commodity market access

It is also believed that new technologies require constant application inputs, for example fertilisers, pesticides and seeds. The introduced high-yield varieties (HYV) of maize and poor infrastructures of roads and market facilities in many developing countries, particularly in the SSA, results in inefficiencies and high fluctuations in agricultural commodities prices. Due to poor transportation systems, such as roads and rural infrastructure and, for example, grain warehousing and cold storage for perishables, farmers are bound to oversupply to the market. This conduct leads to glut in local markets just after the harvest and, in turn, results in lower prices for agricultural produce (Zeller *et al.*, 1998; Markelova *et al.*, 2009). The lack of warehousing and storage facilities could also mean that a lot of output rots, sometimes before it could be sold or even reach the market, depending on the perishability or lifespan of the farm produce. This leads to a scarcity of the commodity in the days or weeks before the inception of the next harvest. Good rural infrastructure, such as sound transportation systems, will enhance the movement of agricultural produce from surplus regions to deficient regions. Where prices may be relatively stable across geographical regions, good rural infrastructure will act as a buffer to both consumer and producer. This will ultimately reduce the post-harvest glut, thereby arrest commodities' price variability. Researchers often use a farmer's proximity to a major road or main markets as a proxy for market accessibility for agricultural produce. They also indicate the likelihood of a farmer adopting new agricultural technology decreases with increased distances from a major road or main market (Feleke and Zegeye, 2006; Simtowe *et al.*, 2010b; Asfaw *et al.*, 2014; Ghimire and Huang, 2015a).

2.4.8 Education

The significant part played by education in influencing adoption of agricultural technology has been discussed extensively by many authors in the literature. The number of years of formal education attained by farmers was found to enhance their decision-making and allocative ability. It enables them to reason critically and process and utilise information at their disposal proficiently. Farm families with high levels of formal education are more capable of exploring different means of getting new information about improved agricultural production technologies. They are, therefore, very articulate in evaluating and interpreting such information about innovations in comparison with their less-educated counterpart (Asfaw *et al.*, 2010, Teklewold *et al*., 2013a). Past studies by, for example Alene, Poonyth & Hassan, (2000) have shown education to influence the adoption of improved maize varieties in West Shoa, Ethiopia positively, Doss and Morris (2001) also found education to positively and significantly influence the adoption of improved maize varieties in Ghana, while (Kenneth *et al.*, 2012) also found the probability of education influencing the adoption of hybrid banana in Uganda was statistically significant. According to Mignouna *et al.* (2011a), education also has the probability of influencing the adoption of IRM maize in Kenya. In their various studies, many researchers such as (Feleke and Zegeye, 2006; Teklewold *et al.*, 2013a) have found education to significantly influences on adoption of agricultural technologies.

2.4.9 Age

Another important factor found to significantly influence the adoption of agricultural technologies is the age of the household head. Conventional approaches to adoption studies consider age to be negatively related to the adoption of new agricultural-based technologies on the assumption that, with age, farmers become more conservative and less open to new ideas. On the other hand, it is also contended that, with age, farmers gain more experience and become more acquaintance with new technologies and hence are expected to have a higher ability to use innovations more efficiently. Some studies (Hassan, Onyango & Rutto, 1998; Johannes *et al.*, 2010; Kaguongo *et al.*, 2012; Kenneth *et al.*, 2012; Tambo & Abdoulaye, 2012), have found age to be a major factor influencing technology adoption, whereas others did not agree (Voh, 1982; Chilot *et al.*, 1998; Krishna and Qaim, 2007; Akpan *et al.*, 2012a).

In their study, (Katungi *et al.*, 2007) applied a probit model to estimate the probability of using improved technology for banana management practices and participation in the farmers' organisation in Uganda. This study also revealed that information generated by early adopters diffuses through sparse social networks, contrary to the assumption of free availability in the whole village (Katungi, 2007). Other studies, such as that of (Kenneth *et al.*, 2012), used zero-inflated Poisson regression models, because of the excess zeros recorded in the farmers' responses, to determine factors that influence the adoption of new hybrid bananas in Uganda.

The studies reviewed above show some inconsistencies in the results about the determinants of adoption and use of agricultural technologies by farm families. Also, only a few of these studies addressed the issues of endogeneity and selection bias. The endogenous nature of technology adoption variables entails the refusal of the conditional independence assumption to hold, which makes ordinary least squares (OLS) estimates unsuitable for estimating the causal effect, since they are biased due to the selection of unobservable characteristics.

However, (Greene (2003); Johannes *et al.* (2010)) used non-parametric statistics (propensity score matching – PSM) and parametric statistics, such as Heckman's two-step procedure, to address the issue of selection bias for the subpopulation of the adopters to be different from the subpopulation of non-adopters, at least regarding covariates. Asfaw *et al.* (2010) and Di Falco *et al.* (2011) employed ESR to address the issue of selection bias (for the subpopulation of adopters to be different from the subpopulation of non-adopters, at least regarding covariates, to avoid a case of encountering the sample selection bias problem that might create inconsistent parameter estimates). To address this problem, they employed the econometric procedure that involves both endogeneity (Hausman, 1978) and sample selection (Heckman, 1979). Some scientists are motivated to use an ESR model that accounts for both endogeneity and sample selection bias, and this allows interactions between adoption and other covariates in the outcome welfare function (Alene and Manyong, 2007; Di Falco *et al.*, 2011; Asfaw *et al.*, 2012a).

2.5 Technology adoption intensity

Adoption of agricultural technology entails a two-part decision-making process: whether to adopt and how much to adopt. These two decisions can be made jointly or separately (Gebremedhin and Swinton, 2003; Johannes *et al.*, 2010). The Tobit regression equation was used to analyse determinants of technology adoption and determinants of adoption intensity when the two decisions are made jointly. Adesina & Zinnah (1993) and Wanjiku *et al.* (2003) used the Tobit model to determine the factors influencing adoption and the intensity of adoption of new agricultural technologies in Burkina Faso and Guinea in West Africa, and Kenya, respectively. However, the Tobit model assumes that the socioeconomic factors determining adoption, in a similar way determine the intensity of adoption. The Tobit model has consideration for a zero value of technology adoption as a corner solution that all non-adopting households are not interested in adoption (Asfaw *et al.,* 2010).

Therefore, when the two decisions are assumed to be made separately, an alternate model that is more applicable is the double-hurdle model, which analyses factors influencing technology adoption and the intensity of adoption. The usual binary-dependent variable models are used for studying the dichotomous problem of the likelihood of adopting a new agricultural innovation or not. Contrary to this, the objective of applying the double-hurdle (DH) model is to help understand the intensity of adoption.

This study applied the DH model for this purpose. In the Tobit model, decisions on whether to adopt or not and how much to adopt are assumed to be made mutually, and hence the factors affecting the two-step decisions are taken to be the same. However, the decision to adopt come first then the decision about how much to adopt, or the intensity of the use of the technology, and hence the explaining variables in the two stages may differ. The second hurdle was the outcome equation, which uses a truncated model to determine the extent of technology adoption (Johannes *et al.*, 2010; Akpan *et al.,* 2012b; Tambo and Abdoulaye, 2012). This stage uses observations only from households that do adopt the technology and use the truncated model. In this study, the proportion of land put under ISM technologies and the total household operational land holding was used.

2.6 Agricultural technology adoption and impact

The critical step of agricultural technology in reducing poverty among the agrarian communities and an overall raising of economic development have been widely acknowledged in the development economic literature. Even though it is complex, the relationship between new technology adoption and reduction in poverty has received a positive perception among scholars

(Becerril and Abdulai, 2010; Asfaw *et al.*, 2012b). Productivity-enhancing agricultural technologies have since been noticed to reduce poverty through increasing farm income; reduction in food prices; aiding the growth and development of non-farm sectors through releasing excess farm labour; and by supporting the changeover from lower productivity agriculture to a higher productivity agro-allied and industrial economy (Just and Zilberman, 1988).

The impact of improved technology on reducing poverty among households may be directly from the farm or indirectly to the consumers. As shown by productivity gains, the direct impact is only enjoyed by farmers who adopt the technology. These gains are manifested in the form of higher incomes from their farm investment. The indirect impact is benefits passed to others because of the productivity gains by adopters of technology. Among these benefits are higher non-farm employment levels or increases in consumption for all farmers as a result of lower food prices (De Janvry and Sadoulet, 2001).

However, the agricultural technology that enhances productivity come in a package or box which consists of many innovations and not just a single unit. The technology's box nature with a bundle of inputs renders the assessment of its tangible impact difficult. However, in recent times, some studies have analysed the impact of agricultural technology adoption at community or household level. Some of the household-level studies include those by Amare *et al*. (2012, Asfaw *et al*. (2012), Di Falco *et al*. (2011), Evenson and Gollin (2003), Mendola (2007) and Simtowe *et al* (2012). Past studies have therefore documented the positive impact of adoption of technologies, with a few results from the household level that explicitly shows the impact of the agricultural technologies adoption on productivity gains and household income.

The acceptance of improved technology by farmers in Asia, for example, the HYVs of maize and wheat that led to the great success of the GR could also significantly lead to increases in agricultural productivity in Africa, hence, stimulating the growth of low farm productivity to a high productivity agriculture-based and industrial economy (World Bank, 2008). It is also observed that the adoption of improved agricultural technologies has a positive and significant relationship with household well-being in Bangladesh (Mendola, 2007).
(Kijima *et al.*, 2008) did a study in Uganda on the impact of New Rice for Africa (NERICA). They found that adopting NERICA technology lead to a decrease in poverty without a corresponding

weakening of income distribution. Many studies revealed a significant and positive impact of agricultural technologies adoption on household welfare such as Amare *et al.* (2011), Asfaw *et al.* (2012), Becerril and Abdulai (2010), and De Janvry and Sadoulet (2002).

Amare *et al*. (2012), in their study examining the impact of improved pigeonpea and maize technology adoption on household welfare in Tanzania, they employed both PSM and switching regression models. Their findings suggest that adoption of maize/pigeonpea technology has a significant and positive impact on household income and consumption expenditure.

Also, (Becerril and Abdulai, 2010) examined the impact of the adoption of improved maize germplasm among maize farmers in Mexico. They applied the PSM approach to estimate the impact of the adoption of different maize varieties on farm income and poverty reduction among the sampled households. Their findings revealed the existence of a positive relationship between adoption of improved maize varieties and household welfare measured in per capita expenditure and poverty reduction. It was shown that the average impact of the technology adoption on per capita expenditure was between 136-173 Mexican pesos across the two regions of their studies, thus, decreasing the adopters' likelihood of falling under the poverty line by 19-31%.

Furthermore, Di Falco *et al*. (2011) did an analysis of factors influencing the adaptation to climate and its impact on Ethiopian farmers on household food productivity. They applied an ESR model to account for the heterogeneity in the adoption decision and unobservable characteristics of the farming households and their farms. It was found that access to extension, farming information and access to credit were found to influence adaptation among the sampled households significantly. They also alluded that adaptation increases farm productivity, while ,in the counterfactual case, farm households that did not adapt could have gotten more benefit had they adapted.

On the contrary, (Hossain *et al.*, 2006) conducted a study in Bangladesh which shows that the adoption of HYVs of rice had a positive effect on richer households but a discouraging effect on their poorer counterpart, due to the high input requirement associated with technology, particularly pesticides, herbicides and fertiliser. Also in Zimbabwe, (Bourdillon *et al.*, 2003) found that adoption of HYVs of maize only increases farm incomes moderately. These contradictory results rationalise the necessity for more investigation on this topic. It is also noted that most of the past researches evaluated technology adoption impact by just obtaining the mean differences in the outcomes of adopters and non-adopters, or by estimating it through regression models that consist of adoption-based variables among a set of independent variables. These methodologies have some drawbacks of failing to appropriately account for the problem of self-selectivity bias in studies by using an observational data set collected through cross-sectional surveys. These approaches have failed to find the causal effect of adoption (Rubin, 1974; Heckman and Vytlacil, 2005). Today, there is high-rising literature to evaluate the impact of agricultural technology adoption on poverty alleviation programs by using experimental and non-experimental approaches that deal with selection bias problems (Ravallion, 2006).

2.7 Profitability assessment

Technological improvement is necessary if sustainable agricultural development is to achieve any benefits (Sanginga *et al.*, 1999). Scientists across the world have developed many improved technologies that are aimed at increasing farm productivity and income with the intention of improving farmers' welfare (Amare *et al*., 2012; Asfaw *et al*., 2011; Awotide *et al*., 2015; Mignouna *et al*., 2011; Mignouna *et al*., 2015. Farmers ordinarily adopt technologies that have a potential of higher economic benefit and the lowest risk when compared to the present ones. Agricultural scientists should be able to prove that new technologies have an economic benefit over the existing ones used by farmers (Langyintuo and Mungoma, 2008; Simtowe *et al.*, 2011). Before switching from a known investment to the unknown, farmers consider many factors, such as agro-climatic and production input requirements, including labour, farmland, skill, finance and other necessary production implements. Additionally, farmers also consider the suitability of the new technology in terms of their socioeconomic values and production goals. It is also of interest for farmers to know the extra cost they will incur and what additional income they will earn from adopting the new technology to justify the extra expenditure (Wale and Yalew, 2007; Kaguongo *et al.*, 2012; Parvan, 2012).

The simplest and most straightforward method of comparing the economic benefit of new agricultural technology is the partial budget (PB) analysis, as indicated by (Badu-Apraku *et al.*, 2012**)**. The PB is a farm management technique that is intended to help researchers and farmers to make decisions. PB compares and quantifies the impact of the proposed technology with other existing ones. PB analyses' results are presented in ratios such as the net present value, BCR, internal rate of return (IRR) and the GM analysis. These ratios guide scientists involved in agricultural and extension to identify weaknesses associated with the new technology, such as high cost of production and low income. A PB is used to help researchers identify technology with the highest profit, which will guide farmers in whether to adopt the technology or not (Olukosi and Erhabor, 2005; Macharia *et al.*, 2012)). PB was used to compare the effect of *Striga*-control practices with farmers' traditional practices in Nigeria (Ellis-Jones *et al.*, 2004).

The net present benefit (NPB) approach discounted the present value of the future benefits associated with today's investment and was also used to determine the profitability of new agricultural technology, as demonstrated by Ellis-Jones *et al.* (2004) and Mignouna *et al.* (2011b). These researchers used discount rates to discount the annual benefits and adopted a sensitivity analysis to validate any consequence that the discount rate might have on the benefit. A sensitivity analysis based on a 50% increase, a decrease in output prices and variations in the discount rate (0%, 5% and 20%) were used to establish the robustness of their findings over the base case. They found a significant overall increase in the productivity of IRM and ISM over normal farmer practices.

This chapter highlighted the institutional concepts that are examined empirically in the subsequent chapters of the thesis. Among the salient points drawn from this chapter is that, while earlier work on *Striga* is centred on improving production and control technologies across different countries, recent efforts have focused on improving the participation of smallholder farmers in the use of ISM technologies in *Striga*-infested areas of SSA.

This chapter also highlighted some of the technologies developed in recent times to control *Striga* and the success stories of those technologies. Some of the factors influencing adoption of improved agricultural technologies were discussed. If the costs of technologies are high, adoption will be reduced and resource-efficient production technology adoption will not take place, leading to low production efficiency. In the absence of proper institutions meant to promote improved agricultural technologies, smallholder producers, in particular, could find themselves excluded from participating in the use of cost-effective technologies. Using lessons drawn from the different studies, the literature indicates that farmers who have access to human, physical, financial and social capital will be more able to obtain the necessary production technologies and market information, and can therefore produce on a larger scale when they combine their resources. Cooperatives of farmer groups also facilitate the provision and coordination of other important services (e.g. training, extension, seeds and credit), which would otherwise be difficult to offer to a large number of individual farmers spread across different communities. By providing the right combination of technologies and enabling the environment for farmer groups to thrive, developing countries can advance agricultural production and commercialisation. Smallholder farmers are thereby enabled to improve their income-generating capacity; hence, ameliorating the pressing challenges of poverty and household food insecurity.

The following chapters (3 to 7) comprise the conceptual framework, empirical methods and research results emanating from the four specific objectives of the study. The next chapter discusses the ISM technology adoption, diffusion and socioeconomic characteristic of maize-producing households and their perceptions of *Striga*-technology attributes in northern Nigeria.

CHAPTER 3

INTEGRATED *STRIGA* MANAGEMENT (ISM) TECHNOLOGY ADOPTION AND DIFFUSION: A CASE OF SMALLHOLDER MAIZE FARMERS IN RURAL NORTHERN NIGERIA[1]

3.1 Introduction

This chapter presents the empirical methods, results and discussion of the socioeconomic characteristics of maize producing households in the study area and their perceptions of *Striga* technology attributes. The rest of the chapter is organized as follows: Section 3.2 outlines the methodology, which constitutes the conceptual and empirical model, and the data collection procedures. Section 3.3 presents the empirical results, while Section 3.4 concludes the chapter with a summary of the findings.

3.2 Research methods

3.2.1 Conceptual framework

The sustainable livelihood framework (SLF) was adopted as a theoretical approach to help understand and analyse the livelihoods of smallholder farmers in the study area (Figure 1). The SLF is a form of livelihood analysis used by some researchers and applied development organisations, for example, the Department for International Development (DFID) of the United Kingdom, The United Nations Development Program (UNDP), as well as non-governmental organisations across the globe. It is principally a conceptual framework for analysing causes of poverty, people's access to resources, their diverse livelihood activities, and their relationships between relevant factors at micro, intermediate and macro levels. It is also a framework for assessing and prioritising interventions.

[1] This chapter gave rise to a paper submitted to Technology in Society, currently under review. M.B. Hassan, L.J.S, Baiyegunhi, & G.F. Ortmann. Integrated *Striga* Management (ISM) Technologies Adoption and Diffusion: a case of smallholder maize farmers in Rural Nigeria.

The framework revealed that every household was endowed with livelihood assets comprising natural, physical, human, financial and social capital. These assets affect various livelihood strategies that may take the lead singularly or in combination. These strategies refer to the choices people employ in pursuit of income, protection, security, well-being and sustainable use of natural resources.

In the maize and cowpea production in Nigeria that represents the livelihood strategy of crop farming that households engage in, *Striga* is the major constraint. *Striga*-control options can be introduced to enable households to reduce their vulnerability to shocks and food insecurity. According to IITA (2013), the benefits of technology to households was determined by all the elements of livelihood mediated by institutions and social relations. The general conceptual framework for sustainable livelihoods is as shown in Figure 3.1.

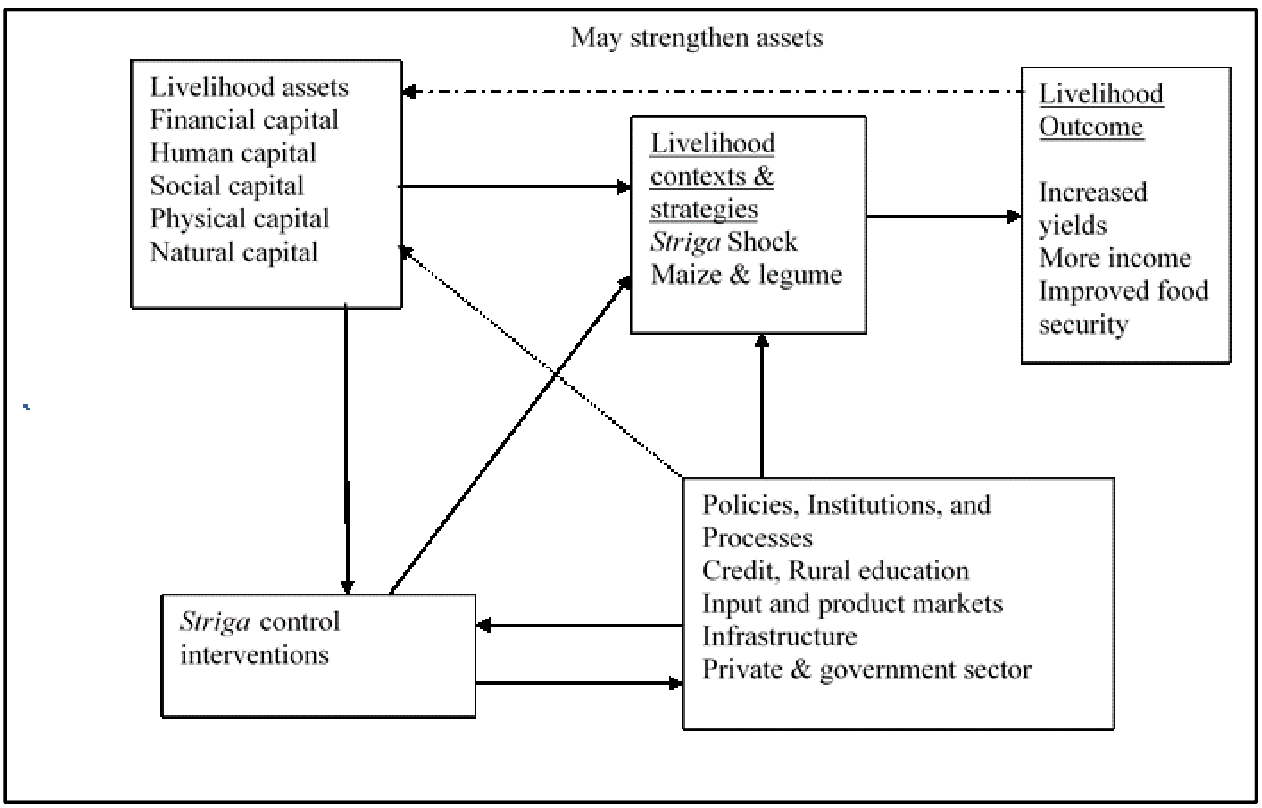

Figure 3.1: Sustainable Livelihood Framework (SLF)
Source: Adapted from DFID, 2002, Mignouna *et al.*, 2013

3.2.2 Empirical model

3.2.2.1 Analysis of household characteristics

Descriptive statistics like t-test and chi-square were used to analyse this study. Adoption could be measured on the level, rate or index, depending on the technologies or technology package. In this study, the adoption rate and indices were employed. Descriptive statistics and tabulation were used to summarise household characteristics such as sex of household head, household size, dependency ratio and the household head's years of schooling. The dependency ratio was calculated by dividing the total number of dependents by the number of working members. Household size was also adjusted by composition and economies of scale. The concept of this adjustment is that it costs less to feed four children than four adults (composition effects) and to double the size of the family does not imply doubling the amount of expenditure necessary to maintain living standards (scale effects). Richards, Davies and Yaron (2003) suggested the equivalent units mentioned below be used to adjust the sample households (Table 3.1).

3.2.2.2 Adjustment of household size by composition

Based on equivalent units presented in Table 3.1, household size was adjusted to address composition effects, as expressed in Equation 3.1:

$$H_i = \alpha_1 N_1 + \alpha_2 N_2 + \alpha_3 N_3 + ... + \alpha_n N_n \tag{3.1}$$

where:

H_i = gender and age weighted by the ith household in the sample;

$\alpha_1 \ldots \alpha_n$ = relative weight given to individuals on age and gender;

$N_1 \ldots N_n$ = size of components of households with similar gender and age range.

3.2.2.3 Adjustment of household size by sex and age weight

The household size was also further adjusted to scale economies in Equation 3.2:

$$HE_i = (H_i)^{\varphi} \tag{3.2}$$

where:

HE_i = household size of the i^{th} household in the sample adjusted for both composition and scale effect;

H_i = gender and age weighted by the i^{th} household in the sample; and

φ = scale economies within the household.

Table 3.1: Adult equivalent scales for adjusting aggregate household size

Age by category (years)	Sex-based adult equivalent scales		Household size*	Economies of scale
	Male	Female		
0 to 2	0.40	0.40	0 to 2	1.000
3 to 4	0.48	0.48	2 to 3	0.946
5 to 6	0.56	0.56	3 to 4	0.897
7 to 8	0.64	0.64	4 to 5	0.851
9 to 10	0.76	0.76	5 to 6	0.807
11 to 12	0.80	0.88	6 to 7	0.778
13 to 14	1.00	1.00	7 to 8	0.757
15 to 18	1.20	1.00	8 to 9	0.741
19 to 59	1.00	0.88	9 to 10	0.729
60+	0.88	0.72	10+	0.719

* Measured in number of ages and gender-weighted adult equivalent units
Source: Richards *et al.* (2003)

Adoption can be measured on the level, rate or index depending on the technologies or technology package. In this study adoption rate and indices were employed.

The mathematical expression of the adoption rate (A_i) is represented by Equation 3.3:

$$A_i = \frac{\mathrm{N}}{\mathrm{T}} \times 100 \qquad (3.3)$$

where,

A_i = percentage of adopters;

N = number of adopters of (total number of farmers using ISM technologies);

T = total number of the entire sample size (or total land under cultivation, or total quantity of both local and improved technologies.

Adoption could also be estimated as a function of performance and penetration indices, as represented by i (Equation 3.4):

$$\mathrm{A}_i = \left(\mathrm{P}_\alpha \times \mathrm{P}_i\right)/100 \qquad (3.4)$$

where:

P_α = performance index; and

P_i = penetration index.

The performance and penetration indices, which have been communicated to farmers in the study areas before adoption decision, were used as indicators to assess the farmers' success or acceptability levels of the deployed technologies.

3.2.2.4 Performance index

Performance index (P_α) shows the actual number of households reached against the target number that should be reached (the total sampled households in this case) (Casley and Lury, 1982). The mathematical expression (P_α) is represented by Equation 3.5:

$$\mathrm{P}_\alpha = \frac{\mathrm{A}}{\mathrm{T}} \times 100 \qquad (3.5)$$

where:

A = actual number reached; and

T = targeted number to reach.

3.2.2.5 Penetration index

The penetration index (P_i) shows the number of households accepting to adopt the ISM technologies out of the number that actually adopted it (Casley and Lury, 1982; Mignouna *et al.*, 2011c). The mathematical expression (P_i) is represented by Equation 3.6:

$$P_i = \frac{D}{A} 100 \qquad (3.6)$$

where;

D = number accepted to adopt ISM technologies; and

A = actual number reached.

Performance difference is the difference in adoption between PIAs and NPIAs in terms of ISM technology adoption.

The performance difference, in this case, is the difference in adoption rates between PIAs and NPIAs of ISM technologies. It was achieved by using a contingency table (Table 3.2) developed by (Msambichaka, 1992).

The difference (D) in performance between farmers in PIAs (P_1) and NPIAs (P_2) is represented by Equation 3.7:

$$D = P_1 - P_2 = [a \div (a+b)] - [c \div (c+d)] \quad (3.7)$$

All of the above were used to achieve objective I of the study.

Table 3.2: Contingency table

	Adoption		**Total**
	Yes	**No**	
PIAs	A	B	(a+b)
NPIAs	C	D	(c+d)
Total	**(a+c)**	**(b+d)**	**n(a+b+c+d)**

PIAs = project intervention areas; NPIAs = non-project intervention areas; Yes = adopted ISM technologies; No = did not adopt ISM technologies

3.2.2.6 Description of the study areas

The study was conducted in the savannahs of two states, Bauchi and Kano, located in north-eastern and north-western Nigeria, respectively (Fig.1). These locations were chosen because of the presence of severe *Striga* infestation in these farmers' fields. The Kano state is located at 12°37' N, 9°29' E, 9°33' S, and 7°43' W and is bordered by the Jigawa state to the east and the Bauchi and Kaduna states to the south. It has a daily mean temperature of 30°C – 33°C during March to May and a temperature as low as 10°C during the months of September to February. The rainfall pattern is unimodal, with an average rainfall of 600 mm per annum. The Kano state has a total land area of 20,760 square kilometres, with 1,754,200 ha of agricultural land and 75,000 ha of forest vegetation and grazing land. Situated in the Sahel Savannah region of West Africa, the Kano state has a rainy season that varies from year to year, starting in May and ending in October. The dry season, on the other hand, runs from November to April. The Kano state has an estimated population of over 12 million people (NPC, 2006). Agriculture is the mainstay of the economy, involving at least 75% of the rural population.

Bauchi is an agricultural state, located in the north-eastern part of the country. The state lies between latitudes 9°30' and 12°30' N and longitudes 8°45' and 11°0' E. The state shares common borders with seven other states: Yobe and Gombe to the north-east; Taraba and Plateau to the south, Kaduna to the west, and Kano and Jigawa to the north. The Bauchi state has a total land area of 49,259 square kilometres, representing about 5.3% of Nigeria's total land mass. Of this land mass, only 34,481 square kilometres is under cultivation (BSADP, 2003). The average maximum temperatures range from 29.2°C in July and August to 37.6°C in March and April. The mean daily minimum ranges from about 11.7°C in December and January to about 24.7°C in April and May. The state has both rainy and dry seasons, with a maximum rainfall of about 700 mm per annum in the north to about 1300 mm per annum in the south.

For this study, exploratory analyses were carried out by using data from a random survey of farming households conducted between January and March 2014 in 16 LGAs, eight LGAs each from the Bauchi and Kano states, based on prior knowledge of *Striga* infestation in these areas. Five of the selected LGAs were from ISM technology PIAs, while 3 LGAs were from non-ISM technology PIAs, the latter serving as counterfactuals. A reconnaissance survey was first conducted in selected areas with the assistance of the government extension officer, the community leaders and the ward heads (*Mai anguwan*) to identify and list farmers in the study areas. The list of households obtained served as the sample frame from which 643 households were chosen for the study. Of these, 309 were from the Bauchi and 334 from the Kano states (25-49 households were randomly selected, depending on the number of farming households in an LGA). The household head was the unit of analysis.

The household questionnaire included sections on

(i) interview and household details;
(ii) household demographic characteristics;
(iii) gender issues;
(iv) productive resources endowment;
(v) production costs and labour inputs;
(vi) inputs in relation to maize
(vii) crop-marketing aspects;
(viii) *Striga* and *Striga*-control technologies;

(ix) vulnerability, capital assets and livelihoods;

(x) livelihood strategies and outcomes;

(xi) household expenditure; and

(xii) other important crops enterprises.

Furthermore, farmers' perceptions of agronomic attributes of technologies and the feasibility of the different *Striga*-control methods were collected. Each technology and method was evaluated by farmers for each attribute by using a 5-point Likert scale, namely, 5 = Very good, 4 = Good, 3 = Fair, 2 = Poor and 1 = Very poor.

Qualitative data was collected through focus group discussions (FGDs), key informant interviews (KII), village meetings and personal field observations. Seven to ten households in each LGA were purposively selected to attend FGDs. Key informants, such as community leaders, were also approached to identify current challenges, adaptations and opportunities regarding ISM technologies in the area. The FGDs, village meetings and key informant interviews were conducted by a moderator and an assistant who prepared a checklist of discussion questions that guided the interviews. Via these methods, background information was obtained on households' assessment and perceptions of *Striga* infestation, extent/severity, traditional control mechanism and ISM technology adoption. The information gathered was then used to design a semi-structured questionnaire that was administered to respondents during the interview to obtain quantitative data. The questions focused on household demographic and socioeconomic characteristics, crop production systems, ISM technology adoption, diffusion process, institutions, etc. To assist with field work and translate the English questionnaire for respondents, local interviewers, who had in-depth knowledge about the *Striga* problem and could speak the native language *(Hausa),* were selected, trained and used to pre-test the questionnaires and, subsequently, the data collection.

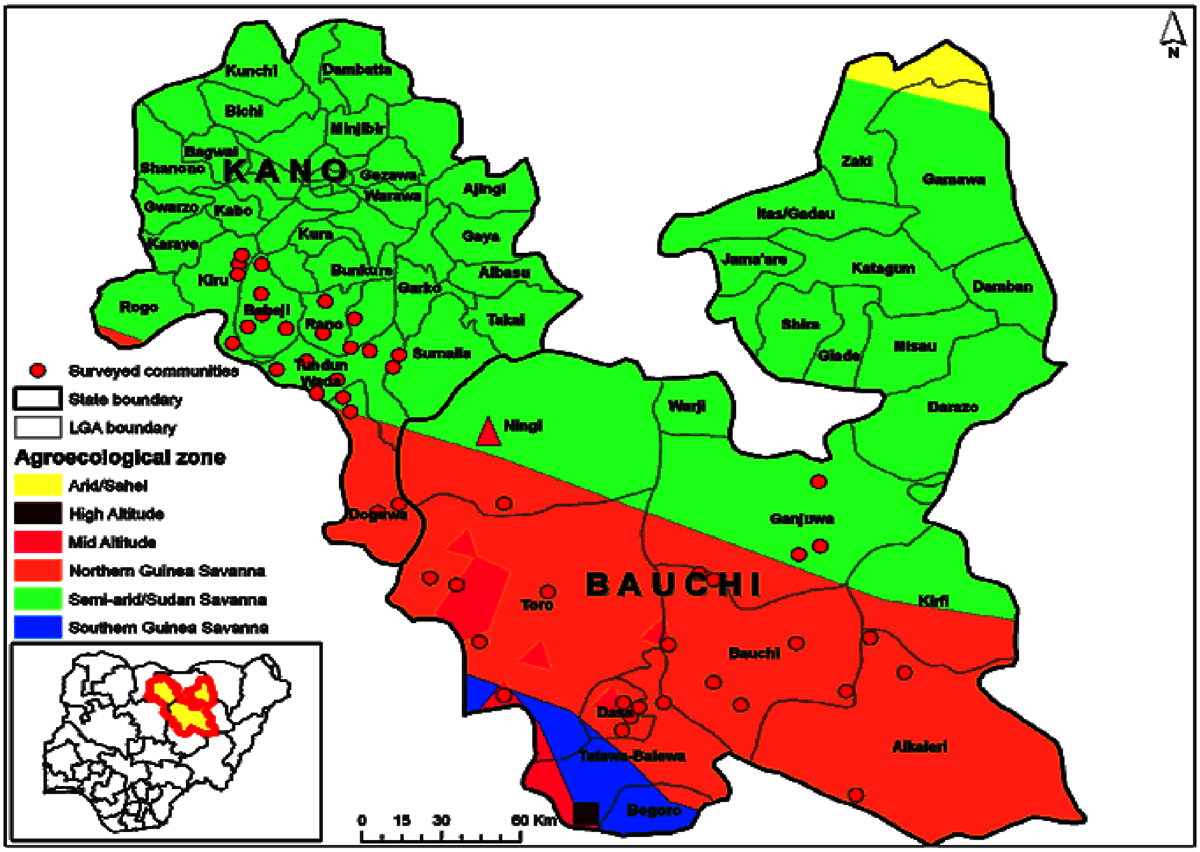

Figure 3.2: Map of the Bauchi and Kano states showing areas of study
Adopted from the IITA (2013)

Table 3.3: Number of sampled households and their adoption status by local government areas (LGAs), Bauchi and Kano states, northern Nigeria

ISM adoption status	**Local Government Areas (LGAs) in the Bauchi state**								
	Alkaleri	Bauchi	Dass	Ganjuwa	Kirfi*	Tafawa Balewa*	Toro	Warji*	**Total**
Non-adopters	9	12	11	9	13	15	13	12	121
Adopters	30	36	34	28	11	8	20	10	188
Total	**39**	**48**	**44**	**37**	**24**	**23**	**33**	**22**	**309**
ISM adoption status	**Local Government Areas (LGAs) in the Kano state**								
	Bebeji	Kiru	Doguwa	Rano	Karaye*	Kibiya*	Sumaila*	Tudun Wada	**Total**
Non-adopters	21	21	6	32	22	9	19	27	166
Adopters	23	24	31	12	23	16	21	18	168
Total	**44**	**44**	**37**	**44**	**45**	**25**	**40**	**45**	**334**

*Non-ISM intervention local government areas (LGAs)
Source: Field survey 2014

For this study, adopters represented farmers who had already used some ISM technologies (STR maize, cereal–legume rotation, i.e. STR maize, in rotation with improved soybean or cowpea, hybrid IRM and *Striga* biocontrol technology), while non-adopters represented farmers who have not yet used any of the ISM technologies. The empirical analysis, therefore, considered the adoption of at least one of the ISM technologies. Figure 3.2 presents a map of the study areas, while Table 3.3 shows the sampled households and their adoption status by LGAs in the study area. Detail of the selection method used is described by the United Nations Statistical Division (2008). The varieties and agronomic practice promoted in the study area are shown in Table 3.4.

Table 3.4: Varieties of maize and soybean used under ISM on-farm trials in the study areas

S/no	Maize varieties used	S/no	Soybean varieties used
1	TZE COMP ISYN (OPV) STR	1	TGX 1448-2E
2	IWDC' SYN (OPV) STR	2	TGX 1904-6F
3	99EVDT (OPV) STR	3	TGX 1955-4F
4	2009EVDT (OPV) STR	4	TGX 1951-3F
5	IITA IR-Maize Hybrid 2	5	TGX1835-10E
6	IITA IR-Maize Hybrid 4	6	TGX 1987-10F
7	Maize resistant to Metsulfuron Methyl	7	TGX 1987-62F
8	STR maize in rotation with soybean/cowpea		

Source: Field survey, 2014

3.2.2.7 Field data collection, data entry and database management

Primary data collection was carried out during March 2014. In each state, a team of 10 enumerators and three supervisors carried out 309 household surveys in 40 communities in the Bauchi state, while 334 households from 40 communities in the Kano state were surveyed. Enumerators, all trained in two different methodology workshops organized by the IITA, administered the structured questionnaire under supervisors. Training modules focused on surveying of objectives and methodology, sample size, techniques for selecting sample households, ways of administering questionnaires with households, the role of enumerators and inter-agency coordination. Some simulation sessions were done to familiarise enumerators with questions in the household questionnaire for a successful collection of information. Enumerators were selected for each state after training and testing for the whole survey were done. The process was steered by factors such as:

(i) willingness to work for a long period;
(ii) academic qualifications and a minimum level of experience in data collection;
(iii) ability to speak Hausa (native language) fluently;
(iv) ability to interact with people from different ethnic groups in a different environment; and
(v) familiarity with places where the project was conducted.

3.3 RESULTS AND DISCUSSION

3.3.1 Farmer's socioeconomic characteristics

The major socioeconomic characteristics of farmers covered in the survey are presented in Table 3.5. These characteristics relate to the relative frequency distribution of household heads by gender, age, farming experience, household size, distance to market, distance to extension office, marital status of household head, and major occupation of the household head.

3.3.2 Age and farming experience of household head

Age, in correlation with farming experience, has a significant influence on the decision-making process of farmers on risk aversion, adoption of improved agricultural technologies, and other production related decisions (Amaza *et al.*, 2007; Amaza *et al.*, 2009). Furthermore, age is said to have a direct bearing on the availability and mobility of farming manpower, the ease with which improved practices is adopted and the size of farm area cultivated by the farmer at any given time. The average age of the respondents in the surveyed PIAs was 43 years in Kano and 41 years in Bauchi, and 42.8 years and 41 years in the NPIAs of the Kano and Bauchi states, respectively (Table 3.5). There seems to be a dominance of old farmers in the study area, which has adverse implications for increasing agricultural productivity, since maize production is largely labour intensive. There is also a positive relationship between the age of farmers and the years of farming experience. The mean years of farming experience of the respondents in the PIAs were 23 years and 21 years in the Kano and Bauchi states, respectively, while it was 21 and 22 years, respectively, in the NPIAs.

3.3.3 Household size

The importance of household size in agriculture hinge on the fact that the availability of labour for farm production; the total area cultivated by different crop enterprises; the amount of agricultural products retained for domestic consumption; and the marketable surplus are all determined by the size of the farm household. The pattern of household sizes was similar across the two states. The mean household size for both states was 13 and 11 persons in PIAs and NPIAs, respectively. However, in relative terms, the mean household size was higher in the Bauchi state for both PIAs and NPIAs. In his findings, Idrisa (2009), recorded an average of seven persons per household in Adamawa state, while he documented an average of nine people per family in the neighbouring Borno state.

3.3.4 Distance to market

The distance to the nearby market has some effects on farmers' production decisions and adoption of agricultural technologies. The states in the study have similar distances. However, distance to market is lower, 8 km, in the PIAs in Kano compared to the 9 km in the project areas in Bauchi. The Kano state is commercialised compared to the Bauchi state. This factor seems to have contributed to the intensity of agricultural activities in the Kano state, which subsequently led to the development of specialised markets within the Kano metropole for agricultural products, including cereals, groundnut (*Dawanau* market), fruit and vegetables (*yan lemo*), and market and tubers (*yan doya).*

3.3.5 Distance to extension office

Table 3.5 also shows that the distance of the respondents to the extension office is similar in both the PIAs and NPIAs in the Kano and Bauchi states. Farmers in the surveyed areas have the potential of equal access to extension services.

3.3.6 Human capital

The basic principle of the diffusion model is that adoption behaviour was inclined by farmers' socioeconomic characteristics, such as human capital, farming experience, age and level of education that, in turn, facilitate accepting, access and exposure to information associated with a particular technology (Pfeffer, 1992; Padel, 2003). Many studies have shown that human capital includes the level of education, skills, participation in on-farm trials and attendance of field days. Therefore, farmers need assistance to use production information resourcefully, as more educated persons gain more information and, to that level, are better farmers (Lockheed *et al.*, 1980; Phillips, 1994; Wang *et al.*, 1996; Yang, 1997). The intensity of farmers' education is believed to influence the use of improved technology in agricultural production and, hence, in farming productivity. Some studies in Nigeria (Durojaiye and Olanloye, 1992; Jones, 2005; Muyanga, 2009; Kudi *et al.*, 2011) report that a high level of formal education among households contribute positively and significantly to agricultural production. Table 3.5 indicates the distribution of the respondents on their level of formal education.

Participation in on-farm trials and field days creates a demand for ISM technologies. The levels of farmers' participation in these events are presented in Table 3.5. In the PIAs, 74% and 77% of the respondents in the Kano and Bauchi states, respectively, participated in on-farm trials. As expected, no farmers participated in on-farm trials in the NPIAs as there were no project activities. The number present at farmers' field days followed a similar pattern in the PIAs, where 63% and 56% of farmers in the Kano and Bauchi states, respectively, attended field days. However, in the NPIAs, field days were not held, although 31% and 18% of farmers in the Kano and Bauchi states, respectively, travelled to attend field days held in PIAs, as indicated in Table 3.5. Information about field days might have emanated from the media, other farmers in project communities, or even via extension agents involved in the ISM project. It might have influenced the farmers' decisions to attend the field days. It is plausible that the level of farmers' participation in on-farm trials and field days influence the adoption levels of ISM technologies.

Table 3.5: Characteristics of respondents in PIAs and NPIAs

Variable	Project Area			Non-Project Area		
	Kano (N=219)	**Bauchi** (N=231)	**Total** (N=450)	**Kano** (N=115)	**Bauchi** (N=78)	**Total** (N=193)
Female	0.7	3.5	2.1	0	5.1	5.1
Male	99.4	96.5	98.0	100.0	94.9	98.0
Single	2.8	4.6	3.7	3.9	7.1	5.5
Monogamous	45.8	42.4	44.1	54.2	43.4	48.8
Polygamous	51.4	53.1	52.3	41.3	46.9	44.1
Divorced	0	0	0	0.7	2.7	1.7
Age mean (years)	43.4	41.3	42.3	42.8	41.1	42.0
Farming experience (years)	22.6	21.4	21.9	21.3	22.2	21.7
Household size (number)	11.4	12.9	12.2	9.9	11.3	10.5
Distance to market (km)	7.7	8.9	8.3	8.5	7.3	8.0
Distance to extension office (km)	9.2	10.9	10.1	8.3	10.8	9.3
Farming	81.0	84.2	82.3	87.1	88.5	87.8
Trading	11.7	6.6	9.2	9.0	7.1	8.1
Civil servant	3.9	4.1	4.0	2.6	1.8	2.2
Technicians	0.6	2.0	1.3	0	0.9	0.4
Others	2.8	3.1	2.8	1.3	1.8	1.7
Education level of respondents						
None	23.5	15.8	20.3	24.5	23.9	24.4
Primary school	26.8	21.9	48.8	30.3	21.2	51.6
JSS	6.2	9.7	15.8	5.8	6.2	12.0
SSCE	21.8	20.9	42.7	12.3	14.2	26.4
OND/NCE	4.5	9.2	13.7	5.8	7.1	12.9
HND and above	3.4	1.5	4.9	2.6	0.9	3.5
Others	14.0	20.9	34.9	18.7	26.6	45.3
Past participation in on-farm trials and field days						
Participated in on-farm trial [1]	N	%			N	%
Kano	133	7			0	0
Bauchi	151	77			0	0
Ever attended field days						
Kano	137	63			36	31
Bauchi	129	56			14	18

Source: Authors' calculations

[1]Participation refers to membership of community-based organization that leads farm trials

3.3.7 Difference in characteristics between adopters and non-adopters

Table 3.6 below presents the t-tests and comparison of means of selected variables by adoption status for the surveyed farmers in respect of ISM technologies in the Bauchi and Kano states, respectively. In both states, the adopters and non-adopters differ significantly regarding maize yield, past participation in on-farm trials and knowledge of the ISM technologies. Additionally, in Bauchi, the adopters and non-adopters significantly differ regarding contact with public extension agents. In Kano, the adopters and non-adopters differ significantly regarding the value of productive assets, the number of the active labour force in adult equivalent, access to formal credit, access to remittances and total farm income. The difference in the average age of household head, walking distance to market, walking distance to extension office, household size, years of education, maize farm size; and perceptions of farm fertility, farm gradient, and ownership of livestock between adopters and non-adopters was not statistically significant. The comparison of these two groups of farmers suggests that adopters in both states differ significantly in some proxies of human, social and physical capital.

Table 3.6: Difference in characteristics of adopters and non-adopters (sample mean), the Bauchi and Kano states, northern Nigeria

Variables	BAUCHI state			KANO state		
	Adopters	Non-adopters	t-test/ χ^2 values	Adopters	Non-adopters	t-test/ χ^2 values
Age of household head (years)	41.37	41.04	-0.23	42.88	43.37	0.43
Years of farming	21.67	21.46	-0.15	22.25	21.88	-0.34
Education of head (years)	6.59	6.27	-0.70	6.45	5.72	-1.55
Household size (number)	12.01	11.58	-0.55	10.67	10.28	-0.34
Total farm under maize (hectares)	2.58	2.68	-1.25	2.90	2.70	-0.22
Distance to agricultural office (km)	11.51	10.64	-0.41	8.54	9.21	0.82
Distance to the weekly market (km)	8.57	8.25	-0.27	7.73	8.9	-1.55
Total value of productive assets (Naira)[2]	150.43	144,94	-0.23	69,97	45,40	-1.77*
Maize yield (kg/ha)	1819.00	984.00	-7.7***	1765	1161	-4.27***
Number of active labour force (AE)	0.49	0.60	0.91	0.79	0.51	-2.52**
Experience in on-farm participation trial 1/0	0.58	0.35	-4.06***	0.54	0.26	-5.6***
Aware of ISM technologies 1/0	0.97	0.65	-8.38***	0.98	0.68	-8.4***
Contact with public extension agent on *Striga*-control 1/0	0.40	0.18	-4.12***	0.095	0.096	0.03
Access to formal credit 1/0	0.10	0.06	-1.42	0.45	0.35	-1.92*
Access to remittances 1/0	0.46	0.39	-1.09	0.59	0.28	5.99***
Ownership of small ruminants	7.65	8.69	1.17	7.39	7.6	0.25
Perception of farm fertility (1-3)	1.93	2.03	0.96	1.5	1.6	1.42
Perception of farm gradient	1.61	1.65	0.32	1.25	1.28	0.52
Total farm income (Naira)	261,458.00	211,373.00	-1.53	349,346.00	261,421.00	-2.38**
Total farm size (ha)	9.34	7.75	-1.35	6.07	5.9	-0.39
Total household annual income (Naira) from all sources	470,881.00	424,175.00	-0.43	319839.00	381,089.00	-1.34

Source: Authors' calculations
*****, **, *** significant at the 1%, 5% and 10% levels, respectively.

3.3.8 Farmers' perception of ISM technology advantages

Farmers' perceptions regarding the advantages of ISM crop technologies are reflected in Table 3.7. This information indicates that the most important characteristics of the ISM crop technologies preferred by these farmers are crops with higher yield potential; more tolerance to *Striga*, drought, wind and lodging, early maturity, more resistance to insects, diseases and storage weevils, better taste, bigger and multiple ears, and bigger stalk than local or farmer varieties. In the project

[2] US$ = ₦162 at the time of the study

communities, over 90% of farmers had either strongly agreed or agreed that ISM technologies entail higher yield level, more tolerance to *Striga*, drought, wind and lodging, early maturity, more resistance to weevil, insects and diseases, better taste when cooked, larger and multiple ears, and more tolerance to and bigger stalks than local or farmer varieties.

Table 3.7: Frequency distribution of farmers' perceptions about ISM technologies in ISM PIAs

Perception statement	KANO (N = 171)					BAUCHI (N = 162)				
	Perceptions about ISM technologies					Perceptions about ISM technologies				
	Strongly disagree (%)	Disagree (%)	Undecided (%)	Agree (%)	Strongly agree (%)	Strongly disagree (%)	Disagree (%)	Undecided (%)	Agree (%)	Strongly agree (%)
ISM varieties have higher yield compared local varieties.	0.58	0	2.92	55.56	40.94	0.62	3.70	4.94	16.05	74.69
ISM varieties are more tolerant to *Striga*.	0	0	2.34	52.63	45.03	0.62	0	5.56	19.75	74.07
ISM maize varieties mature early.	0	0.58	2.92	54.39	42.11	0	3.16	3.80	17.72	75.32
ISM varieties are more resistant to insects and diseases.	0.60	0	7.78	56.89	34.73	0.64	2.55	10.83	29.94	56.05
ISM varieties are more resistant to storage weevil.	0	0	8.19	58.48	33.33	1.27	2.53	15.82	35.44	44.94
ISM varieties are more resistant to wind and lodgings.	0	0.59	5.88	58.82	34.71	0.63	1.27	12.66	30.38	55.06
ISM varieties have better taste when cooked.	1.17	0.58	5.85	53.22	39.18	0	1.91	6.37	19.75	71.97
ISM varieties have multiple and bigger ears than local varieties.	0	0	2.96	55.03	42.01	1.25	6.88	7.50	20.63	63.75
ISM varieties are more tolerant to drought.	0.58	0.58	5.26	60.23	33.33	0.63	2.53	14.56	29.11	53.16
ISM technologies have bigger stalk.	11.11	7.60	4.09	57.31	19.88	40.25	30.19	10.69	9.43	9.43

Source: Authors' calculations

The perception among farmers in the non-project communities follows a similar trend to those in project communities (Table 3.8). However, a lower proportion of farmers, at least 80%, perceived that ISM crop technologies have the identified advantages compared with local or farmer varieties.

Table 3.8: Frequency distribution of farmers' perceptions about ISM technologies in ISM NPIAs

Perception statement	KANO (N = 126) Perceptions about ISM technologies					BAUCHI (N = 31) Perceptions about ISM technologies				
	Strongly disagree (%)	Disagree (%)	Undecided (%)	Agree (%)	Strongly agree (%)	Strongly disagree (%)	Disagree (%)	Undecided (%)	Agree (%)	Strongly agree (%)
ISM varieties have higher yield compared	0.79	1.59	28.57	40.48	28.57	0	8.11	10.81	24.32	56.76
ISM varieties are more tolerance to *Striga*.	0.8	1.6	29.6	54.4	13.6	3.23	0	12.9	29.03	54.84
ISM maize varieties mature early	0.8	1.6	28	44.8	24.8	0	0	6.45	25.81	67.74
ISM varieties are more resistant to insects and diseases.	0.8	1.6	30.4	53.6	13.6	0	0	16.13	29.03	54.84
ISM varieties are more resistant to storage weevil	0.8	1.6	30.4	44	23.2	0	0	19.35	25.81	54.84
ISM varieties are more resistant to wind and lodgings.	0.08	2.4	30.4	46.4	20	0	0	9.68	32.26	58.06
ISM varieties have better taste when cooked	1.63	4.07	29.27	46.34	18.7	0	0	20	30	50
ISM varieties have bigger and multiple ears than local varieties.	0.81	0.81	25.81	52.42	20.16	3.23	0	9.68	41.94	45.16
ISM varieties are more tolerant to drought	0.8	1.6	29.6	50.4	17.6	0	0	22.58	25.81	51.61
ISM technologies have bigger stalk	4	8	28.8	40.8	18.4		41.94	22.58	12.9	16.13

Source: Authors' calculations

Higher grain yield is a desirable quality that has the potential to enhance farmers' income from sales of maize and households' food security. Good grain quality and early maturity of maize and cowpea varieties are other desirable characteristics. In the farming systems of the study area, cowpea is usually the last crop to be planted, generally towards the end of the raining season. Thus, cowpea crops are constantly under threat of crop failure should the rain suddenly cease. To forestall such possibilities of crop failure, farmers prefer planting improved cowpea varieties that mature early.

3.3.9 Performance of ISM technologies

The general performance of ISM technologies was very satisfactory in both surveyed PIAs and NPIAs. The proportion of farmers who indicated that they were dissatisfied was non-existent in the PIAs and negligible (less than 1%) in the NPIAs of both the Kano and Bauchi states (Table 3.9).

Table 3.9: Farmers' perception of performance of ISM technologies

Level of satisfaction with ISM technologies	Project Area		Non-project Area	
	KANO (168)	BAUCHI (152)	KANO (125)	BAUCHI (26)
Very satisfied	44.66	80.77	79.76	82.89
Somewhat satisfied	16.50	11.54	10.12	11.84
Neutral	36.89	7.69	7.14	4.61
Somewhat dissatisfied	1.94	0	2.38	0
Very dissatisfied	0	0	0.6	0.66

Source: Authors' calculations

3.3.10 Adoption rate

In this study, respondents were asked to provide information about the ISM technologies that they know. As reported in Table 3.10, 83.5% of the respondents were aware of at least one ISM technology (ISM technologies include maize-legume intercropping. maize-legume rotation, STR maize, IRM, Biocontrol Technology). Knowledge of ISM technologies is more prevalent in the Kano state (51.2%) than in the Bauchi state, where 48.8% of the farmers indicated their awareness of ISM technologies.

Among the improved technologies, the maize-legume rotation is the most widely known (66.9%), while the second-most widely known improved technology is maize-legume intercropped that is known by about 62% of the respondents. About 54% of respondents are aware of STR maize. Opportunity exists for IITA and other partners to use existing structures for government extension services to disseminate the information to farmers in potential maize-growing areas with *Striga* infestation.

More (83.5%) respondents expressed awareness of ISM technologies, while fewer reported ever having used them in the 2013/2014 season. However, 55% reported that they had used at least one of the technologies in the 2013/2014 season. The maize-legume rotation is the most widely practiced, used by 52.7% of the respondents (Table 3.10). This sample adoption rate may, however, not provide a reliable estimate of the population adoption rates, due to the non-random nature (individual choice) of adoption of the varieties which farmers are exposed to. Therefore, these sample adoption rates are likely to be biased downwards because they include farmers who are not exposed to the varieties – they cannot adopt unless they are exposed. In fact, some farmers would have adopted ISM technologies if they had been exposed to them, but in the sample adoption rates, they are considered as non-adopters. Therefore, an estimation of technology adoption rates amongst the exposed subpopulation appears more appealing in terms of explaining the potential adoption rates because it does not address the problem of non-exposure bias.

Table 3.10: Exposure and adoption of ISM technologies in the study areas, 2013/14

State	KANO (N = 334)	BAUCHI (N = 309)	All (N = 643)
Aware of the technology (%)			
Maize-legume rotation	69.05	64.86	66.86
Maize-legume intercropping	64.88	58.91	61.75
STR maize	60.71	47.02	53.54
Imazapyr-resistant maize (IRM)	13.69	11.89	12.74
Biocontrol Technology	13.69	9.70	11.61
Know at least one technology	51.21	48.79	83.51
Ever used it (%)			
Maize-legume rotation	57.74	48.1	52.69
Maize-legume intercropping	46.43	38.91	42.49
STR maize	39.29	33.51	36.26
Imazapyr-resistant maize (IRM)	0.60	0	0.3
Biocontrol Technology	4.17	1.62	2.83
Used at least one technology	47.59	52.41	55.00

Source: Author's calculation from survey data

As indicated in Table 3.11, the adoption rate among the sub-sample of farmers who were aware of ISM technologies is much higher than the adoption rates reported earlier for the whole sample. The overall adoption rate for at least one improved ISM technology among the sub-sample of exposed farmers in the 2013/2014 season were higher (57%, 46%, 34%, 2.9% and 3.2%) for the different technologies, compared to the whole sample of 48%, 40%, 30%, 2.4% and 3%, respectively (Table 3.11). The adoption rates are higher in the Kano state when compared with those in the Bauchi state. Adoption rates for the exposed sub-sample seem more plausible when explaining possible population adoption rates (Diagne, 2006; Simtowe *et al.*, 2010a; Diagne *et al.*, 2011). Using the whole sample is likely to overestimate the population adoption rate significantly, due to the positive population selection bias by which the population that is most likely to adopt gets exposed first. Diagne (2006) points out that the positive selection bias arises from two sources. The first is the farmer's self-selection to gain awareness and the second is the fact that researchers and extension workers target their technologies at farmers who are more likely to adopt.

Table 3.11: Comparison of adoption rates between exposed sub-sample and the entire sample

Technologies	% of entire sample	% of exposed sub-sample
Maize-legume rotation	48.0	57.0
Maize-legume intercropping	39.6	46.0
Striga-resistant (STR) maize	29.5	34.0
Imazapyr-resistant maize (IRM)	2.4	2.9
Biocontrol Technology	3.0	3.2

Source: Author's calculation from survey data 2014

In the study area, the adoption and diffusion of ISM technologies were illustrated by the adoption rate, performance and penetration indices (Table 3.12).

Table 3.12: Performance and diffusion index of ISM technologies

Adoption items	Unit	PIA_s	$NPIA_s$	Total
Target number to be reached (T)	N	450	193	643
Population aware (A)	N	386	151	537
Number of ISM adopters (D)	N	262	91	353
Performance index (Pα = (A ÷ T) * 100)	%	86	78	83
Penetration index (Pi = (D ÷ A) * 100)	%	68	60	66
Adoption rate (AR = Pα * Pi) ÷ 100 or AR = D ÷ T	%	58	47	55

Source: Author's calculation from survey data 2014
N = number of respondents; PIAs = project intervention areas; NPIAs = non-project intervention areas

More than 50% of the sampled households adopted at least one of the ISM technologies, which might be due to high inter-community contact between the PIAs and NPIAs, as indicated earlier in Table 3.11. It indicates that the adoption of ISM technologies is on the increase when compared to the baseline study. The adoption of ISM technologies was high, due to the aggressive deployment of the technologies across the two states through the effort of the ISMA project. About half of the responses for non-adoption of ISM technologies was due to the non-availability of the IRM seeds and the high cost of technologies. It was probably due to the poor performance of community seed producers and the inefficient commercial seed supply chain in the rural market places. Adoption rates varied across the 16 studied areas, as presented in Figure 3.3.

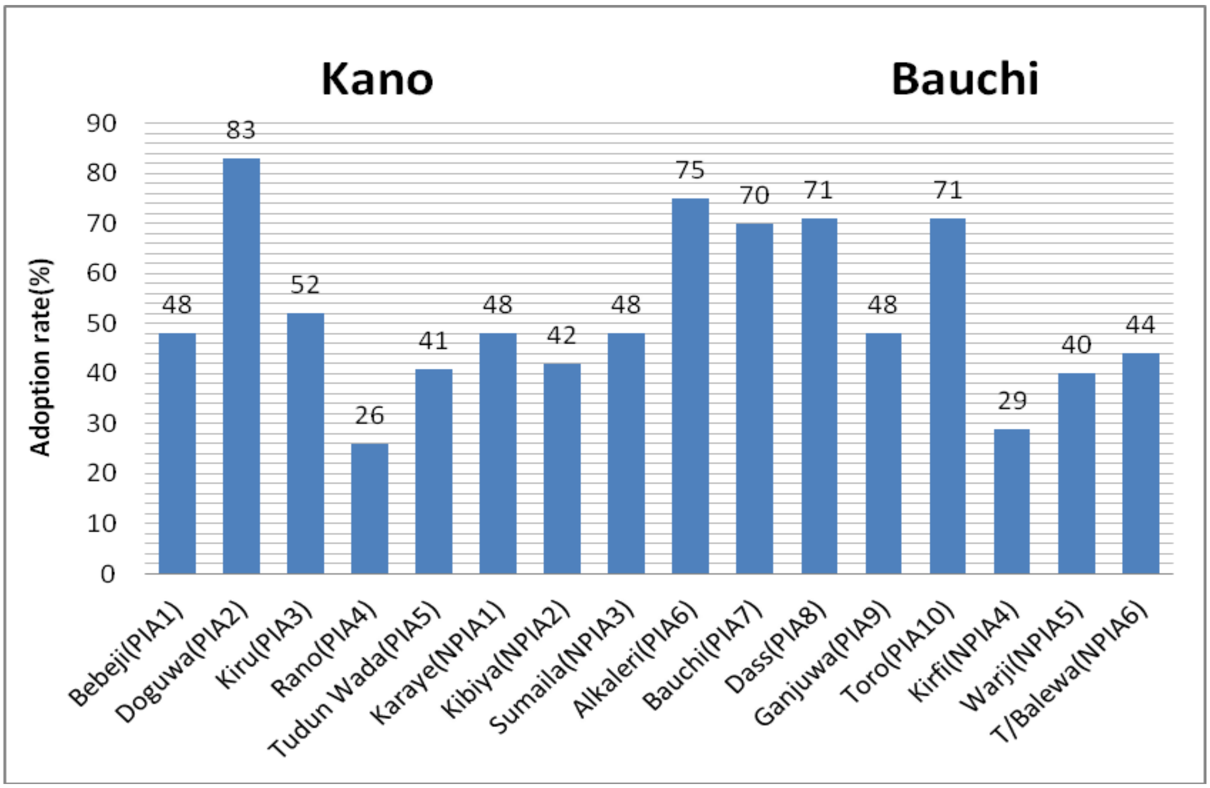

Figure 3.3: Adoption rates of ISM technologies per LGA of intervention and counterfactual in the Kano and Bauchi states of northern Nigeria (2014)
Source: Survey data 2014

The rate was highest in Doguwa in the Kano state (PIA_2), followed by Alkaleri (PIA_6), and then Dass (PIA_7) and Toro (PIA_{10}) in the Bauchi state. It was lowest in Rano (PIA_3) of the Kano state and Kirfi ($NPIA_4$) of the Bauchi state. The observed low adoption rate in Rano can be explained by the poor infrastructure in the area, such as road networks, which likely limits the communication between smallholder farmers and the villages, and constrained the accessibility of farmers to seeds.

These constraints likely prevent farmers from adopting technologies. Tafawa Balewa recently faced an ethno-religious crisis that led to major emigration from the area and created fear and halted interpersonal visits among the neighbouring communities. Incidents like this may likely prevent farmers in the area from accessing technologies. Farmer contact with extension agents that is supposed to contribute to the general knowledge of technologies and exposure to information that favour farmers to adopt these technologies, was low among the non-adopters. The difference between adopters was significant ($p<0.01$), as shown previously in Table 3.6. It could have led to reduced awareness of ISM technologies (11%) in the NPIAs, and moderate adoption that justified the effort by IITA and other institutions in promoting technologies for farmers to adopt.

3.3.11 Performance index

The performance index for ISM technologies in the study area is presented in Table 3.12. About 83% of the farmers in the target population were informed about the existence of ISM technologies. It may be due to the aggressive deployment of ISM technologies through on-farm training, field days and collective evaluation, and the results likely encouraged adoption. However, being part of the ISMA project was not necessarily sufficient to ensure benefits from ISM technologies, because adoption of technology is a matter of individual choice – the farmer may know about the technology and yet may not adopt it due to personal reasons that are not known to the researcher.

Therefore, despite the intervention with ISM technologies by IITA, a performance index of 0.78 was obtained in the NPIAs. This result was surprising, as it was just a little below that of the PIAs. It could be due to greater interpersonal contact between households in the PIAs participating in the project and their non-participating neighbours. The details of the adoption rates in different LGAs are presented in Figure 3.3.

In the adoption process of new technology, farmers must, first of all, be aware of the new technology, including its advantages, before they accept and adopt the technology. In the ISM project intervention LGAs in the Kano and Bauchi states, a large proportion of the farmers knew about ISM technologies.

The adoption rates of ISM technologies before the ISM project intervention (2010) compared with four years after ISM intervention (2014) are presented in Figure 3.4. There is a similar trend in the adoption rates of ISM technologies with the level of awareness of these technologies presented in Table 3.12. The adoption rates of ISM technologies had increased by well over 100%, that is from less than 10% to over 30% for all the three technologies under consideration, compared with baseline results (see Figure 3.4).

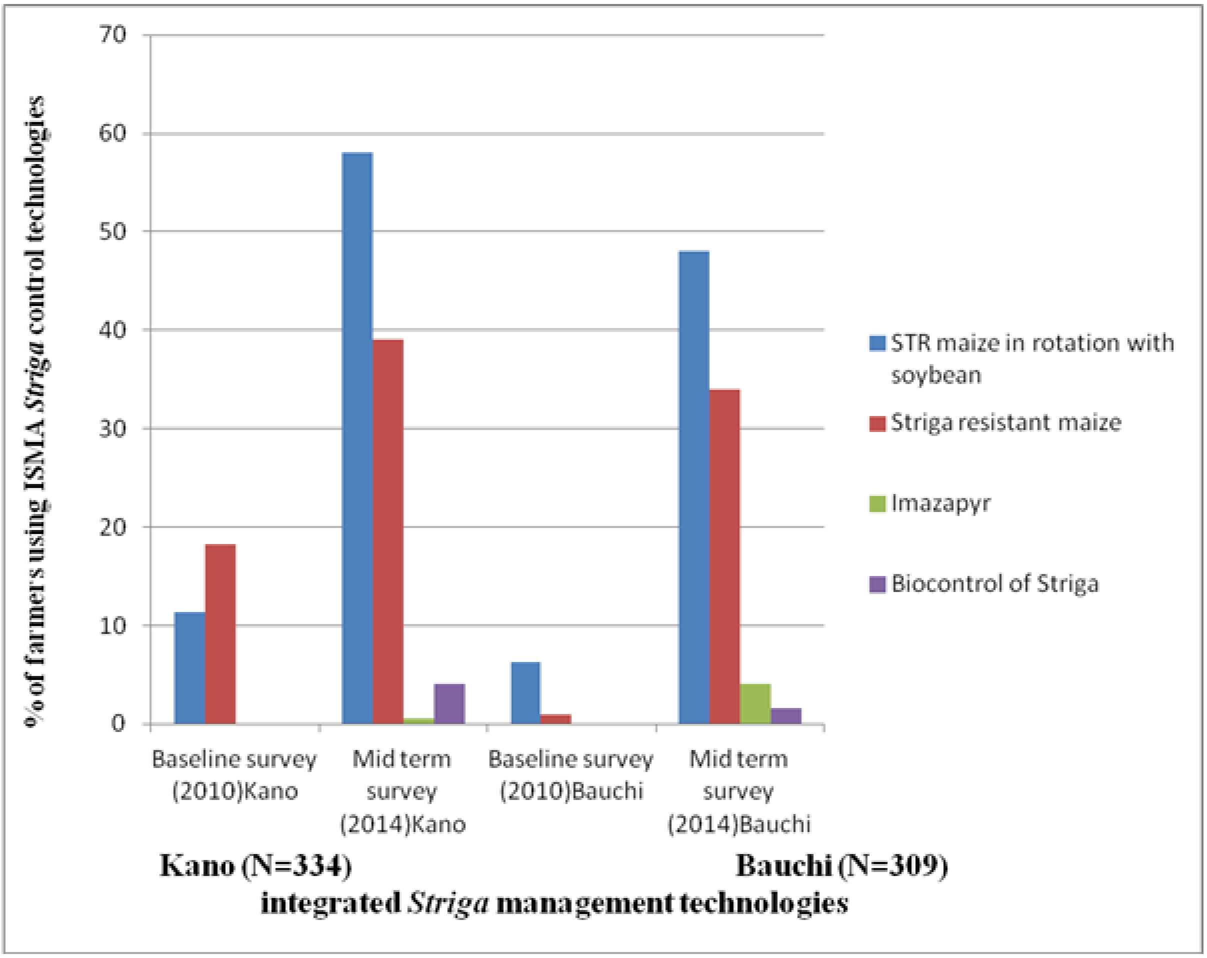

Figure 3.4: Comparison of adoption rates of ISM technologies before ISMA project intervention (2010) and current mid-term period (2014).
Source: Survey data (2014)

Also, there is a positive correlation between the levels of awareness and the adoption rates of ISM technologies before project intervention and four years after intervention (2014). The shift in technology adoption in the intervention areas before the intervention and four years after intervention (Figure 3.3) clearly demonstrates the effectiveness and acceptability of the ISMA project in influencing the changes in adoption rates of the ISM technologies.

3.3.12 Diffusion index

The diffusion index result obtained from the penetration index was consistent with the outcome of the performance index in both PIAs and NPIAs (Table 3.12). The penetration index in PIAs was 0.68 and in NPIAs 0.60, implying that 68% and 60% of farmers in PIAs and NPIAs, respectively, were aware of ISM technologies, became interested and decided to use it. Though not much, the difference in the penetration index between the PIAs and the NPIAs could be due to the absence of intervention in NPIAs. The direct or indirect involvement of stakeholders in the dissemination of ISM technologies may likely affect farmers' decisions to adopt them. The situation was different in the NPIAs where the diverse action of stakeholders' actions, serving as catalyst for adoption, was absent.

Despite the absence of intervention in the NPIAs, the value of the penetration index still shows the relevance of technologies in coping with *Striga*, thus justifying why many farmers from the NPIAs decided to learn about the technologies and use them. This study does not agree with the findings of (Bokanga, 1960) and Mignouna *et al.* (2011c) that farmers need technical information for the adoption process. The penetration index emphasises that technology adoption can be diffused through farmer-to-farmer contact and that it can be fast-tracked with supportive services from the scheme.

3.3.13 Performance difference

There is a margin of 11% between respondents' adoption rates in PIAs and NPIAs (Table 3.12). Although small, this margin is important because it illustrates the contribution of different stakeholders in ISM technology transfer. Out of the 353 adopters, 58% and 47% were sensitised on the advantages of the ISM technologies in the PIAs and NPIAs, respectively. Knowledge sharing of ISM technologies among farmers seems to have a strong influence through farmer-to-farmer diffusion, as justified by the performance difference, even though sensitisation was directly carried out by IITA and the technical extension staff in the NPIAs. Sensitisation was achieved through demonstrations, on-farm trials, radio and television programs by the IITA team and other stakeholders who accelerated the diffusion of the technologies. Adopters and their local communities were associated, as shown by the result, that being an adopter or non-adopter depended on the area where the farmer resides ($p<0.05$).

Table 3.13: Contingency table showing performance difference

Adopters/Non-adopters	Adopters	Non-adopters	Total	P_1, P_2 (%)
PIAs households (P_1)	262	188	450	58
NPIAs households (P_2)	91	102	193	47
Performance difference ($D = P_1 - P_2$)	353	290	643	11

PIAs = Project intervention areas; NPIAs = Non-project intervention areas
Source: Author's calculations

3.3.14 ISM technologies diffusion

Figure 3.4 presents the ISM technology diffusion chart from the baseline study period to the mid-term survey period, and the adoption rates of ISM technologies before the ISMA project intervention (2010) compared with four years after the ISM intervention (2014). Figure 3.4 reveals a similar trend in the adoption rates of ISM technologies with the level of knowledge of these technologies presented in Table 3.5. The adoption rates had more than doubled for all the technologies under consideration. Also, there is a positive correlation between the levels of awareness and the adoption rates of ISM technologies before the project intervention and four years after the intervention (2014). The changes in technology, which improved *Striga* practice before the project intervention and four years after the intervention (Figure 4), clearly demonstrate the effectiveness of the ISMA project to influence the changes in adoption rates of ISM technologies. It is consistent with the adoption theory (Rogers, 1995) and concurs with many studies in the past with the same features (Lionberger, 1960; Mansfield, 1968; Mignouna *et al.*, 2011c). The result shows that more farmers in the two states adopted STR maize-soybean rotations than other technologies. It could be due to the importance that soybean is gaining among communities in the north, especially in the making of soybean cheese, which has become very popular, particularly among young children, according to extra information gathered during the study.

3.3.15 Factors militating against the adoption of *Striga*-management technologies

The perception of respondents gave an insight into the factors likely to limit their use of improved *Striga*-control technologies. Such perceived constraints include the lack of awareness about the technologies, beliefs that the traditional control practices are better than ISM technologies, fear of technology failure, cost and non-availability of STR varieties (Table 3.14). About 46% of the overall responses for non-adoption was related to the non-availability of the improved IRM. Slightly more than one-third of all responses were concerned about the relatively high cost of technologies. Fear of technology failure consequences to traditional conservatism and lack of awareness were also significant obstacles hindering farmers from using the new technologies.

Table 3.14: Factors militating against adoption of integrated *Striga*-control (ISC) technologies, northern Nigeria, 2013/14

Reason for non-adoption	All		BAUCHI		KANO	
	Counts	%	Counts	%	Counts	%
Lack of adequate information about the technology	122	19.0	27	8.8	95	28.4
Traditional control practice is better	193	30.0	73	23.7	120	35.9
Fear of technology failure	199	30.9	85	27.6	114	34.1
High cost of technology	265	41.2	113	36.7	152	45.5
Non-availability of improved seed STR	102	15.9	57	18.5	45	13.5
Non-availability of improved seed IRM	296	46.0	119	35.6	177	53.0
Non-availability of improved soybean seed	102	15.9	64	19.2	38	11.4

Source: Author's calculation from survey data 2014

3.4 Conclusions

Farmers in the PIAs and NPIAs were different in several ways. The deployment of ISM technologies will be of the utmost importance to communities where *Striga* poses a serious problem in cereal production. As more awareness about *Striga* management is created, farmers become more informed, and decision to adopt becomes easier. It is, therefore, recommended that further studies be conducted on quantitative changes as a result of the on-farm trials, demonstration and field days, community seed production and ISM technology dissemination in the study areas. Awareness could be accomplished by more on-farm trials, and demonstrations are extended to other areas in the ongoing initiatives to introduce the procedures of managing *Striga* in the region. On-farm trials are justified educational and training activities just like farmers' field schools (FFS) that encourage feedback. On-farm trials can inform policy makers and farmers of appropriate environmentally friendly technologies. These on-farm trials can successfully facilitate learning so that maize farmers from northern Nigeria can understand and practice ISM technologies. On-farm trials, philosophy and field day methods can be encouraged and tested among smallholder farmers in other parts of the country and in the rest of SSA where there are similar types of *Striga* problems.

Public knowledge about ISM technologies can be advanced through the creation of mass public awareness in the print and electronic media, such as television documentaries and cinema shows in the rural areas. The next chapter presents the empirical results and discussion on factors influencing ISM technology adoption and the intensity of its adoption and some perceived constraints to adoption.

CHAPTER 4

ADOPTION OF *STRIGA* (*Striga* hermonthica) MANAGEMENT TECHNOLOGIES IN NORTHERN NIGERIA[3]

4.1 Introduction

This chapter presents the empirical methods, results and discussion of the factors that influence farmers' decisions on whether or not to adopt ISM technologies. The rest of the chapter is organized as follows: section 4.2 outlines the methodology, which constitutes the conceptual and empirical models, and the data collection procedures; section 4.3 presents the empirical results; section 4.4 presents perceived constraints to adoption; while section 4.5 concludes the chapter with a summary of the findings.

4.2 Research methods

4.2.1 Conceptual and empirical models

The theoretical framework here is built on the general agricultural household model theory (Singh *et al.*, 1986) that was used by previous studies (Adesina and Zinnah, 1993; Wale and Yalew, 2007; Cavatassi *et al.*, 2011). In the model, it is assumed that farmer decision to adopt a new agricultural technology at a given time is based on the expectation of maximizing his utility subject to credit, land availability and other production constraints (Feder *et al.*, 1985) which are known as the characteristic theory of consumer choice. Therefore, commodities are as good as their desired and undesired physical characteristics, and the characteristics enclosed therein give rise to consumer utility. Farmers' demand for improved *Striga* control practices is derived from the utility that the farmer would gain from the agronomic practice characteristics rather than from agronomic packages as a whole.

For that reason, technology adoption by farmers is demand-driven for some technology attributes (Smale *et al.*, 2001). Farmers may likely not adopt an ISM technology if it does not possess the attributes of their choice. Hence, a farmer's demand for agricultural technology is, among other

[3] This chapter gave rise to the following publication: M.B. Hassan, L.J.S. Baiyegunhi, G. F. Ortmann and T. Abdoulaye 2016. Adoption of integrated *Striga* (*Striga hermonthica*) management technologies in northern Nigeria. *Agrekon, 55(1-2):168-188.*

exogenous features, derived from the production and consumption qualities provided by the technology (Edmeades and Smale, 2006). Farmer decision to adopt a new technology or not centres on a careful assessment of a significant number of socioeconomic, institutional and technical factors (Alene *et al.*, 2000; Alene and Manyong, 2007; Khonje *et al.*, 2015).

A usual farming technology expresses some essential features that may influence the adoption decision of new technology. After thorough comparison of a combined set of technology preference, farmers are presumed to make the witnessed adoption choice on an agricultural technology, such as improved sorghum, rice, maize, and cassava, chickpea and pigeonpea varieties (Adesina and Baidu-Forson, 1995; Langyintuo and Mungoma, 2008; Johannes *et al.*, 2010; Simtowe *et al.*, 2011; Asfaw *et al.*, 2012b). Assuming:

- *b*(*m*) and *b*(*l*) denote the benefits derived from using a new and a local technology, respectively;
- p_im and p_il represent the it^h farmer's perceptions of the technology-specific attributes of the new and local technologies, respectively;
- c_i denotes the other household's socioeconomic characteristics affecting the technology adoption decision,

"the relationships is simply expressed as $b_{mi} = q(P_{im}, P_{il}; C_i)$ and $b_{li} = w(P_{im}, P_{il}; C_i)$, respectively" in modelling the perception effects of new technology attributes on the decisions to adopt, according to a Tobit regression applied by Adesina and Baidu-Forson (1995). This is symbolized using an index function approach.

$$V_i^* = \beta^T \chi_i + \varepsilon_i \qquad (4.1)$$

$V_i = 0$ if $V_i^* \leq 0$

$V_i = V_i^*$ if $V_i > 0$

where:

V_i = a limited dependent variable and the perceived benefit from the adoption of the new technology;

Vi^* = a fundamental latent variable that indicate adoption;

X = a vector of the technology perceptions and socioeconomic characteristics of the farmer;

β^T = the parameters to be estimated; and

ε_i = an error term.

When the intertechnology characteristic inclination comparisons are as follows:
$b_{mi} - b_{li} > 0$ (i.e. $V_i^* > 0$), the farmer is perceived to adopt the new technology ($V_i = V_i^* > 0$). Otherwise, if $b_{mi} - b_{li} \leq 0$ (or $V_i^* \leq 0$) i.e., $V_i = 0$, no adoption is observed.

The study employed both descriptive and econometric procedures. Descriptive analysis was achieved by using Chi-square (X^2) for categorical variables and a t-test for continuous variables. Limited dependent variable models have been used widely by many researchers in the area of agricultural technology adoption (Diagne, 2006; Mendola, 2007; Simtowe *et al.*, 2011). These models assumed that, in adopting a new agricultural technology, the farmer decision is assumed to maximize anticipated utility from using a new agricultural technology subject to some existing constraints (Feder *et al.*, 1985).

The econometric analysis employed the DH approach, involving a probit model as the first hurdle and a truncated regression as the second hurdle, to identify factors influencing adoption and the intensity of adoption of ISM technologies among the sample of smallholder farmers. The assumption of this model is that a farmer has to cross two hurdles before adopting technology. The first hurdle is the decision to adopt the technology or not. The second hurdle is the portion of farmland a farmer allocates for the new technology, representing the intensity of adoption. The second hurdle is conditional on the first hurdle. This model allows or permits for the likelihood that the probability and intensity of adoption may have different explanatory variables influencing the two hurdles, and the variables in the two hurdles may even have different effects ((Teklewold *et al.*, 2006; Simtowe *et al.*, 2010b; Akpan *et al.*, 2012a). The model is specified as follows:

$$\left.\begin{aligned} I^* &= z'_i\,\alpha + \varepsilon_i \\ I_i &= 1\,if\;\; I_i > 0\; and\; I_i^* \leq 0 \end{aligned}\right\} \quad \text{First hurdle (decision to adopt)} \qquad (4.2)$$

$$\left.\begin{aligned} y^* &= x'_i\,\beta + \mu_i \\ y_i &= y_i^*\; if\;\; y_i^* > 0\; and\; I_i^* > 0 \\ y_i &= 0\; otherwise \end{aligned}\right\} \quad \text{Second hurdle (intensity of adoption)}$$

where:

I_i* = latent variable that describes a farmer's decision to adopt;

I_i = observed farmer decision to adopt ISM technology, and takes a value of 1 and 0 otherwise;

y_i* = latent variable showing the intensity of ISM technology adoption;

y_i = observed response on the intensity of ISM technology, and is measured by the proportion of farm area under ISM technology;

x and *z* = vectors of variables that explains the decision to adopt and intensity of use of ISM technologies, respectively, which can intersect;

α and β = parameters to be measured;

ε_i = error term with mean 0 and variance 1; and

μ_i = another error term with mean 0 and variance σ.

Built on the assumption that the two error terms are independent, the adoption model and the adoption intensity model can be estimated by applying the maximum likelihood estimate (MLE) method involving probit and the truncated regressions, respectively (Gebremedhin and Swinton, 2003; Akpan *et al.*, 2012b; Tambo and Abdoulaye, 2012).

The marginal effect of a variable X_j on the probability of adopting the technology can be calculated by differentiating P_i , with respect to X_j (Wooldridge, 2003).

$$\frac{\alpha P_i}{\alpha X_{ij}} = f(X_i \beta).\beta_j \tag{4.3}$$

where:

f (.) = marginal probability density function of α; and

j = 1, 2, ..., j is the number of explanatory variables.

4.2.2 The empirical model

A probit regression equation makes use of the cumulative distribution function (CDF) to describe the behaviour of a dummy dependent variable. Given the normality assumption, the likelihood that I^*_i is less than or equal to I_i can be estimated from the normal CDF as:

$$P_i = P\left(Y = \frac{1}{X}\right)$$

$$= P(I^*{}_i \leq I_i)$$
$$= P(Z_i < B_i + B_2 X_i)$$
$$= P(B_i + B_2 X_i) \quad (4.4)$$

where:

I^* = critical or threshold level index, such that if I_i go above I*, the farmer adopts ISM technology, otherwise did not;

P_i = likelihood that an event happens given the values of explanatory variable X_i ; and

Z_i = normal variable.

The probit model is defined as:

$$= \Pr\left(y = \frac{1}{X} \right) = \Phi(xb)$$

where:

xb = probit score or index; and

Φ = standard cumulative normal probability distribution.

The log-likelihood function for the probit model is:

$$\ln L = w_j \ln \theta(x_j b) + \sum w_j \ln\left(1 - \theta(x_j b\right) \quad (4.5)$$

where:

w_j = optimal weights.

The implicit model of ISM technology adoption is specified as:

$$P_i = F(X_1 X_2 X_{3,} - X_n) \quad (4.6)$$

Explicitly, it is specified as

$$P_i = \beta_0 + \beta_1 \chi_1 + \beta_2 \chi_2 + \beta_3 \chi_3, -\beta_n \chi_n + \varepsilon_i \quad (4.7)$$

These variables were define in Tables 3.5 and 3.6 and their significant mean test were also presented in Chapter 3, pages 56-58.

4.3 RESULTS AND DISCUSSION

4.3.1 Specification tests

A variance inflation factor (VIF) test was carried out before the analysis of the probit regression model to examine any correlation between the independent variables and to detect the possibility of collinearity. The results indicate no collinearity between the variables since all the VIF values are below 10 (Wooldridge, 2009). The VIF values of the exogenous variables range from 1.04 to 2.31 and have a mean of 1.33, as shown in Table 4.1.

Table 4.1: Results of the multicollinearity diagnoses

Variable	VIF	1/VIF
Age	2.31	0.4320
Marital status	1.29	0.7754
Years of farming	2.31	0.4320
Education	1.12	0.8924
Household size	1.53	0.6527
Farm size	1.15	0.8712
Maize yield/ha	1.04	0.9591
Farm income	1.20	0.8317
Log total household income	1.17	0.8527
Dependency ratio	1.11	0.8958
Cooperative membership	1.23	0.8146
Market distance	1.17	0.8513
Extension distance	1.16	0.8654
Extension contact with public extension agent	1.25	0.8027
Attending field days	1.44	0.6962
Aware of ISM	1.08	0.9228
Past participation in on-farm trial	1.56	0.6405
Access to remittance	1.13	0.8827
Decision-making	1.05	0.9510
Mean VIF	1.33	0.7900

Source: Authors' calculations

The DH model, which is independent, assumes that the error terms from the two hurdles are uncorrelated and normally distributed. This suggests that the two-level decision of adoption of the ISM technology and the intensity of adoption is done independently by farmers. The relationship between the error term in the first and second hurdle in the models was tested to see whether the two decisions were independent. The finding showed that the error terms were uncorrelated, which suggests that the factors that influence decisions to adopt ISM technology were not related to those influencing the intensity thereof. The result confirmed that the significance of the DH approach applied in this study.

The diagnostic tests, the log likelihood of -169.60 and the LR chi^2 (19) of 214, significant at the 1% level of probability, show that the model is well fitted, as all the independent variables together explain ISM adoption among maize farmers. Parameter estimates from the probit analysis reveal marital status, farm income, off-farm income, distance to extension office, participation in past on-farm trials, awareness of technology, maize yield obtained per hectare and access to remittance as factors that explain ISM technology adoption among sampled maize farmers in northern Nigeria. These variables were significant at the 5% and 1% levels of probability (Table 4.2).

4.3.2 Double-hurdle (DH) model results of determinants of ISM technology adoption and intensity

The estimated results of the probit regression (first hurdle – the determinant of the likelihood of adoption of ISM technologies) and truncated regression (second hurdle – determinants of adoption intensity) are presented in Table 4.2.

Marital status: The statistical significance of marital status indicates that polygamous household heads are more likely to adopt ISM technologies than the monogamous household because it is more likely they have more household members to feed. The estimated coefficient of marital status indicates that being polygamous increases the likelihood of adopting ISM technology by 13.6%. Thus, polygamous households are also likely to have more labour so they are likely to adopt these technologies. This result corresponds with the findings of (Tambo and Abdoulaye, 2012) in their study of the adoption of drought-tolerant maize in northern Nigeria.

Total farm income: The estimated parameter of the total farm income in the model has a positive sign and is statistically significant at a 1% level. This suggests that households with relatively higher farm income have higher chances of being ISM adopters than their counterpart with lower farm income. It implies that the adoption of ISM technologies will increase as total farm income increases, *ceteris paribus*.

Table 4.2: Double-hurdle model results of determinants of ISM technology adoption and intensity, Bauchi and Kano states, northern Nigeria

Variables	Double-Hurdle (DH) Regression Estimates			
	Probit (first hurdle) Coefficient	Truncated (second hurdle) Coefficient	*X*-value	Marginal effect
Age	-0.141 (0.011)	0.0117 (0.031)	42.60	-0.006
Marital status	0.342 (0.150)**	-0.958 (0.424)**	2.48	0.136**
Years in farming	0.005 (0.012)	-0.072 (0.032)**	21.82	0.0002
Education	-0.007 (0.020)	-0.065 (0.056)	6.18	-0.0029
Household size	0.016 (0.018)	0.127 (0.046)***	10.80	0.0064
Dependency ratio AE	-0.076 (0.052)	-0.437 (0.141)***	2.58	-0.0304
Total farm income	1.15e-06 (3.89-e07)***	4.55e-07 (6.67e-07)	305,280.00	4.59e-07***
Total exogenous income	-1.05×10^{-6} (3.54×10^{-7})***	-4.21×10^{-7} (7.96×10^{-7})	387,216.00	-4.19×10^{-7}***
Total farm size	0.022 (0.019)	0.127 (0.034)***	6.72	0.0089
Field days attendance	-0.014 (0.197)	-0.888 (0.496)*	0.40	-05708
Market distance	0.006 (0.011)	0.028 (0.027)	8.54	0.0023
Extension distance	-0.024 (0.010**)	-0.033 (0.025)	9.20	-0.0094**
PPOFT	0.854 (0.208)***	-0.337 (0.507)	0.42	0.3287***
Aware	0.222 (0.351)***	0.301 (1.629)	0.83	0.6239***
Cooperative	0.155 (0.168)	0.725 (0.457)	0.47	0.0618
Access to remittances	0.0826 (0.172)***	0.791 (0.467)*	0.44	0.3190***
Yield (kg/ha)	0.00034 (0.00001)***	-0.000 (0.0002)	1536.65	0.0001***
Extension contact	0.0563 (0.206)***	0.623 (0.511)	0.24	0.2178***
Decision-making	-0.189 (0.132)	0.206 (0.383)	1.19	-0.0752
Constant	-3.107 (0.637)***	3.053 (2.223)		
Log likelihood	-169.61	-547.22		
Lr Chi2 (19)	214			
Prob > Chi	0.0000	0.0000		
Pseudo R^2	0.387	---------		
/Sigma	------------	20.74 (0.149)***		
Wald chi^2		339.51		
Number of observations	403	215		
Software used: Stata13				

*****, **, * denote** significance at the 1%, 5% and 10% levels, respectively. Figures in parentheses are standard errors.
Source: Calculated from ISM project survey data, 2014

Exogenous income: A household's exogenous (or off-farm) income is another significant factor that influences the adoption of ISM technologies among sampled households. The estimated coefficient was positive and statistically significant at the 1% level, which suggests that farmers with fairly lower exogenous income are more likely to adopt ISM technologies (Asfaw *et al.*, 2012b). On the other hand, households with high exogenous incomes can purchase fertilizer and herbicide in order to cope with *Striga* that usually survives and causes more damage in marginal soils. This result implies that ISM technologies are more suitable to resource-poor maize farmers, These findings are consistent with that of (Mignouna *et al.*, 2011c; Mignouna *et al.*, 2013) in their studies on IRM adoption in Nyanza and Western Kenya.

For farmers to adopt newly introduced technologies, they need to obtain knowledge of the available technologies. Adoption is at times hindered not only by the innate characteristics of the technology itself but also likewise by the absence of awareness of technologies by the final beneficiaries. The distance to the nearest agricultural extension office, number of contacts with extension agents and distance to the nearest main weekly market were used as proxies for access to information.

Distance to extension office: The estimated coefficient of distance to the extension office was negative and significant at the 5% level. This suggests that the chance of adopting ISM technologies tend to be higher for farmers residing closer to extension offices than for those residing further away. The coefficient of -0.024 for extension distance, *ceteris paribus*, implies that the probability in favour of adopting ISM technologies declines by a factor of 2.4% as the extension distance increases by a unit (one kilometer).

Also, a number of contacts with agricultural extension services have a positive and significant estimated coefficient. This implies that both distance to extension services and number of contacts with extension officers have positive influences on the probability of ISM technology adoption in the study area, *ceteris paribus*. The finding indicates the important role of extension provision in creating an awareness of available ISM technologies. Most ISM technologies are first disseminated through participatory on-farm trials and field days, activities in which public extension staff plays an important role. It is, therefore, not amazing that distance to public extension offices increases the probability of adopting ISM technologies. The findings also provide evidence of the effectiveness of participatory on-farm trial and extension activities, and provide justification for scaling-up participatory on-farm trial activities and dissemination efforts through extension.

Agricultural extension is the method of learning and advancing the human capital of farmers by providing information and exposing them to improved agricultural technologies which can enhance their productivity and, subsequently increase their household welfare (Mignouna *et al.*, 2011c; Asfaw *et al.*, 2012b)). Farmers, who are constantly in contact with extension staff, are inclined to be more proactive and prepared to try out new technologies. The coefficient of the number of visits, 0.056, implies a unit increase in the number of visits by extension agents, increasing the probability of farmers adopting ISM technologies by 5.6% ($p<0.01$). As expected, the positive effect of farmer awareness of technology is consistent with the findings of (Kapalasa, 2014) for adoption of improved soybean in Malawi, (Asfaw *et al.*, 2012b) for improved pigeonpea in Tanzania and chickpea in Ethiopia, and (Tambo and Abdoulaye, 2012) for drought-tolerant maize in Nigeria.

Access to cash remittances: The importance of access to finance in enhancing farmers' adoption of agricultural technologies is well documented (Cornejo and McBridge, 2002; Mendola (2007); Lopes, 2010; Katengeza *et al.*, 2012). Nigerian farmers have very limited access to finance due to a lack of collateral, especially formal credit, because of the high risk inherent in rain-fed agricultural production. Thus, smallholder farmers in Nigeria often cited a lack of credit as a major constraint hindering them from adopting improved technologies (Tambo and Abdoulaye, 2012). It is not surprising that access to remittances becomes statistically significant and is positively related to the probability of ISM technology adoption in the study areas. The more farmers have access to remittances, the more likely they are to adopt a new technology because they can now purchase the required inputs. The implication is that household heads having access to finance through remittances increases the probability of them adopting ISM technologies by 32%, *ceteris paribus*.

Maize yield: The total maize yield obtained by a farmer is another important factor influencing ISM technology adoption. The estimated coefficient of a maize yield is statistically significant at a 1% level, suggesting that the yield obtained has a positive correlation with the ISM technology adoption status of a farmer. The high significance level of a maize yield/ha obtained under ISM technologies is not surprising as farmers tend to shop for a technology that gives optimum yield, as reported by (Mignouna *et al.*, 2011c) on IRM adoption in Kenya, (Diagne, 2006) on his study of Nerica rice adoption in Côte d'Ivoire, and (Amare *et al.*, 2012; Asfaw *et al.*, 2012b) on their study of adoption and impact of chickpea and pigeonpea in Tanzania and Ethiopia. This implies that obtaining a higher yield by means of ISM technologies as compared to other varieties will increase the probability of adopting technologies by a factor of 0.0003 for every 1kg increase in maize yield, *ceteris paribus*.

The result of the intensity of ISM technology adoption, representing the second hurdle as indicated in Table 4.2, shows that, after the adoption decision had been made, most of the factors that determine the probability of adoption are no longer significant in influencing the intensity of adoption. However, marital status and access to remittances still appear to determine the intensity of adoption significantly. The estimated marital status coefficient changed from positive in the adoption model to negative in the second hurdle, which implies that, for each additional wife (the more polygamous the household head becomes), the probability of intensifying the use of ISM technology decreases by a factor of -0.96 (96%) ($p<0.05$), *ceteris paribus*.

Years of farming experience: The estimated coefficient of the variable is statistically significant, with a negative sign. This implies that household heads with more years of farming experience have higher probabilities of rejecting ISM technologies, *ceteris paribus*. This may be due to the conservative nature of older farmers being laggards regarding adopting new technologies. The probability of intensifying ISM technology adoption among farmers with more farming experience is likely to decrease by a factor of 7% for every additional year of experience.

Household size: Household size has an influence on labour availability, the estimated coefficient of household size being positive and significant regarding the intensity of adoption. This shows that larger households are more likely to intensify the use of ISM technologies. The larger the household size, the more income is required to take care of the family. Thus large size households would have a high probability of intensifying the use of any available technology that would likely increase their productivity. For every unit increase in the farming household, the intensity of adoption is likely to increase by 12.7%.

Dependency ratio (in adult-equivalent): the degree of child and old-aged dependency in a given household is expected to have an influence on the welfare of such a household. This study has shown that the estimated coefficient of dependency ratio was found to influence the adoption intensity of ISM technologies negatively and statistically significant ($P>0.001$), which is contrary to *a priori* expectation. The coefficient of -43.7 for the dependency ratio suggests that any additional unit in the dependency ratio would invariably reduce the probability of adoption intensity of ISM technologies in a household in the study area by 43.7%, *ceteris paribus*. This may be due to the commitment of the household resources having to meet other household welfare needs such as clothing, feeding and education.

Farm size: The estimated coefficient of farm size is statistically significant and positively associated with the intensity of ISM technology adoption, indicating that relatively well-endowed farmers in terms of farm size will have a higher probability of intensifying the use of ISM technologies compared with those with small farm sizes, *ceteris paribus*. As indicated in Table 4.2, any additional unit in household farm size would probably increase the adoption intensity of ISM technology by 13%. It is expected that farming households with larger farm holdings will have an advantage in their capacity to acquire new technologies and put it on trial. Their farm size will give them a greater ability to take a risk in case the technology fails (Feder *et al.*, 1985a; Samson *et al.*, 2012). This finding is consistent with findings of (Nkonya *et al.*, 1997) on fertilizer-use intensity in Tanzania; (Kebede *et al.*, 1990) in Ethiopia; (Hassan *et al.*, 1998) in Kenya; and (Awotide *et al.*, 2012) on the adoption of improved rice varieties among smallholder farmers in the Kwara state of Nigeria. However, farm size in Nepal did not matter (Shakya and Flinn, 1985). It is also reported that households with larger farm sizes adopt newly improved technologies because they have better access to finance in the form of credit that can be used as collateral (Alene *et al.*, 2000; Doss, 2003; Awotide *et al.*, 2012). These researchers also documented that households with bigger farm sizes adopt improved technologies because they generally have better access to information and credit, which have been generally acknowledged to influence technology adoption intensity.

Field day attendance: Whether or not a household head attended field days is another critical factor that influence the intensity of adoption of improved agricultural technology among households in the study area. The estimated coefficient of field day attendance was found to be negative and statistically significant at the 10% level. This suggests that household heads who do not attend field days had higher probabilities of low intensification of ISM technology adoption, *ceteris paribus*. This can be closely related to the exposure of smallholder farmers to other farmers and agricultural experts, and the knowledge gained on the utilization of scarce resources. Attending field days may likely help them to optimize the use of their scarce resource through increased productivity rather than expansion.

Access to cash remittances: The estimated coefficient of access to the cash remittances variable is the only statistically and positively significant variable influencing both adoption decisions and intensity of adoption. It suggests the importance of access to finance to farmers' adoption decisions and its intensity. The positive relationship between access to remittance and intensity of adoption suggest that households with higher access to remittances tend to have a higher probability of adoption intensification than households that have no access to remittances. The access to remittances' estimated coefficient of 0.79 implies that, *ceteris paribus*, the probability of the intensity of ISM technology adoption among households with access to remittances was higher than that of households without access to remittances by 79% ($p<0.1$).

4.4 Summary and conclusions

With the challenges of *Striga* growth, efforts are being made to address the threat through helping farmers in affected areas to adopt the developed and promoted new agricultural technologies. The chapter analysed the factors influencing adoption and the intensity of adopting these technologies among smallholder farmers in northern Nigeria, by using ISM. The findings revealed that farmers make ISM technology adoption decisions firstly by deciding whether or not to adopt and, secondly, to what extent they would adopt. But, the likelihood of adoption is more significant in the adoption behaviour of farmers because, once a farmer adopts a new technology, the chance of increasing the intensity of adoption would be high. Therefore, to increase the likelihood of adoption among smallholder farmers would require more efforts.

This implies the need for policy makers and development agencies to leverage and strengthen public and private extension services, in collaboration with rural institutions, to promote and create knowledge and awareness of the existing ISM technologies. Barriers in obtaining information could be reduced through improvement in social capital (such as community-based organizations, cooperatives and group formations), information dissemination, transportation and infrastructure, and deeper penetration of ISM technology distributors (agro-dealers). ISM technologies are key to assisting smallholder farmers to keep producing food despite the threat of *Striga*. More support is also required from different stakeholders if these technologies are to be adopted by farmers on a larger scale. Support from policy makers can further play an important role in assisting farmers to invest in these technologies in the form of credit in cash and in kind.

Awareness creation through campaigns for promoting ISM technologies, combined with the improvement of access to these technologies and complementary inputs such as fertilizer, herbicide-resistant seeds and accessible rural micro-finances at moderate costs, will offer the most favourable policy thrust to speed up and increase the adoption of ISM technologies.

The study findings on the adoption of ISM technologies could have significant implications for the ongoing agricultural transformation agenda of the Federal Government of Nigeria, particularly in the *Striga*-affected areas, whereby every household, particularly smallholder farmers affected by *Striga*, will benefit. This applies especially to farmers residing in remote rural areas who should be able to access and afford the technology and other complementary requirements for adoption.

The next chapter discusses the effect of adoption of ISM technologies on households' agricultural productivity in the study areas.

CHAPTER 5

THE IMPACT OF INTEGRATED *STRIGA* MANAGEMENT (ISM) TECHNOLOGY ADOPTION ON AGRICULTURAL PRODUCTIVITY IN NORTHERN NIGERIA: A TREATMENT EFFECT (TE) APPROACH[4]

5.1 Introduction

The impact of ISM technology adoption on agricultural productivity in the study area using a treatment effect (TE) approach is presented in this chapter. The rest of the chapter is organised as follows: Section 5.2 outlines the methodology used, constituting the conceptual and empirical models. Section 5.3 presents the empirical results, while Section 5.4 concludes the chapter with a summary of the findings.

5.2 Methodology

5.2.1 Empirical models

The study employed both descriptive and econometric techniques. A descriptive analysis was performed by using the summary statistics for continuous and dummy variables. The econometric analysis employed the treatment procedure to determine the impact of ISM technology adoption on household farm productivity. The TE corrects selection bias and endogeneity.

5.2.1.1 The treatment effect (TE) model

The major econometric problem in evaluating the project impact is selection bias, sometimes called selectivity bias (Maddala, 1983), overt bias and/or hidden bias (Rosenbaum, 2002), and the selection problem (Abadie, 2003; Heckman & Vytlacil, 2007; Imbens, 2004; Manski, 2007). However, the label selection bias, selection effects, and simply selection are the most common, especially in observational and quasi-experimental studies (Guo & Fraser, 2015). The selection problem does not exist in classic randomised experiments. Therefore, a natural starting point for examining selection bias is to consider the conditions under which the classical argument and

[4] This chapter gave rise to the following manuscript: M.B. Hassan, L.J.S. Baiyegunhi, G.F. Ortmann & T. Abdoulaye (revised and resubmitted). The impact of Integrated *Striga* Management (ISM) technologies on maize productivity in northern Nigeria: A treatment effect approach. Submitted to Food Security.

assumptions for randomised experiments do not hold. ISM usually purposively targets the poor, who are presumably more likely to be poor without controlling *Striga* (AATF, 2009; IITA, 2013). Therefore, it is expected that ISM technology adopters would have far less farm productivity in the absence of ISM technology (Mignouna *et al.*, 2011c), and sample selection bias arises due to this self-selection. Using OLS to estimate the impact of ISM technology adoption on household farm productivity when there is selectivity bias, produces biased and inconsistent estimates (Heckman, 1979; Heckman & Vytlacil, 2005). The productivity difference between technology adopters and non-adopters, therefore, cannot be attributed to access to technology as long as selection bias exists (Guo & Fraser, 2015).

A variety of techniques and strategies for correcting selectivity bias was developed. Furthermore, Wooldridge (2003) advocated three methods for controlling selection: the maximum likelihood for TEs, the Heckman two-stage procedure, and instrumental variable estimation.

Heckman's (1979) basic model of selectivity in evaluating program benefits (or TEs) (Maddala, 1983; Greene, 2003) was widely used. The model corrects the selectivity bias that arises from unobservable factors by estimating two equations: the selection (adoption) equation and the response (outcome) equation. The discussion of the TE model below derives from mainly Heckman (1979), Greene (2003) and Heckman and Vytlacil (2005).

A probit model assumes that ISMA technology adoption is a linear function of the exogenous covariates (χ_i) and the residual error (v_i). The ISMA technology adoption model is specified as follows:

$$\mathrm{A}_{1i} = \alpha_1 + \beta\chi_i + v_{1i} \tag{5.1}$$

$$\mathrm{A}_{0i} = \alpha_0 + \beta\chi_i + v_{0i} \tag{5.2}$$

$$\mathrm{A}_i^* = \beta\chi_i + v_i \quad \text{(Data is observed only when } \mathrm{A}_i = 1 \text{ if } \mathrm{A}_i^* > 0\text{, and 0 otherwise)} \tag{5.3}$$

where:

A_i^* = the endogenous latent variable, such that Y_i takes a value of 1 when A_i^* is greater than zero;

χ_i = a vector of household characteristics that influence adoption of ISM technologies;

β = the coefficients to be estimated;

v_i = the residual term.

The adoption model is used to produce a selection variable, which is the inverse Mills ratio (IMR). When included in the OLS equation, the IMR produces consistent and unbiased estimates. The IMR method addresses selection bias due to unobservable factors, by estimating a bias correction term in the first stage through the choice model and adding it to the second-stage outcome regression. As the label suggests, selection bias due to unobservable factors has much to do with the unobservable in the outcome and the choice models.

Y_i is a continuous variable computing household maize productivity per hectare per year.

A crude ATE estimator could be calculated by simply comparing the average outcome difference of the ISM technology adopters and non-adopters (Heckman & Vytacil, 2005).

$E(Y_{1i} \mid \mathrm{T}_{i=1}) - E(Y_{0i} \mid T_{i=0})$, because this is all that can be observed. Here

$$E(Y_{1i} \mid T_{i=1}) = \alpha_1 + \chi_i\beta + E(v_{1i} \mid T_{i=1}) = \alpha_1 + \chi_i\beta + E(v_{1i} \mid \varepsilon_i > -\mathrm{Z}_i\gamma \quad (5.4)$$

$$E(Y_{1i} \mid T_{i=0}) = \alpha_0 + \chi_i\beta + E(v_{0i} \mid T_{i=0}) = \alpha_0 + \chi_i\beta + E(v_{0i} \mid \varepsilon_i \le -\mathrm{Z}_i\gamma \quad (5.5)$$

assuming:

binomial distributions of (v_1, ε) and (v_0, ε) with 0 means and covariances $\sigma_{\varepsilon v_1}$ and $\sigma_{\varepsilon v_0}$; and

normalize σ_ε at 1 as in binary probit models (hereafter probit).

Following the properties of truncated binomial distributions (Green, 2003), the following is obtained:

$$E(v_{1i} \mid \varepsilon_i > -\mathrm{Z}_i\gamma) = \sigma_{\varepsilon vi}\frac{\phi(-\mathrm{Z}\gamma}{1-\Phi(-\mathrm{Z}_i\gamma} = \sigma_{\varepsilon vi}\frac{\phi(\mathrm{Z}_i\gamma)}{\Phi(\mathrm{Z}_i\gamma)}$$

$$E(v_{0i} \mid \varepsilon_i \le -\mathrm{Z}_i\gamma) = \sigma_{\varepsilon v0}\frac{\phi(-\mathrm{Z}\gamma}{\Phi(-\mathrm{Z}_i\gamma)} = \sigma_{\varepsilon v0}\frac{\phi(\mathrm{Z}_i\gamma)}{1-\Phi(\mathrm{Z}_i\gamma)}$$

After differencing equation (4) and (5) yield equation (6)

$$E(Y_{1i} \mid T_{i=1}) - E(Y_{0i} \mid T_{i=0} = \underbrace{(\alpha_1 - \alpha_0)}_{\text{True ATE}} + \underbrace{\left[\sigma_{\varepsilon vi}\frac{\phi(\mathrm{Z}_i\gamma}{\Phi(\mathrm{Z}_i\lambda)} - \sigma_{\varepsilon v0}\frac{-\phi(\mathrm{Z}_i\gamma)}{1-\Phi(\mathrm{Z}_i\gamma)}\right]}_{\text{Selection bias due to unobservables}} \quad (5.6)$$

Where:

ϕ = the normal probability density function (PDF) and **Φ** is the CDF, respectively.

ATE is the average TE of farmers adopting ISM technologies and the non-adopters. Equation 5.7 indicates the crude estimator on the left-hand side and estimates ATE with bias due to unobservables. However, the differences in observables have already been controlled for and removed by $X\beta$. To correct the bias due to unobservables, using the IMR method, would estimate γ of the choice model, Equation 5.3 in the first stage and add $\frac{\phi(Z_i \hat{\gamma})}{\Phi(Z_i \hat{\gamma})}$ to Equation 5.1 and $\frac{-0\phi(Z_i \hat{\gamma})}{1-\Phi(Z_i \hat{\gamma})}$ to Equation 5.2, where $\hat{\gamma}$ is the estimated γ.

The second stage of the TE regression involves the addition of the IMR to the response equation and then estimate the equation using ordinary least square (OLS) regression as follows:

$$Y_i = \alpha X_i + \delta A_i + \alpha_\lambda \lambda_i + \mu_i \tag{5.7}$$

where:

Y_i = the log of mean household maize productivity per hectare in a specified year;

X_i = a vector of household characteristics;

A_i = whether a household is an adopter or non-adopter of ISM technology;

λ_i = the inverse Mills ratio (IMR);

μ_i = the error term; and

α and δ = parameters to be estimated.

Although the impact coefficient in Equation 5.7 is unbiased due to the inclusion of the selectivity term, it is inefficient as the disturbance term is heteroscedastic (Greene, 2003). However, Stata automatically corrects the bias in the standard errors, in which an assumption to guarantee reliable estimates of the outcome equation require the addition of at least one regressor (with a non-zero coefficient) in the selection equation that has no direct influence on the outcome model (Blundell & Costa Dias, 2000; Heckman & Vytlacil, 2005). Allowing an equal number of variables in the selection and outcome models would lead to a multicollinearity problem in the outcome equation that can result in a very imprecise and inconsistent estimate (Gujarati, 2012). Thus, three variable less than the outcome equation were included in the selection equation for the model identification.

These variables influence the adoption of ISM technologies but not the impact of technology adoption. They represent past participation in on-farm trials, attending field days and major occupation as identifying factors. These factors influence adoption but not productivity. The selection of these variables is based on the belief that one has to be a farmer and be aware of the ISM technologies before adoption. Past participation in on-farm trials and attending field days or FFS increase farmers' awareness about *Striga* management technologies that may subsequently lead to adoption. It is also expected that exposure to technologies through past participation in these events can affect farm productivity only through the actual adoption of the technologies. Simply knowing about the existence of the technologies without adopting it cannot affect the outcome, that is, farm productivity. Therefore, the two systems of equation allow the identification of factors influencing ISM technology adoption by means of the probit model, and factors, including the use of the technologies, influencing their impact.

In terms of the estimation procedure, both the two-step estimator (described above) and maximum likelihood were used (Maddala, 1983). When compared to the maximum likelihood method, the Heckman two-step estimation procedure is less efficient (Puhani, 2000). The full information maximum likelihood (FIML) estimation procedure was, therefore, used in this study.

5.3 RESULTS AND DISCUSSION

5.3.1 Some welfare indicators of sampled households

The indicators for measuring productivity are presented in Table 5.1. The t-test statistics were used to test for differences in the variables between the adopters and non-adopters of ISM technologies. It was found that there is a statistically significant difference in most of the selected variables between adopters and non-adopters. Farmers who adopted ISM technologies had better production efficiency and income than the non-adopters in all of the selected variables, except in terms of weekly food expenditure incurred, where non-adopters spent more on average than adopters did. In addition, the non-adopters earned higher off-farm income than the adopters, although these differences were not significant.

The results also showed that adopters had larger farm sizes, yield per hectare, total maize output, maize income per hectare, and total farm income than the non-adopter group. This suggests that the increase in yield per hectare could not be the result of an increase in hectarage cultivated, but rather of the adoption of the ISM technology under *Striga* infestation. Likewise, the adopting households had higher income from other crops than their non-adopting counterparts did. Findings like this could imply that the higher income realised as a result of the increase in maize yield brought about by the adoption of ISM technologies, which would also improve overall household income that would probably have a positive effect on poverty reduction and improve household food security. However, these observed differences have no causal interpretation, as they cannot be exclusively credited to technology adoption. It may be due to the influence of other exogenous variables outside of this study.

Table 5.1: Showing some welfare indicators of sampled households by adoption status

Variable	Adopters	Non-adopters	Mean difference
Farm size under maize cultivation (ha)	3.11	2.51	0.60**
Maize yield kg/ha	2,204.05	1,262.06	942.00***
Total maize output (kg) in 2013	5,820.00	3,023.00	279.00***
Average selling price per 100 kg bag (₦)	6,453.59	6,336.57	117.00
Maize income per ha (₦)	136,700.00	78,288.00	58411.00***
Total farm income from maize (₦)	371,958.00	193,171.00	178787.00***
Total income from other crops per ha (₦)	82,103.36	81,802.75	296.39
Total farm income (₦)	516,084.00	334,418.00	181665.00***
Total off-farm income (₦)	126,290.00	145,738.00	19488.00
Total household income (₦)	642,374.00	478,662.00	163711.00
Mean weekly household expenditure on food (₦)	22,316.22	24,552.07	-2,235.75
Mean income from livestock selling (₦)	96,064.75	97,002.03	938.72
Annual mean household expenditure (₦) per adult equivalent (PAE)	131,341.07	115,440.00	15,900.35

Denote ***, **, 1% and, 5% significance levels, respectively.
Values in parenthesis are standard deviations (SDs)
Source: Survey data and own calculations

5.3.2 Descriptive analysis of maize productivity impact of ISM technologies based on adoption status

The yield or production effect of the ISM technologies is presented in Table 5.2. The source of the observed productivity effect of the adoption of ISM technologies is expected to be the result of an increase in maize yield and adoption of these technologies. As shown in Table 5.2, the yield obtained from improved ISM technologies across the two states and the LGAs is over and above that of the non-adopters and statistically significant in most of the LGAs. The yield gap between adopters and non-adopters in the Kano ranges between 134 kg/ha (8%) in Kiru to 1,241 kg/ha

(192%) in Doguwa LGAs. Also in Bauchi, the yield gap ranges between 672 kg/ha (36%) in Kirfi to 1,596 kg/ha (117%) in Warji LGAs.

Table 5.2: Comparative maize productivity differences between ISM technology adopters and non-adopters

State	LGA	N	Maize yield (kg/ha)			Yield difference (kg/ha)	MT
			Adopters	N	Non-adopters		
KANO	Bebeji	23	1753	21	971	781	2.48**
	Doguwa	30	1886	5	645	1241	2.62**
	Karaye	23	1629	21	1075	554	2.62**
	Kibiya	18	1644	13	852	791	2.88***
	Kiru	24	1650	21	1515	134	0.40
	Rano	12	1836	32	912	926	2.63**
	Sumaila	21	2184	19	1870	313	0.55
	Tudun Wada	17	1743	24	1006	737	4.09***
BAUCHI	Alkaleri	30	2831	9	1775	1053	2.44**
	Bauchi	36	2540	12	1166	1374	4.10***
	Dass	33	2739	12	1477	1260	3.21***
	Ganjuwa	28	2300	9	1412	887	2.34**
	Kirfi	11	2542	14	1860	672	1.17
	Tafawa Balewa	8	2406	15	1213	1193	2.90***
	Toro	19	2517	14	1446	1071	2.40**
	Warji	9	2955	13	1359	1596	3.28***

Notes: MT = Test of difference between means of adopters and non-adopters
***, ** denote statistical significance at the 1%, 5% and 10% levels, respectively.
Source: Calculated from field survey (2014)

5.3.3 Empirical results of the treatment effect (TE) regression

In this study, the TE regression was used to appraise the impact of ISM technology adoption on household maize productivity. The first stage of the TE equation involved the estimation of the adoption model. The results are presented in the next section; the results of the impact model, the second stage of the TE model, are presented in the subsequent section; and the results of the binary probit model is presented in Table 5.3.

5.3.3.1 The determinants of ISM technology adoption in the study areas

The results of the binary probit model of the determinants of households' ISM technology adoption decision (Table 5.3) show that, collectively, all the estimated coefficients are statistically significant,, since the likelihood ratio (LR) statistic has a p-value less than 1%. The pseudo R^2 value is 16%, which is acceptable for cross-sectional data, confirming that the model fits the data well (Wooldridge, 2003; Wooldridge, 2009; Wooldridge, 2012).

The results presented in Table 5.3 show that only six out of the 16 regressors were significant. These include household head's age, cooperative membership, past participation in on-farm trials of new agricultural technologies, access to cash remittances, access to fertilizer and perception of yield potential.

Age of the household head was the only household specific variable that had a significant influence on adoption of ISM technologies. The negative relationship between age and adoption of technology indicates that the older the farmer are less likely to adopt ISM technologies. This may be due to older farmers being more conservative and therefore not easily accepting change, while younger farmers are more dynamic and can afford to bear the risk of adopting new ISM technologies. Additionally, the age of a farmer reduces the probability of ISM technology adoption by about 0.2%, which contradicts the findings of other authors (Langyintuo & Mungoma, 2008; Mignouna *et al.*, 2011a; Mwangi *et al.*, 2014), who reported a positive association between age and adoption of improved maize in Zambia, and the adoption of IRM and push-pull technologies for controlling *Striga* in Western Kenya. This negative relationship between farmer age and adoption may, in this case, be due to their attitude towards modern technology and the traditional belief of the older farmers who believe that *Striga* cannot be controlled because it is a witch weed. On the other hand, the reason for this behaviour of older farmers could be because of the fact that younger farmers are more likely to be interested in trying out new technologies and bear more risk than their older colleagues due to their exposure to new ideas and better education (Awotide *et al*. 2012).

It was found that the greater the participation of farmers in cooperative membership, the more likely they will adopt ISM technologies. The likelihood of adoption of ISM is 10% higher for farmers belonging to cooperative societies than for those who are not members of cooperatives. This finding concurs with many previous studies (Amudavi *et al.*, 2008; Ghimire and Huang, 2015a; Mignouna *et al.*, 2011a; Shiferaw *et al.*, 2008; Shiferaw *et al.*, 2009), while it contradicts the finding of Murage *et al.* (2011) which showed that farmers who are members of groups/ cooperatives are less likely to adopt push-pull technologies than non-group members.

Table 5.3: Factors influencing households' adoption of ISM technologies: Probit model results

Variables	Adoption decision	
	Adoption Coefficient	Marginal effect Coefficient
Respondent's age (years)	-0.058 (0.0055)***	-0.0022
Gender (male = 1; female = 0)	-0.0356 (0.4099)	-0.0138
Major occupation (farmer = 1; otherwise = 0)	0.0564 (0.1029)	0.0220
Education (years)	-0.0041 (0.0144)	-0.0016
Farm size (ha)	0.0077 (0.0106)	0.0041
Household size (number)	-0.0031 (0.0112)	-0.0012
Cooperative membership (yes = 1)	0.2475 (0.1206)**	0.0964
Attending field days (yes = 1)	0.0656 (0.1304)	0.0255
Past participation in on-farm trial (yes = 1)	0.6171 (0.1338)***	0.2354
Wealth status (poor = 1, otherwise = 0)	0.1252 (0.1298)	0.0499
Access to cash remittances for agricultural purposes (yes = 1)	0.5208 (0.1165)***	0.1992
Used herbicides (yes = 1; no = 0)	0.0095 (0.0004)	0.0037
Access to ISM seed technologies (yes = 1; no = 0)	0.001 (0.000)**	0.0020
Access to manure (yes = 1)	-0.0525 (0.1217)	-0.0205
Access to fertilizer (yes = 1; no = 0)	0.001 (0.0004)*	0.0030
Total household labour (man-day)	-0.0201 (0.0485)	-0.0078
Perception of yield potential = 1, if ISM technology to yield better than the local variety, otherwise = 0	0.200 (0.034)***	0.0785
Constant	-0.8036	
Number of observations	580.00	
Log likelihood	-331.64	
LR chi^2 (17)	128.56	
Prob > chi^2	0.0000	
$PseudoR^2$	0.1624	

Notes: ***, **, * denote statistical significance at the 1%, 5% and 10% levels, respectively.
Figures in parenthesis are robust standard errors.
Source: Based on survey data (2014)

Past participation in on-farm trials of ISM technologies has a positive and significant influence on farmers' ISM technology adoption decisions. This implies that the likelihood of adoption is 24% higher among farmers who participated in ISM technology on-farm trials than those who did not participate. This finding corresponds with those of Adesina and Zinnah (1993), Mignouna *et al*. (2011a) and Ghimire and Huang (2015). Therefore, it is not surprising that farmers, who participated in the on-farm trials, adopted ISM technologies, since they had seen the beneficial attributes of technology over local practice.

The estimated coefficient of access to cash remittances was positive and statistically significant in influencing the adoption decision of ISM technologies. The likelihood of adoption of ISM technologies among farmers who have access to cash remittances is 24% higher than those who have no access to cash remittances. This is expected, as farmers living in rural communities have little access to both formal and informal credit. Therefore, cash remittances from relatives play an important role in relaxing their liquidity constraints and helping to buy improved technologies as well as other inputs. Access to cash for agricultural production was reported to have a positive effect on technology adoption (Asfaw, 2010; Di Falco *et al.*, 2011; Langyintuo & Mungoma, 2008). In addition, the estimated coefficient of access to fertilizer is positive and significant, which implies that ISM technology adoption increases with increasing access to fertilizer by about 0.3%.

The perception of yield potential had a positive and significant effect on farmers' decisions to adopt ISM technologies. The likelihood of adopting ISM technologies was higher by 8% among farmers with positive perceptions of technologies in terms of yield potential than those farmers who have negative perceptions of ISM technologies. This is not unexpected given that maize is a staple crop and is produced for consumption as well as marketable surplus. This finding is consistent with those of other researchers (Asfaw *et al.*, 2011; Di Falco *et al.*, 2011; Ghimire & Huang, 2015a; Langyintuo & Mungoma, 2008; Simtowe *et al.*, 2012), namely that the likelihood of adopting improved farming technologies increases once a farmer is convinced that the benefit from the new technology is greater than the local practice.

The estimated coefficients of most of the variables that influence adoption in the probit model were also significant in the outcome model (production function) of TE, except field day attendance that emerged to influence adoption of ISM technologies positively and significantly ($p<10\%$). A possible explanation for this is that farmers who attended field days (used as a proxy of access to extension services) from the neighbouring communities tend to see the efficacy of ISM technologies in combating *Striga*. Thus, the estimated probability of ISM technology adoption increases with increasing participation in field days by about 16%, *ceteris paribus*. This is a proxy for access to extension information and the finding is consistent with Asfaw *et al*. (2012) for pigeon pea in Tanzania and chickpea in Ethiopia, Amare *et al.* (2012) for maize-pigeon pea intensification in Tanzania, Mignouna *et al.* (2011a) on IRM adoption in Kenya, Shiferaw *et al.* (2008) on improved pigeon pea varieties in Tanzania, Kristjanson *et al.* (2005) for cowpea varieties in Nigeria, and Kaliba, Verkuijl and Mwangi (2000) for maize varieties in Tanzania.

5.3.3.2 The impact of ISM technology adoption on household farm productivity

The results from the second stage of the TE model are presented in Table 5.4. The motive for the study is an attempt to determine the likelihood of endogeneity between adoption of technologies and farm productivity. The Hausman test ($F = 3.4$ and $p<0.051$) suggested that the null hypothesis is rejected at a statistically significant level. There was evidence of endogeneity between the two variables at the conventional 10% significance level in this study. Thus, the OLS model cannot be used in the second stage of the TE regression. The three variables (major occupation, past participation in on-farm trial, and field day attendance) excluded in the outcome equation were included in the selection model of the TE model to satisfy the condition for model identification and estimate of the coefficients. The three variables on their own do not influence productivity, but can influence adoption. The positive estimated coefficient indicates a positive correlation between variance v and ε. Those unmeasured factors making it more likely for an individual to have higher farm productivity, also make it more likely that the individual will have adopted ISM technologies, conditional on other regressors that are included in the model.

The significant λ, which is the Mills ratio or non-selected hazard in the TE model, indicates that there is evidence of selection bias at the statistically significant 1% level. This justified the use of the TE regression model to estimate household maize productivity under *Striga* infestation. These findings demonstrate the possible significant effect of unobservable factors on household farm productivity. The significant λ implies that sample farmers who adopt ISM technology have higher maize output than those with average characteristics. Therefore, the TE regression results in Table 9 are considered consistent and unbiased after correcting the unobserved. The TE model fits the data very well, as indicated by pseudo R^2 and the high χ^2 value. Stata 13 was used for the analysis and it automatically corrects the standard errors for heteroskedasticity.

Table 5.4: Treatment effect (TE) regression – dependent variable: log maize productivity (yield kilogram per hectare)

Variables	Impact equation (maize productivity/ha)	Robust standard error
	Coefficient	Coefficient
Respondent's age (years)	-0.0055*	0.0032
Gender (male = 1; female = 0)	0.3081	0.2311
Education (years)	0.001	0.008
Farm size (ha)	0.021***	0.008
Household size (number)	-0.007	0.008
Cooperative membership (yes = 1; no = 0)	0.103	0.069
Farm size adult equivalent (ha)	-0.049	0.045
Wealth status (poor = 1; otherwise = 0)	0.126*	0.075
Access to cash remittances (yes = 1; no = 0)	0.185***	0.070
Access to herbicides (yes = 1; no = 0)	0.010*	0.006
Access to ISM seed technologies (yes = 1; no = 0)	0.002	0.002
Total household labour (man-day)	-0.009	0.023
Yield potential = 1, if ISM technology to yield better than the local variety, otherwise = 0	0.223***	0.021
Access to manure (yes = 1; no = 0)	-0.174**	0.068
Access to fertilizer (yes =1, no = 0)	0.001	0.001
Adoption of ISM technology (yes = 1, no = 0)	0.475***	0.130
Constant	6.672	
Rho	0.8394	0.0512
Sigma	0.7805	0.4285
Mills ratio (λ)	0.6552***	0.0729
Wald test of independent equations (ρ = 0): χ 2(1)	10.41	
Prob > chi2	0.0000	
Wald χ2	178.58	
Number of observation	580.00	

Note: ***, **, * denote statistical significance at the 1%, 5% and 10% levels, respectively.

The estimated coefficients are, therefore, unbiased and consistent, while the standard errors are efficient. The likelihood ratio test compares the joint likelihood of an independent probit model for the selection equation and the regression equation on the observed data against the TE likelihood, given that x^2 = 10.41 (p<0.01). The null hypothesis is, therefore, rejected, which justifies the use of the TE model. The reported model x^2 = 178.56 (p<0.0001) indicates the goodness of fit of the model. The results from the TE model show that adoption of ISM technologies had a positive and significant impact on maize productivity of adopters by 47% higher than that of non-adopters ($p<0.001$). This finding shows that adoption of ISM technologies has brought about a positive change in the sampled farmers' productivity.

The finding of this study agreed with a similar study reported on the impact of IRM technologies on managing *Striga* in Western Kenya (Mignouna *et al.*, 2011a), which reported IRM technology adoption to increase adopter income over non-adopters by US$362. Other studies also reported on the positive impact of adoption of agricultural technology (Becerril & Abdulai, 2010; Asfaw *et al.*, 2012b). The result of the TEs model is also consistent with the findings of other authors (Ellis-Jones *et al.*, 2004; Kamara *et al.*, 2008; Mignouna *et al.*, 2011a; Mignouna *et al.*, 2013; Schulz *et al.*, 2003) on *Striga* management. They too reported positive effects of using cereal-legume rotations involving *Striga*-resistant maize and improved cowpea, and the use of IRM in Nigeria and Western Kenya, respectively. The results showed that the use of STR varieties and improved agronomic practices in combating *Striga* problems among smallholder farmers plays a significant role in increasing household maize productivity, which could reduce rural poverty and food insecurity.

Other factors that affect household maize productivity under *Striga* infestation include farmer age, farm size, wealth status, access to cash remittances, access to herbicides, yield potential and access to manure. Contrary to *a priori* expectation, the age of the farmer tends to affect maize productivity negatively and is statistically significant. An increase in the age of the farmer reduces maize productivity by 0.5%. This may be due to conservative behaviour of the older farmers, who tend to hold on to their traditional way of doing things and rejecting all new technologies at the initial stage. This finding contradicts that of Mignouna *et al*. (2011b), who found that, in Kenya, farm productivity increases with increasing age.

Consistent with basic economic theory, inputs such as herbicides, manure and farm size significantly relate to an increase in the quantity of maize produced per hectare by the sampled farmers. Farm size and access to herbicides influence maize production positively. The results suggest that an increase of farm size by one hectare increases maize productivity by about 2.1%, *ceteris paribus*, whereas accessibility to herbicides increases maize productivity by 1%, *ceteris paribus*. Contrary to expectation, access to manure influences maize productivity negatively. This could be due to the recycling of *Striga* plant seeds among farms and animals, since farmers tend to feed their animals *Striga* plants and then collect the animal dung and apply it to their farms to improve soil fertility (Amaza *et al.*, 2014). Because *Striga* seeds are not digested in the rumen of animals and is consequently discharged in their faeces, farmers unknowingly builds up *Striga* seed banks in his or her field, leading to a build-up of *Striga* plant populations.

Another variable of interest that affects maize productivity positively is the wealth status of the farmer. This finding suggests that poorer smallholder farmers are the most likely to benefit more from ISM technologies since they are the ones most affected by *Striga.* They can, therefore, take advantage of the ISM technologies since they are often financially incapable to apply the minimum required amount of nitrogenous fertilizer and herbicides, which are two major ways of controlling *Striga* (Joel *et al*., 2007). Many of them, therefore, accept the use of ISM technologies, which are purposely targeted at poor farming households in *Striga*-infested areas, particularly in the savannas of northern Nigeria.

Access to cash remittances is statistically significant and positively influences maize productivity. Cash plays a major role in improving farmers' access to improved inputs, ensuring the acquisition of inputs at the right time in the right amount, and eventually influencing farmers' productivity. Increased access to cash remittances will increase maize productivity by 18.5%. In many past studies, households with better access to cash were reported to have better farm productivity (Di Falco *et al*., 2011) and better household consumption expenditure (Sinyolo, Mudhara & Wale, 2014). This finding shows that there are other important socioeconomic, farm level and institutional factors that influence maize productivity other than the adoption of ISM technologies among the farming households in the study areas.

5.4 Summary and conclusion

The objectives of this chapter were to analyse the factors influencing farmers' decision to adopt ISM technologies to combat *Striga* in their fields and to examine the productive consequences of the decision. Cross sectional data was collected at farm level to estimate a treatment equation model to account for unobservable factors that influence maize yield per hectare and the decision to adopt. The analysis of the factors influencing adoption highlighted very remarkable results. All of the following: access to finance through cash remittance, access to improved seed, the perception of yield potential, access to fertilizer, past participation in on-farm trials and attending field days have a positive and significant effect on the probability of ISM technology adoption.

Two main conclusions can be drawn from this study on the effect of ISM technology adoption on household welfare. First, the group of farm households that did adopt ISM technologies has systematically different characteristics to the group of farm households that did not adopt. These differences represent sources of variation in the productivity between the two groups. Therefore, estimation by an OLS model using a dummy variable for adoption cannot take into account the variation. Second, the TE regression results suggest that adopters of ISM technologies have significantly higher yield potential, which could translate into higher income PAE than non-adopters could, even after controlling for all confounding factors. The results revealed that the productivity of maize under *Striga* infestation have significantly increased after the adoption of ISM technologies in the PIAs. Therefore, the ISMA project intervention provides farmers with access to production inputs, especially *Striga*-resistant maize and the improved legumes such as soya beans and cowpea. This could potentially be a way forward to reduce poverty among the smallholder farmers in rural northern Nigeria.

The results of this study confirm the potential direct role of ISM technology adoption in improving smallholder households' maize productivity with intended less poverty and enhancement of food security.

There is need for government and non-governmental organisations, including private partners, to help smallholder farmers produce more food, especially cereals, under *Striga* infestation, by

- intensifying the deployment of ISM technologies to other *Striga*-infested areas;
- enhancing the extension services and creating more awareness of information delivery systems through on-farm trials, demonstrations and field days;
- providing farmers with credit and financial capital, which is of paramount importance, through cash or input credit facilities. Since farmers in the study area have limited access to credit, the only source of finance is through cash remittance. However, government and NGOs cannot meet their demands for both cash and input. Therefore, farmers should be encouraged to form savings and thrift cooperative societies where they can save and harvest

on rotating or non-rotating bases, and be advised to save a certain percentage of their total profit at the end of the season.

- disseminating information to farmers in potential maize-growing areas with *Striga* infestation. This is an opportunity for the IITA and other partners to use existing structures (such as ADP Agencies) for government extension services.

The state and local government will need to take the lead in technology promotion and dissemination at the initial stages to create an enabling environment and incentive for effective participation of the private sector and community-based organisation. Awareness campaigns for improved STR varieties and varieties that induce suicidal germination of *Striga* production at community level, combined with improved training on local seed production, processing and marketing at reasonable prices, may present the best policy act to speed up and expand adoption of ISM technologies. Access to seed was also a constraint to adoption. It is therefore recommended to improve the seed system by giving more attention to community seed producers.

Finally, to understand the full potential of adopting ISM technologies, further research is needed to measure and quantify the indirect effects of ISM adoption (e.g. on income, wages, employment, and food prices, as it relates to consumers), nutritional benefits, and change in the biophysical in *Striga* level and severity in the production systems. Having determined the impact of ISM technologies on maize productivity in the *Striga*-infested areas of northern Nigeria, the next chapter presents the empirical results and discussion on the potential impact of ISM technologies on households' income by controlling selectivity bias and endogeneity.

CHAPTER 6

THE IMPACT OF INTEGRATED *STRIGA* MANAGEMENT (ISM) TECHNOLOGY ADOPTION ON HOUSEHOLDS' INCOME IN NORTHERN NIGERIA[5]

6.1 Introduction

The purpose of this chapter is to evaluate the potential impact of ISM technology adoption on smallholder maize farmers' income in the Bauchi and Kano States of northern Nigeria. All confounding factors are controlled in the study, such as farm level and farmer socioeconomic characteristics, resource endowments and other exogenous factors. This chapter examines the potential impact of ISM technology adoption on farming household incomes by means of the ESR model. The poverty measurements model, developed by Foster, Greer Thorbecke (FGT), was used to determine poverty indices in the area of study. The remaining part of the chapter is presented as follows: section 6. 2 presents the methodology that constitutes the empirical model and estimation techniques, the empirical results of the study were presented in section 6.3, while Section 6.4 contains the conclusion and a summary of the findings.

6.2 Methodology

6.2.1 Econometric model and estimation strategies

The two econometric problems, selection bias, and endogeneity motivate the application of the ESR model that control selectivity bias and endogeneity. This allows positive interaction amongst technology adoption, and traditional and non-traditional production inputs (in this case income) models – one model represents the case of the adopters and the other model that of the non-adopters (Alene & Manyong, 2007; Asfaw *et al.*, 2012b; Di Falco *et al.*, 2011; Feder *et al.*, 1990; Freeman Ehui & Jabbar, 1998; Lee, 1978). The ESR modelled the adoption decision by using the standard limited dependent dummy variable approach. The model for other decision variables, such as the impact on income, is then estimated separately for each of the two groups (adopters and non-

[5] This chapter gave rise to the following manuscript: M.B. Hassan & L.J.S. Baiyegunhi (under review). The impact of integrated *Striga* management (ISM) technologies on households' income in northern Nigeria. Submitted to Technological Forecast & Social Change.

adopters), conditional on the decision on technology adoption. In the switching regression model, a two-stage approach was involved. A probit model was applied in the first stage to determine the relationship between technology adoption and farm level, households and technology-specific attributes. In the next stage, different regression models were applied to modelled household income, conditional on some specified standard function.

ISM technology adoption gave a yes or no choice (dichotomous), where a household decided to use the ISM technology when he/she perceived a positive difference in the marginal net benefit of the new technologies and the traditional methods of *Striga* management.

The selection equation for technology adoption, in this regard ISM technologies, is as follows:

$$D^*_i = \beta X_i + \eta_i = \begin{cases} 1 \; if \;\; D^*_i > 0 \\ 0 \; otherwise \end{cases} \tag{6.1}$$

where:

D^*_i = the unobservable variable for ISM technology adoption and it represent the expected gains of adopting when compared to not adopting;

D_i = its observable counterpart (the dependent variable for ISM adoption = 1, if the farmer has adopted at any ISM technology during the survey and 0 otherwise);

X_i = non-stochastic vectors of the observed farm and non-farm level attributes influencing the adoption decision; and

η_i = the random disturbance term related to *ISM* technology adoption.

In order to control for selectivity bias, the ESR model was used for income per capita where farmers are faced with two scenarios: (1) to adopt ISM technology, or (2) not to adopt, defined as shown below:

Scenario 1: $y_{1i} = \alpha_{1i} j_{1i} + \varepsilon_{1i}$ if $D_i = 1$ (6.2a)

Scenario 2: $y_{2i} = \alpha_{2i} j_{2i} + \varepsilon_{2i}$ if $D_i = 0$ (6.2b)

where:

y_i = income of the household PAE in the two scenarios 1 and 2; and

j_i = a vector of exogenous variables that are expected to determine households' income PAE.

The error terms were assumed to have a trivariate normal distribution with non-singular covariance matrix and zero mean (Asfaw *et al.*, 2012b; Di Falco et al., 2011; Lokshin & Sajaia, 2004; Maddala, 1983), expressed as: $Cov(\varepsilon_1, \varepsilon_2, \eta_1)' \sim N(0, \Sigma)$

$$\Sigma = \begin{pmatrix} \sigma^2{}_\eta & \sigma_{\eta 1} & \sigma_{\eta 2} \\ \sigma_{1\eta} & \sigma_1{}^2 & . \\ \sigma_{2\eta} & . & \sigma_2{}^2 \end{pmatrix}, \qquad (6.3)$$

where:

σ_η^2 = the variance of the error term in the selection model (6.1), which can be assumed to equal 1, since the coefficients are only estimated to a scale factor (Di Falco *et al.*, 2011);

$\sigma_1{}^2$ and $\sigma_2{}^2$ = the variance of the error terms in the outcome models, in this case the income model (6.2a) and (6.2b); and

$\sigma_{1\eta}$ and $\sigma_{2\eta}$ = the covariance between η_1 and ε_{1i} and ε_{2i}.

Since y_{1i} and y_{2i} cannot be observed concurrently, the covariance between ε_{1i} and ε_{2i} is therefore not defined and they are represented as dot in the covariance matrix (Asfaw *et al.*, 2012b; Di Falco *et al.*, 2011; Lokshin & Sajaia, 2004; Maddala, 1983). The most significant effect of the error term is that, in the correlation between the error term of the selection Equation 6.1 (η_i) and the error terms of the outcome of Equation 6.2a and 6.2b, and ε_{1i} and ε_{2i}, the expected values of the error terms, ε_{1i} and ε_{2i} conditional upon sample selection, are non-zero.

$$E[\varepsilon_{1i} \mid D_i = 1]\sigma_{1\eta} \frac{\phi(\beta\chi_i)}{\Phi(\beta\chi_i)} = \sigma_{i\eta}\lambda_{1i}, and\ E[\varepsilon_{2i} \mid D_1 = 0] = -\sigma_{2\eta} \frac{\phi(\beta\chi_i}{1 - \Phi(\beta\chi_i)} = \sigma_{2\eta}\lambda_{2i},$$

where:

ø (.) and (.) = the standard normal probability density and the standard normal cumulative density function; and

$$\lambda_{1i} = \frac{\phi(\beta\chi_i)}{\Phi(\beta\chi_i)} \text{ and } \lambda_{2i} = -\frac{\phi(\beta\chi_i)}{1-\Phi(\beta\chi_i)}.$$

If the estimated covariances, $\sigma_{1\eta}$ and $\sigma_{2\eta}$, are significant (that is the *rho* value), then the adoption decision of ISM technology and the potential outcome variables are related. With that, providing an evidence to the applied ESR model and rejecting the null hypothesis that says there is no sample selection bias, this model is called "switching regression model with endogenous switching" (Asfaw *et al.*, 2012b; Di Falco *et al.*, 2011; Lokshin & Sajaia, 2004; Maddala & Nelson, 1975).

The most efficient approach to estimate ESR equations is by means of FIML (Lokshin & Sajaia, 2004). The FIML approach at once estimates selection and outcome equations and give consistent standard errors. Considering the trivariate normal distribution assumption for the error terms and log likelihood function, Equations 6.1, and 6.2a and 6.2b, are presented as:

$$Ln\, L_i = \sum_{i=1}^{N} D_i \left[\ln\phi\left(\frac{\varepsilon_{1i}}{\sigma_i}\right) - \ln\sigma_i + \ln\Phi(\theta_{1i} \right] + (1-D_i)\left[\ln\phi\left(\frac{\varepsilon_{2i}}{\sigma_2}\right) - \ln\sigma_2 + \ln(1-\Phi(\theta_{2i})) \right], \quad (6.4)$$

where:

$\theta_{ji} = \dfrac{(\beta\chi_i + \rho_j\varepsilon_{ji}/\sigma_j)}{\sqrt{1-\rho^2{}_j}},\ j = 1{,}2, with\ \rho_j$, representing the correlation coefficient between the error terms, η_i, of selection equation, Equation 6.1, and the error term, ε_{ji}, of the outcome equations, Equation 6.2a and 6.2b, respectively.

According to Di Falco *et al.* (2011), "for the equation identification in the empirical analysis it is a worthy method "to apply restriction" by omission not only those variables automatically generated by the nonlinearity of the selection model but all other factors that affect the selection variables directly but not the outcome variables. The chosen specification for the household income equations (household income PAE) (6.2a) and (6.2b) which follows the conventional approach in the literature (Coelli and Battese, 1996; Solís *et al.*, 2007; Di Falco *et al.*, 2011), allows the use of omission by restrictions on the variables related to the sources of information, the farm and the socioeconomic characteristics of the farmer."

6.2.2 Conditional expectations, treatment and heterogeneity effects

The ESR model, mentioned above, can be applied in comparing household income expected of farming households (a) that adopted ISM technology with (b) those that did not adopt. Moreover, ESR was also applied to determine the expected household income in the counterfactual situation, hypothetically, that (c) adopters did not adopt, and (d) non-adopters had adopted (Asfaw *et al.*, 2012b; Di Falco *et al.*, 2011). Thus, these conditional expectations for farmer income in the four respective situations are presented below:

(a) $E(y_{1i} \mid D_i = 1) = \chi_{1i}\beta_1 + \sigma_{1\eta}\lambda_{1i}$ (6.5a)

(b) $E(y_{2i} \mid D_i = 0) = \chi_{2i}\beta_2 + \sigma_{0\eta}\lambda_{2i}$ (6.5b)

(c) $E(y_{2i} \mid D_i = 1) = \chi_{1i}\beta_2 + \sigma_{2\eta}\lambda_{1i}$ (6.5c)

(d) $E(y_{1i} \mid D_i = 0) = \chi_{2i}\beta_1 + \sigma_{1\eta}\lambda_{2i}$ (6.5d)

Table 6.1: Conditional treatment, expectations, and heterogeneity effects

Subsamples	Decision stage		Treatment effects (TE)
	To adopt	**Not to adopt**	
ISM technology adopters	(a) $E(y_{1i} \mid D_i = 1)$	(c) $E(y_{2i} \mid D_i = 1)$	TT
Non-adopters	(d) $E(y_{1i} \mid D_i = 0)$	(b) $E(y_{2i} \mid D_i = 0)$	TU
Heterogeneity effects	BH_1	BH_2	TH

Notes: (a) and (b) represent household income per AEU, those expected to be observed;;
(c) and (d) represent counterfactual household income per AEU, those expected to be observed;
D_i = 1 if households adopted ISM technology;
D_i = 0 if households did not adopt:
Y_{1i} = household income per AEU for ISM technology adopters;
Y_{2i} = household income per AEU for ISM technology non-adopters;
TT = effect of the technology on the adopters;
TU = effect of the technology on the non-adopters;
BH_i = effect of the heterogeneity-base for adopters (i = 1) and non-adopters (i = 2);
TH = (TT - TU), i.e. transitional heterogeneity.

Following Asfaw *et al.* (2012b) and Heckman (2001), the effect of the treatment ‘‘to adopt’’ on the treated (TT) can be calculated as the change between Equation 6.5a and 6.5c:

$$TT = E(y_{1i} \mid D_i = 1) - E(y_{2i} \mid D_i = 1) = \chi_{1i}(\beta_1 - \beta_2) + (\sigma_{1\eta} - \sigma_{2\eta})\lambda_{1i} \quad (6.6)$$

that represent the impact of *ISM* adoption on households’ income.

Similarly, the impact of the adoption on non-adopters (TU), for the farm households that did not adopt ISM technology, was calculated as the difference between Equation 6.5d and 6.5b,

$$TU = E(y_{1i} \mid D_i = 0) - E(y_{2i} \mid D_i = 0) = \chi_{2i}(\beta_1 - \beta_2) + (\sigma_{1\eta} - \sigma_{2\eta})\lambda_{2i} \quad (6.7)$$

The expected outcome described in Equation 6.5a to 6.5d can also be used to compute the heterogeneity effects. For example, adopters of ISM technologies may have more household income than non-adopters, irrespective of the decision to adopt but due to unobservable characteristics such as farmers' innate abilities. This study, adapted by Asfaw *et al*., (2012b), Carter and Milon (2005), and Di Falco *et al*., (2011), define the "effect of base heterogeneity" for the group of adopters of ISM technology as the difference between Equation 6.5a and 6.5d.

$$BH_1 = E(y_{1i} \mid D_i = 1) - E(y_{1i} \mid D_i = 0) = (\chi_{1i} - \chi_{2i})\beta_{1i} + \sigma_{1\eta}(\lambda_{1i} - \lambda_{2i}) \quad (6.8)$$

Also, for the non-adopters, ''the base heterogeneity effect'' is the difference between Equation 6.5c and 6.5b,

$$BH_2 = E(y_{2i} \mid D_i = 1) - E(y_{2i} \mid D_i = 0) = (\chi_{1i} - \chi_{2i})\beta_{2i} + \sigma_{2\eta}(\lambda_{1i} - \lambda_{2i}) \quad (6.9)$$

Lastly, ''the transitional heterogeneity'' (TH) was investigated to ascertain if the effect of adopting ISM technologies is greater or smaller for farm households that adopted the ISM technology. Alternatively, for households that are non-adopters but in the counterfactual case did adopt, that is the difference between Equation 6.6 and 6.7 (i.e. TT and TU).

6.2.3 The Foster, Greer and Thorbecke (FGT) indices for poverty measurement

The indices developed by Foster, Greer and Thorbecke (1984) for measuring poverty were applied to calculate the poverty incidence, poverty depth and severity of poverty among ISM technology adopters and non-adopters, as indicated in Equation 6.10:

$$P_\beta = \frac{1}{N}\sum_{t=1}^{R}\left[\frac{x - Y_i}{x}\right]^\beta \quad (6.10)$$

where:

P_β = Foster, Greer and Thorbecke poverty index;

N = total of number households;

$Y_i =$ income PAE of the i^{th} household, obtained by dividing total household income by adult equivalent unit, following Richards *et al.* (2003);

x = threshold poverty line;

R = households numbers below the poverty threshold; and

β = assigned number which takes 0, 1, or 2 value for poverty aversion factor.

The β is a non-negative value and is the poverty aversion parameter that indicates the degree of sensitivity of poverty measure to inequality among the poor households. When $\beta = 0$, equation (1) measures the proportion of the population below the poverty threshold, which is the headcount index. When $\beta = 1$ in equation (1), it measures the poverty gap, which is the poverty depth index. This captures information on how far households are distanced from the poverty threshold, or how far their average income is below the cut-off poverty line. The poverty severity index is the square of the poverty gap and the estimated result of Equation 6.10, when $\beta = 2$, and is considering not only the distance between poor households from the poverty line, but also the inequality that exists among the study samples.

A larger β value gives higher importance to the poorest of the poor, signifying the larger response of poverty extent to inequality within poor households (Foster *et al.*, 1984; Namara *et al.*, 2008). It is, therefore, imperative to indicate that x - Yi takes the value of zero when Yi>x in Equation 6.10. Stata 13 was used to calculate the FGT poverty measures by using the component of the Distributive Analysis Stata Package (DASP) version by Araar and Duclos (2012). The poverty line of 3000 calories per adult, according to the official definition of Nigeria's poverty line (NBS, 2013), generates a poverty threshold of ₦180 per capita per day in 2010, adjusted for purchasing power parity (PPP). The poverty line is equivalent to US$1.4 per capita per day, which is about $0.15 above the US$1.25 PPP line used by the World Bank National Economic research (NER, 2014) for international comparison at the time of the survey. Therefore, the ₦82,782.00 poverty line per capita, based on 2014 prices, was used in this study[6].

[6] Exchange rate of ₦162 to a US$ 1 at the time of data collection

6.3 Empirical results and discussions

Summary statistics and significance tests on equality of means for continuous variables and equality of proportions for binary variables for adopters and non-adopters are presented in Table 6.2. Adopters are not distinguishable from non-adopters regarding total farm size, entire farm under maize cultivation and total assets holding. However, adopters own more ox-bull, and productive assets and the difference regarding these are statistically significant. A significant difference between adopters and non-adopters is observable in access to extension services from both public and non-governmental institutions. Adopters seem to have more access to both public and private extension services.

Average distance to the extension office and main market does not indicate a statistically significant difference between adopters and non-adopters, as indicated in Table 6.2. There is no statistical difference regarding farmer secondary occupation after farming among adopters and membership to various agricultural associations. The findings also indicated that the adopter group perception on the cost of the technologies is low in comparison with non-adopters, and have more access to technologies.

Table 6.2: Definition and summary statistics of selected variables used in the estimations

Variable	All sample	ISM adopters	Non-adopters	t-test/ χ^2 value
Dependent	**Mean**	**Mean**	**Mean**	
Adoption	0.55	1.00	0.00	
Income per adult equivalent (PAE) (₦)	93,430.00	106,151.00	77,945.00	7.16
Explanatory variables				
Farming experience (years)	21.79	22.03	21.49	0.64
Education formal (years)	6.27	6.52	5.98	1.67
Total household labour (AEU)	2.89	2.87	2.91	0.42
Total maize farm (ha)	2.72	2.74	2.68	0.26
Ox-bull PAE	0.18	0.20	0.14	1.35
Contact with Gov. Ext. Agent (yes = 1)	0.34	0.43	0.22	5.71
Contact with NGO. Ext. Agent (yes = 1)	0.28	0.36	0.19	4.73
Extension distance (km)	9.98	10.13	9.80	0.31
Main market distance (km)	8.38	8.18	8.62	0.65
Tropical livestock unit (TLU)	4.36	4.36	4.37	0.01

Table 6.2 continues / ...

... /Table 6.2 continues

Variable Dependent	All sample Mean	ISM adopters Mean	Non-adopters Mean	t-test/ χ^2 value
Past participation in on-farm trials (yes = 1)	0.45	0.57	0.30	7.01
Distance to field day site (km)	0.41	0.48	0.33	3.06
Major occupation (farming = 1)	1.21	1.22	1.19	0.73
Secondary occupation (yes = 1)	0.64	0.69	0.59	2.30
Income diversity (continuous)	1.04	1.12	0.93	1.02
Household size (continuous)	11.14	11.43	10.79	1.32
Decision-making	1.28	1.25	1.32	1.19
TTVPASSETS	101,265.00	113,558.00	86,303.00	1.99
Income from ha of maize	111,807.00	136,700.00	78,289.00	9.97
Access to information (yes = 1)	0.46	0.48	0.44	0.52
Fear of tech. (failure yes = 1)	0.30	0.29	0.31	0.51
High cost of technology	0.31	0.28	0.34	1.98
Seed constraint (yes = 1)	0.41	0.39	0.44	2.89
Coop member (yes = 1)	0.45	0.53	0.34	4.81
Access to formal credit (yes = 1)	0.25	0.27	0.22	1.37
Access to informal credit (yes = 1)	0.35	0.40	0.29	2.83
Access to cash remittance (yes = 1)	0.44	0.53	0.33	5.25
Access to off-household income (yes = 1)	0.73	0.76	0.70	1.51
Practice fallow	0.37	0.38	0.35	0.77
Striga a constraint (yes = 1)	0.90	0.93	0.87	2.23
Striga severity (low = 1, medium = 2, high = 3)	1.89	2.00	1.75	3.74
Quantity of manure used (kg)	0.38	0.34	0.44	1.23
Seed quantity used (kg)	61.71	76.49	43.72	1.99

Notes: ***, **, * denote significant at 1%, 5% and 10% levels, respectively.
Chi-square and t-test are used for categorical and continuous variables, respectively.
1 US$ = ₦162 (Nigerian Naira)

Adopters are statistically different in terms of access to informal credit, formal credit and cash remittance for agricultural production. Adopters also differ significantly regarding the perception of *Striga* constraint as well as its severity. This straightforward comparison of adopters and non-adopters among smallholder farmers suggests that they differ significantly in their household income.

6.3.1 The empirical results and discussion of maximum likelihood estimates of household income effect of ISM technology adoption

The maximum likelihood estimates of ISM technology adoption using probit model is presented in Table 6.3. It presents the factors influencing farmers' decisions to adopt ISM technologies where the dependent variable is 1 for adopters of ISM technology and 0 for non-adopters. However, only the result of the second stage ESR is discussed, as determinants of adoption were presented in the previous chapters.

Table 6.3: Parameter estimates of ISM technology adoption and household income equations

Dependent variable	Model			
	OLS	Endogenous Switching Regression (ESR) using FIML*		
	(1)	(2)	(3)	(4)
	Log of income PAE unit	Adoption = (1/0)	Adopters Log of household income PAE unit	Non-adopters Log of household income PAE unit
Adoption	0.35 (0.0630)***			
Farming experience (years)	0.005 (0.004)	0.007 (0.005)	-0.010 (0.004)**	-0.014 (0.006)**
Household education (years)	0.008 (0.007)	0.001 (0.001)	0.005 (0.01076)	0.004 (0.016)
Total household labour AEU	0.0242 (0.024)	-0.141 (0.0418)***	0.1749 (0.03293)***	0.160 (0.047)***
Total farm size (ha)	0.005 (0.001)	0.008 (0.011)	-0.006 (0.007)	-0.003 (0.015)
Farm size under maize (ha)	0.116 (0.011)***	-0.0165 (0.0216)	0.129 (0.01712)***	0.114 (0.025)***
Cooperative (1 = member)	0.177 (0.058)***	0.03184 (0.1063)***	0.2128 (0.07825)***	0.111 (0.172)
Seed quantity (kg/ha)	0.000 (0.000)	0.001 (0.000)	-0.0001 (0.0002)	-0.000 (0.001)
Manure used (kg/ha)	0.0000087 (0.00001)	0.00005 (0.00004)	-0.000022 (0.00002)	-0.000 (0.000)
Inorganic fertilizer (kg/ha)	0.00002 (0.00001)	0.00002 (0.00003)	0.000 (0.000)	0.000
Insecticide used (litre/ha)	0.00108 (0.0018)	0.00354 (0.0041)	0.002 (0.002)	-0.010 (0.007)
Herbicide used (litre/ha)	0.00159 (0.0049)	0.0190 (0.0104)*	-0.006 (0.007)	-0.0237 (0.017)
Tropical livestock unit (TLU)	0.012 (0.004)***	0.0098 (0.0044)**		
Contact with public Ext.	0.136 (0.069)**	0.3441 (0.096)***		
Contact with NGO Ext.	0.185 (0.074)**	0.244 (0.104)**		
Distance to field days site (km)	-0.295 (0.067)***	-0.277 (0.094)***		

Table 6.3 ccontinues / ...

... / Table 6.3 continues

Dependent variable	Model			
	OLS	Endogenous Switching Regression (ESR) using FIML*		
	(1)	(2)	(3)	(4)
	Log of income PAE unit	Adoption = (1/0)	Adopters Log of household income PAE unit	Non-adopters Log of household income PAE unit
Log total farm size	-0.014 (0.095)			
Constant	11.1876 (0.174)***	0.6956 (0.2510)***	11.020 (0.190)***	9.706 (0.287)***
σ_i			0.8770 (0.04594)	1.1106 (0.082)
ρ_j			-0.8861 (0.033)***	-0.785 (0.068)***
LR test of independent equations			45.13***	

Notes: ***, **, * denote significant at 1%, 5% and 10% levels, respectively.
*Estimation is by using full information maximum likelihood (FIML);
Standard error in parentheses, the number of observation is 583;
σ_i = ancillary parameters used in the maximum likelihood procedure, they are the square roots of the variances of the error terms ε_{ji} of the outcome Equations 6.2a and 6.2b;
ρ_j = correlation coefficient between the error term, η_i, of the selection equation (1) and the error term ε_{ji} of the outcome Equations 6.2a and 6.2b, respectively.
Source: Survey data (2014)

The relationship between agricultural technology adoption and household income is theoretical and complex, and there are more empirical shortcomings concerning the problem of impact assessment of improved technologies, such as ISM on household income using the available cross-sectional data to estimate.

Table 6.3 presents the estimated results of the ESR model using FIML at local government level with clustered standard errors. The first column in Table 6.3 reflects the estimated results (by using OLS) of the household income function PAE unit, with no switching and with a categorical variable represented as 1 if the household adopted ISM technologies, otherwise represented as 0, considering the income implication of technology adoption. The straightforward method to determine the effect of ISM technology adoption (using the OLS regression model) on household income includes a dummy variable among the independent variables that is represented by 1 if the household is an adopter of ISM technologies, otherwise represented as 0. Relying on this method could lead to a conclusion that households that adopted ISM generated more income PAE than non-adopting households, and could specifically get about 35% more income PAE than non-adopting households, *ceteris paribus*. The coefficient of the adoption variable is positively significant at a 1% level, however, this approach could assume that adoption of ISM technologies is determined exogenously, while it potentially is an endogenous variable. Therefore, estimation by using OLS could result in inconsistent and biased results. Additionally, estimation via OLS does not clearly account for the likely structural differences between the household income equation for ISM technology adopters and the household income equation for non-adopters in PAE unit.

The second column in Table 6.3 reflects the estimated coefficient of selection equation (1) on adopting or not adopting ISM technologies, the third and fourth columns present, respectively, the income functions 6.2a and 6.2b for adopters and non-adopters of ISM technologies. Findings estimated from the ESR model, using FIML, indicated that the correlation coefficient between the adoption of the ISM technology function and the household income PAE unit functions (ρ_j) carries a negative sign and is significantly different from zero.

The finding showed that both observed and unobserved variables have an influence on the ISM technology decision and household welfare outcome, the latter of which is measured in the form of income PAE given the adoption decision. The significance of the correlation coefficient between the adoption function and the household income functions of adopters have shown that self-selection took place in the adoption of ISM technologies. The difference in the household income equation coefficient between adopters and non-adopters of ISM technologies also proves the existence of heterogeneity in the population sample. The household income function of adopters is significantly different from that of the non-adopters of ISM technologies. That is to say, ISM technology adoption had a significant impact on farm household income PAE on adopters and also, adopters could obtain less income PAE unit from ISM technology adoption than their counterpart if non-adopting households had selected to adopt ISM technologies. Conversely, the calculated correlation coefficient between the selection function and the non-adopters' income function, ρ_j, carries a negative sign and is significantly different from zero. This implies that adopters and non-adopters could obtain different average household incomes PAE using the traditional method of *Striga* control, given their physical characteristics (years of farming experience, available household labour, farm size under maize enterprise and cooperative membership). The household income function of adopters of ISM technologies and that of non-adopters differ significantly. This brought about different effects of technologies between them, proving the sensitivity of the role of technology adoption impact due to unobserved factors of the initial differences.

Table 6.4 present the expected household income per AE under the actual and counterfactual situations for farm households that adopted and those that did not adopt ISM technologies. The estimated household income per AEU from the switching regression was used to look at the average household income difference between ISM technology adopters when compared to the counterfactual situation as if they were non-adopters of the technology. Cells (a) and (b) represent the anticipated household income per AE, as reflected in the sample, while the household income that adopting households expect per AEU is larger than that of non-adopters of ISM technologies. But comparing them using these differences can be misleading in pointing to the difference in the observed household income to the adoption of ISM. The last column of Table 6.4 shows the TEs of adoption of ISM technology on household income.

Table 6.4: Average expected household income per AEU ISM technology adopters and non-adopters

Sub-samples	**Decision stage**		
	To adopt	**Not to adopt**	**Treatment effects (TEs)**
Farm households that adopted ISM	(a) 11.68 (0.027)	(c) 11.16 (0.047)	TT = 0.5176***
Farm households that did not adopt ISM	(d) 11.67 (0.028)	(b) 10.76 (0.063)	TU = 0.9182***
Heterogeneity effects	BH_1 = -0.006 (0.039)	BH_2 = 0.397 (0.077)***	TH = -0.401***

Notes: ***, **, * denote significant at 1%, 5% and 10% levels, respectively.
The number in parenthesis are standard errors.

These results have shown that ISM technology adoption have raised farm household income per AEU. Although, the transitional heterogeneity effect for household income per AEU is positive; which shows that the effect is larger for the farm households of non-adopters when to compare to those households that adopted. In order have more understanding about the impact of ISM technology adoption on the two different groups of adopters and non-adopters. This study also examined the impact gap of ISM technology adoption by categorising the households into groups constructed on education level, major occupation, and farm size.

The result from switching regression showed that ISM technology adoption has a significant and positive impact on household income per AEU. The results obtained evidently showed that the TE for ISM technology adopters' average household income per AEU is 0.52. This is equivalent to 68% on the average household income per AEU, while, if non-adopters could adopt ISM technologies in the counterfactual situation, their income per AEU would raise by 154%.[7]

Table 6.5: Differential impact of ISM technology adoption (stratification by farm size, level of formal education and major occupation)

Farm size own	Observation	Maize area (ha)	Treatment effect (TE) household income PAEU
Group 1	378	<2.7	10.9833 (3.36)***
Group 2	170	2.7-5	11.3362 (7.13)***
Group 3	30	5.1-7.4	11.72 (4.18)***
Group 4	11	7.5-10	12.13 (8.53)***
Group 5	52	>10	10.24 (3.43)***
Education levels			
Group 1	133	No formal education	10.82 (1.72)*
Group 2	333	Completed primary	11.02 (9.51***)
Group 3	46	Completed Jnr. Sec.	10.88 (5.83)***
Group 4	115	Completed Senior. Sec.	11.03 (4.14)***
Group 5	14	Completed Post Sec.	11.54 (2.10)**
Major occupation			
Group 1	556	Farming	11.02 (4.42)***
Group 2	56	Trading	10.86 (0.17)
Group 3	21	Civil servant	10.55 (1.40)
Group 4	6	Technician	01.85 (0.03)
Group 5	2	Other	10.48 (0.84)

Notes: ***, **, * denote significant at 1%, 5% and 10% levels, respectively.
The number in parenthesis are absolute value of t-statistic.

[7] The treatment effect (TE) is % difference. When the outcome variable is log-transformed, multiplying the average treatment effect (ATE) by 100 is an approximation, close only for differences <0.05 (5%). The exact % difference is given by $100(e^{ATT}-1)$, where e is the exponential, and ATT provided by the analysis of the log-transformed variable (that is log-level).

Based on the stratification of the households as indicated[8] in Table 6.5. Remarkable results were found from the impact of ISM technology adoption built on farm size, educational level and major occupation. Even though there is significant household income benefit in all groups of farm size, the benefit is highest for the fourth groups (7.5-10 ha), followed by the third, second, first and fifth group. On the other hand, household income benefits from adoption are greater among more educated households, especially for households in education groups 4 and 5. In the major occupation groups, the benefit of technology adoption is highest among the groups that admitted farming to be their major occupation. As observed in Table 6.5, the impact of ISM technology adoption on household income per AEU increases with farm size in ha, but later start decreasing with an increase in farm size, depicting the law of diminishing returns comes into play. Interestingly, the total benefit in household income is more in the middle farm-size groups (3 and 4). As revealed in Table 6.5, the potential impact of adoption of ISM technologies is at a maximum among the most educated groups (5). This finding corresponds with the findings of Alene and Manyong (2007), Amare *et al*. (2012), Asfaw *et al.* (2012a) and Mignouna *et al.* (2011a), who found that improved agricultural technology adoption have a positive impact on per capita household income, consumption and expenditure, and also on poverty reduction, as reported by Becceril and Abdulai (2010), which can lead to a reduction in poverty. The findings also revealed that adoption of ISM technologies decline with farm size, as indicated in Table 6.5. This suggests that poorer farmers, in terms of farm size, and the most educated farmers may derive more benefit from ISM technology adoption. This finding is consistent with the findings of Becerril and Abdulai (2010) and Simtowe *et al.* (2011) which confirms that providing farmers with education may likely improve their productivity. As this finding indicated, farmers without formal education are the worst regarding household income per AEU. It is, therefore, imperative to keep in mind that the estimated impact of ISM technologies may not be representative of the broader scope of maize farmers in Nigeria, but rather of the selected survey districts in the two states with high *Striga* infestation and are maize producing areas, as previously indicated in the methodology section.

[8] The stratification of the household is based on sample averages of farm size and education level. Landholding area is greater than 2.7 hectares, which was the mean for the whole sample. Similarly, households were classified as too low or high education status, depending on whether they have less or more education than the mean of the full sample (7 years of schooling).

6.3.2 Results of the Foster-Greer-Thorbecke approach for poverty indices

The results of poverty indices using FGT are presented in Table 6.6, which shows that ISM technology adopters are better off than non-ISM technology adopters. Table 6.6 also shows that the poverty incidence is higher among non-ISM technology adopters in comparison with adopters, about 68% of non-adopters were categorised as poor in comparison with the 58% of adopters.

Table 6.6: Poverty measures by adoption status of the pooled sample

FGT Poverty measures	Adopters (N = 353)	Non-adopters (N = 290)	Total (N = 643)	Difference
Poverty headcount (α = 0)	0.5751	0.6827	0.6236	-0.1076***
Poverty gap index (α = 1)	0.2814	0.3964	0.3333	-0.115***
Poverty severity gap (α = 2)	0.1667	0.2681	0.2124	-0.1014***

Notes: ₦226.80 per person per day is used as poverty line (NBS, 2014) during the survey period, while the food poverty line was ₦180 per person per day, which was used as the base.
*** significant at 1% confidence level
Source: Authors' computation using FGT poverty formula

The overall poverty incidence across the whole sample of households is as high as about 62%. Poverty depth and severity were higher among non-adopters than among adopters. The poverty gap index (α = 1) is 39.64% for adopters and 28% for non-ISM technology adopters. This finding suggests that the current level of per capita income of poor non-adopters and adopters have to be raised by an average of 39.64% and 28%, respectively, in order to pull them out of poverty. The squared poverty gap index shows that inequality is higher among poor non-ISM technology adopters than among ISM technology adopters. Therefore, the FGT poverty indices result above show that poverty is widespread for both groups, but it is more prominent among ISM technology non-adopters.

The rate of poverty in the survey areas is high, and the depth and severity indices show a shortfall in calorie intake and inequality among the poor, as indicated in Table 6.6. Non-adopters of ISM technologies are poorer than the corresponding adopters. The total headcount ratio of poverty among adopters is about 10.76% lower in comparison to non-adopters.

6.5 Summary and conclusion

This chapter evaluates the potential impact of ISM technology adoption on household income per AEU among smallholder farmers in some rural areas infested with *Striga* in northern Nigeria. The study utilised cross-sectional data from households collected in 2014, using multi-stage sampling of 643 households. ESR was applied to estimate the causal impact of ISM technology. This approach is suitable for estimating the exact benefits of adoption of ISM technologies by controlling the role of the selectivity bias problem on adoption decisions and the outcome of adoption. Two major conclusions were drawn from the results of this study on the impact of technology adoption on households' income per AEU. Firstly, farm households that adopted ISM technologies have significantly different socioeconomic characteristics than non-adopting households. These dissimilarities represent a basis of variation between the two groups. The OLS regression model used to estimate the impact, including a dummy variable for adoption or not among the independent variables, cannot account for this variation. Secondly, the results from the switching regression suggest that adopters of ISM technologies have a significantly higher household income per AEU than non-adopters, even after all the confounding factors are controlled. From the results obtained, the study can conclude and confirm the potential role of adoption of improved agricultural technology in improving rural household welfare. As a result of a higher gain of household income from ISM technology adoption, it can also translate into a reduction in farming households' poverty. The study, therefore, concludes that the deployed ISM technologies are effective in managing *Striga* and improving household income.

The analysis generated interesting results considering the damaging effect of *Striga* that sometimes leave farmers with very little or no harvest. This suggests the need for policy to support government extension services and rural institutions to create and promote awareness of the existence of ISM technologies. The public and NGO's extension department will be of immense importance in the promotion and dissemination of ISM technologies at the initial stages, through conducting on-farm trials and demonstrations to help create an enabling environment for active participation of farmers and other stakeholders.

In conclusion, the adoption of ISM technologies can be a major approach for smallholder maize farmers to increase their agricultural income and alleviate poverty. Technology adoption, however, is constrained by access to information due to a lack of contact with extension agents, past participation in on-farm evaluation trials and ownership of both human capital (household labour in PAE) and total livestock unit (TLU). Also, social capital (cooperative membership), the formation of which can enhance adoption of ISM technologies, is identified as a key determinant for ISM technology adoption. Policies should address these constraints by strengthening local institutions to expand information dissemination and enhance adoption. Lastly, to capture the full potential impact of ISM technology adoption, further studies is required. This will quantify and measure secondary effects of adoption (e.g. on employment and food prices as it relates to consumers' and farm wages), benefits in terms of nutrition, change in *Striga* incidence and severity in crops production systems. Scaling-up and -out strategies adopted under the ISMA project in Nigeria will help to facilitate improved *Striga*-management technologies in order to reach more farmers. This may lead to an increased adoption of *Strig*a-control technologies in *Striga*-infested areas, which could result in a reduction in *Striga* infestation, and improve maize yield and household income security.

Based on the stratification indicated (e.g. farm size, educational level and main occupation), remarkable results were found on the impact of ISM technology adoption. Even though there is a significant household income benefit in all groups of farm size, the benefit is highest for the fourth group (7.5-10 ha). On the other hand, household income benefits based on adoption are greater among more educated households, especially among households in education groups 4 and 5. In the major occupation groups, the benefits of technology adoption is highest among groups that indicated farming as their main occupation. These findings suggest that promoting ISM technologies is likely to benefit the poor and those with more education, since it influences their skills and enhance their productivity. Hence, from the study area outlook, the findings revealed in this chapter represent the impact of ISM technology adoption on household income. The next chapter examines the economic assessment and profitability of ISM technologies when compared to farmer practice, by using the PB analysis.

CHAPTER 7
ECONOMIC ANALYSIS OF INTEGRATED *STRIGA* MANAGEMENT (ISM) IN NORTHERN NIGERIA[9]

7.1 Introduction

The purpose of this chapter is to assess the profitability of ISM technologies on smallholder maize farmers' income in the Bauchi and Kano States in northern Nigeria. This chapter presents the empirical methods, results and discussion of the profitability of ISM technologies when compared to farmer practices. The rest of the chapter is structured as follows, section 7.1 being the introduction: section 7.2 outlines the methodology, which constitutes the conceptual framework, empirical model, and data collection procedures; section 7.3 discusses the empirical results; and section 7.4 concludes the chapter with a summary of the findings.

7.2 Analytical framework on economic performance of the maize enterprise by using net present value and benefit: cost ratio

7.2.1 Gross margin (GM) analysis

The feasibility and viability of a project can be evaluated by using several financial ratios including GM, break-even, payback period analyses, the BCR, NPV, IRR and modified IRR. All of these approaches have their merits and demerits. The BCR, NPV, and IRR analyses are used for this study based on their simplicity and straightforward approaches with wide appeal among financial experts.

The simplest and fastest approach of making adjustments to farm business is the GM. GM is simply the difference between gross revenue (GR) and the total variable cost that are incurred from a particular farm business. Where several farm enterprises are undertaken, the summation of the individual GMs produce the total GM. GM analysis can justify the selected combination of the farm enterprise to determine whether it is financially and technically feasible and viable to meet

[9] This chapter gave rise to the following manuscript: M.B. Hassan & L.J.S. Baiyegunhi (under review). Economic Analysis of Integrated *Striga* management (ISM) technology in northern Nigeria. Submitted to *International Journal of Innovation and Technology Management.*

the expectations of the targeted beneficiaries (Ghimire, 2003; Kalash, 2010; Macharia *et al.*, 2012; Mignouna *et al.*, 2015; Olukosi & Erhabor, 2005). Parameters used to express performance of the maize enterprise under *Striga* infestation included yield in ton, GM per hectare, or returns to land and return to capital, expressed as return per naira (₦) invested. The revenue was calculated by multiplying the crop yields obtained with the 2013 average price received by farmers, the latter represented by the average of the lowest and highest prices over the year. GM was calculated by deducting the total variable costs (TVCs) from the GR. In this study, only the GR and the TVCs incurred were considered, mathematically shown as follows:

$$GM_{ij} = \frac{1}{n}\sum_{i=1}^{\propto}(P_{ij}Q_{ij} - TVC_{ij}) \qquad (7.1)$$

where:

GM_{ij} = average GM earned by i^{th} household for j^{th} maize crop enterprise in Naira (~~₦);~~

P_{ij} = unit price of output received by i^{th} household for j^{th} maize crop enterprise in Naira (₦/kg);

Q_{ij} = quantity marketed by i^{th} household for j^{th} maize crop enterprise in kg;

TVC_{ij} = total VCs incurred by i^{th} household for *jth* maize crop enterprise; and

n = number of households involved in j^{th} enterprise.

Return to labour was obtained by dividing the GMs by the number of man-days supplied through the family labour in the farm production activities in the study area. One person working for five hours per day on the farm is equivalent to one man-day. Naira was used as the monetary unit at an exchange rate of ₦162 to US$1.

7.2.2 Profitability assessment of integrated *Striga* management (ISM) technologies

It was germane to inform farmers, communities and policy targeting interventions about the analysis of long-term economic feasibility and viability of ISM in the African project.

In the calculation of NPV and IRR, a difficulty exists in the practical application of the opportunity cost of using capital, which is the forgone alternative with an unknown exact value. The choice of a discounting rate depends on producer preference. A producer with a preference for the certainty of the present when compared to the uncertainty associated with the future, could use a high rate for discounting his or her investments. Another producer may be more willing to take a gamble on forecasts holding true by utilising a small discount rate which makes future cash flows of the production nearly as valuable as present value. There is no single and accurate discount rate for a set of future cash flows and there is no exact way to choose one. Farmers usually have the short-term horizon in view. Applying a discount rate that is too high cannot compensate for risk and will result in an NPV that would be forthrightly low. On the other hand, using a discount rate that is too low will produce a high value.

For this analysis, a time spread of 10 years was chosen. Some assumptions, considered as reasonable, were made, including the following:

(i) Maize yields would increase by 50% for the first four years of ISM technology adoption and become stable from the 4th year up to the 10th year, while the local maize yield production practice under *Striga* infestation was assumed to decrease by 20% annually.

(ii) Fixed costs were not considered because the fixed cost of smallholder production that could be part of such cost are either provided by nature, or is done only once ever and bore negligible cost when spread over a long period of investment (Mignouna *et al.*, 2011c; Mignouna *et al.*, 2015).

(iii) The average maize productivity obtained was used (harvest of 2013 production), as calculated from the household survey.

(iv) A sensitivity analysis based on the discount rate (5%, 10% and 12%) was applied to establish the robustness of findings over the base case.

(v) The financial streams of future benefit and costs were discounted so that the NPV and BCR could be determined. The discounted budgeting technique was used in this study despite the criticisms bestowed in its underlying static production economics theory, which ignores the dynamics practically facing farm firms in the real world.

The issue with the static assumption was that budgeting could not address the issue of future inflationary changes, or market shifts in the prices of inputs and outputs (Mignouna *et al.*, 2015). However, budgeting remained a useful planning tool in agricultural production and farm management. The NPV of an agricultural investment is the current value of a series of future benefits that will result from an investment. The criterion for the acceptance of investment is that the NPV value must be positive and the BCR greater than 1 (Gittinger, 1982; Mignouna *et al.*, 2015; Stutely, 2007).

The IRR is the capital budgeting technique that equates the NPV to zero. The IRR was calculated in Equation 7.5 to determine the unknown IRR (r*).

The calculation of the stream revenues' present value and costs was done using the built-in command in the Microsoft Excel worksheet. Mathematical equations underlying the computation of NPV, NPB, BCR and IRR are as follows:

$$NPV_s = \sum_{t=1}^{n} R_t \left(\frac{1}{(1+r)^t} \right) - \sum_{t=1}^{n} C_t \left(\frac{1}{(1+r)^t} \right) \tag{7.2}$$

$$BCR_s = \sum_{t=1}^{n} \frac{\sum_{t=1}^{n} R_t \left(\frac{1}{(1+r)^t} \right)}{\sum_{t=1}^{n} C_t \left(\frac{1}{(1+r)^t} \right)} \tag{7.3}$$

$$NPB = \sum_{f=1}^{N(t)} \sum_{t=1}^{n} d^{t-1} \left[(r_s(f,t)P_s(f,t) - C_s(f,t)) - (r_{F(f,t)}P_F(f,t) - C_F(f,t)) \right] \tag{7.4}$$

$$\sum_{t=1}^{n} R_t \left(\frac{1}{(1+r^*)^t} \right) - \sum_{t=1}^{n} C_t \left(\frac{1}{(1+r^*)^t} \right) = 0 \tag{7.5}$$

where:

R_t = revenue in year t (Naira);

r = discount rate (depends on the prevailing interest and inflation rates in the study area);

C_t = costs in year t;

t..... n = year t to the n^{th} of the project time horizon;

NPV = net present value of the ISM scheme (Naira);

BCR_s = discounted benefit-cost ratio of the scheme;

NPB = net present benefit (Naira per hectare);

r_s (f, t) = yield obtained from ISM technologies at farm f in year t;

r_F (f, t) = yield obtained from the counterfactual farmers plot at farm f in year t;

C_s (f, t) = cost incurred under ISM technologies at farm f in year t;

C_F(f, t) = cost incurred under counterfactual at farm f in year t;

P_F(f, t) = crop market value under counterfactual practice at farm f in year t;

P_s (f, t) = crop market value under ISM technologies at farm f in year t;

Nt = benefit (Naira per hectare);

d = discount factor; and

r*= IRR.

The IRR is the interest earned on the investment and indicates the efficiency of the investment. It is the annualised actual compounded rate of return that can be generated from the invested capital. Both IRR and NPV are widely used in the real world to decide which alternative investment to undertake and which to reject. The main difference between NPV and IRR is that NPV is expressed in monetary terms, while IRR is the real interest expected from an investment, expressed as a percentage. While NPV is preferable among academics, studies indicated that company executives prefer IRR to NPV. Most managers find it naturally more interesting to appraise investments considering the percentage rates of return rather than the monetary value of NPV. Nevertheless, NPV remains the most precise image of value to the business. Assuming *ceteris paribus* among the several investments, the investment with the highest IRR would possibly be considered the finest and accepted first. These economic indicators were estimated for the two different maize production scenarios. Scenario 1 (production under ISM technologies) and scenario 2 (local production practice under *Striga* infestation).

7.3 Results and discussions

7.3.1 The benefit-cost computations

In the Kano State, outputs obtained from different crops, as indicated in Table 7.1, showed that productivity across all the crops were significantly higher for adopters than non-adopters of ISM technologies. In the PIAs, the highest maize yields were from hybrid maize varieties with an average of 2.40 ton/ha, followed by sole improved open-pollinated varieties (OPVs) maize with 1.87 ton/ha, while the least yield, 1.28 ton/ha, was obtained from farmer varieties.

The output was highest for sole improved cowpea, at 0.78 ton/ha, and lowest for local cowpea, at 0.62 ton/ha. The sole improved OPV maize and sole improved cowpea are ISMA project *Striga*-control varieties that have the ability to lessen the effect of *Striga* on the crops' output. It was clear that farmers using ISM technologies promoted by the ISMA project obtained higher farm output when compared to farmers using traditional varieties and practices. Therefore, the use of the *Striga* management practice positively contributed to the yield of adopters across the two locations.

Table 7.1: Summary of benefit-costs analysis of crop technologies by project and NPIAs of ISM technologies in the Kano State.

Project area	**Maize local sole**	**Maize hybrid sole**	**Maize improved OPV sole**	**Cowpea local sole**	**Cowpea improved sole**	**Cowpea improved intercropped**
Yield (ton/ha)	1.28	2.40	1.87	0.62	0.78	0.65
Price (₦/ton)[10]	44,586.72	50,446.67	51,408.02	118,279.03	106,571.28	64,000.00
Revenue ₦	57,071.00	121,072.00	96,133.00	73,333.00	83,266.00	41,600.00
TVC (₦/ha)	23,947.00	24,440.00	23,861.00	22,356.00	19,718.00	18,450.00
GM (₦/ha)	33,124.00	96,632.00	72,272.00	50,977.00	63,548.00	23,150.00
Benefit:cost ratio (BCR)	**2.40**	**5.00**	**4.00**	**3.30**	**4.22**	**2.30**
Non-project area	**Maize local sole**	**Maize hybrid Sole**	**Maize improved OPV sole**	**Cowpea local sole**	**Cowpea improved sole**	**Cowpea improved intercropped**
Yield (ton/ha)	0.80	0.90	1.22	0.47	0.45	0.48
Price (₦/ton)	48,000.00	55,000.00	54,000.00	95,000.00	96,000.00	85,000.00
Revenue ₦	38,400.00	49,500.00	66,042.00	44,650.00	43,200.00	40,800.00
TVC (₦/ha)	28,929.00	28,942.00	39,936.00	48,304.00	39,142.00	38,650.00
GM (₦/ha)	9,471.00	20,558.00	26,106.00	-3,654.00	4,058.00	2,150.00
Benefit:cost ratio (BCR)	**1.30**	**1.70**	**1.70**	**-0.90**	**1.10**	**1.10**

Note: ₦ (Naira) is the symbol of Nigerian currency unit.
Source: Survey data (2014)

The total revenue was obtained by multiplying average unit market prices with the mean output of the various crops per hectare. Generally, factors such as yield, crop variety, crop market price, farm size, technologies used, cropping patterns, and overall socioeconomic factors affect gross farm income. The comparatively higher farm income realised from the use of hybrid maize, sole improved open-pollinated maize variety and sole planting of improved cowpea is correlated to the observed yields obtained from these crops. The total variable cost (TVC) includes all costs that changes with any change in the level of production. These costs are within the control of the farmer, because they are only incurred during production. Some of the variable cost includes: land

[10] 1US$ = ₦162 at the time of data collection

preparation, planting, seeds, fertilizers, herbicides, pesticides, weeding, harvesting, storage and transportation. The TVC incurred varies among crops and according to the inputs involved in the production process. As expected, improved technologies recorded the highest variable costs (VC) due to the additional cost of technology, depending on the productivity of the technology. The VC is the highest for hybrid maize, follow by sole improved OPV maize, and sole improved cowpea. Also, these technologies being associated with a high demand of herbicides, pesticides, fertilizers, and improved crop management practices, particularly herbicide application is necessary for improved cowpea to give a better result. Correspondingly, the use of these inputs have a tendency to increase the level of TVC. Conversely, the increased income from the use of these technologies compensate for the increase in TVC, as shown by the respective GMs obtained.

Table 7.1 generally reveal that for all crops, the attained BCR is higher for adopters of ISM technologies. While non-adopters of ISM technologies, particularly those who continued to grow local cowpea, have BCRs below 1, those who grew sole improved cowpea and improved cowpea intercrop have BCRs just a little above 1 in the non-PIAs. This could be due to seed adulteration, or use of recycled seeds among farmers.

Table 7.2 presents a summary of the GM BCR analyses of crops grown by adopters and non-adopters of ISM technologies in the PIAs and NPIAs surveyed in the Bauchi State. The table generally revealed that, for all crops, the achieved BCR was comparatively higher for farmers in the ISMA project areas of the Bauchi State.

In the PIAs, improved cowpea variety monocrop gave the highest profit margin with a BCR of 3.17, followed by hybrid maize with 3.16 and improved maize OPV monocrop with 2.44. In the NPIAs, the observed BCRs were far below those of the PIAs, as earlier observed in the Kano State. The reason for the observed low benefit could be the same as earlier mentioned (i.e. due to seed adulteration, or use of recycled seeds among farmers). It is remarkable that all adopters of ISM technologies got the highest benefit under *Striga* across all the locations. The significant benefit of adopting ISM technologies reaffirmed their success in controlling *Striga* and enhancing crop productivity, which could result in improved livelihood.

Table 7.2: Summary of benefit-costs analysis of crop technologies by project and non-project intervention areas of ISM technologies in Bauchi State

Project area	Maize local sole	Maize hybrid sole	Maize improved OPV sole	Cowpea local sole	Cowpea improved sole	Cowpea improved intercropped
Yield (ton/ha)	0.95	1.753	1.523	0.58	0.80	0.75
Price (₦/ton)	55,000.00	59,000.00	60,000.00	118,000.00	90,000.00	95,000.00
Revenue ₦	52,250.00	103,42.007	91,380.00	68,440.00	72,000.00	71,250.00
TVC (₦/ha)	24,255.00	32,731.00	37,520.00	32,316.00	22,705.00	36,570.00
GM (₦/ha)	27,995.00	70,696.00	53,860.00	36,124.00	49,295.00	34,680.00
Benefit-cost ratio (BCR)	**2.15**	**3.16**	**2.44**	**2.12**	**3.17**	**1.95**
Non-project area	**Maize local sole**	**Maize hybrid sole**	**Maize improved OPV sole**	**Cowpea local sole**	**Cowpea improved sole**	**Cowpea improved intercropped**
Yield (ton/ha)	0.90	2.15	1.50	0.62	0.61	0.85
Price (₦/ton)	55,000.00	55,000.00	54,000.00	95,000.00	100,000.00	110,000.00
Revenue	49,500.00	118,250.00	81,000.00	58,710.00	61,000.00	93,500.00
TVC (₦/ha)	54,966.00	55,282.00	53,056.0	59,497.00	43,284.00	54,460.00
GM (₦/ha)	-5,466.00	62,968.00	27,944.00	-787.00	17,716.00	39,040.00
Benefit-cost ratio (BCR)	**0.90**	**2.14**	**1.53**	**0.99**	**1.41**	**1.72**

Source: Survey data (2014)

The observed benefit-cost ratio suggest that revenues are steadily higher among adopters of ISM technologies in PIAs when compared to those in NPIAs. This happens as a result of the following three main factors working autonomously or together:

(i) Firstly, selectivity bias – It cannot be ruled out that, at the beginning of the ISMA project, affluent farmers were selected to participate in the project. Hence, it was expected that this group of affluent farmers were more likely to do better than their counterparts in NPIAs.

(ii) Secondly, the complementarity influence of ISM technologies – At the inception phase of the project, intervention assisted farmers' in accessing *Striga* management practices and technologies and other inputs such as seeds and fertilizers. These practices might have helped farmers to enhance their production efficiency, leading to increase in crop productivity.

(iii) Thirdly, the diffusion effect of technology adoption – Farmers had consciously or unconsciously been exposed to technologies either through participation in field days, or by sighting on-farm trials along their way, appreciating the technology and thus, looking for and adopting it. This group of farmers are considered as project non-participant farmers, because they were not directly involved in the initial project activities within the project areas, and might have simply appreciated and adopted the practices of ISM technologies from project participants. Therefore, this category of farmers may likely attain higher productivity levels through the acquired techniques from the initial users of technologies.

7.3.2 Economic evaluation of ISM technologies and local variety options

The financial and economic evaluation of ISM technologies and local varieties is presented in Table 7.3. The NPV estimates of scenario 1 (ISM technologies) and scenario 2 (local maize variety) were ₦1.128 billion and ₦202.32 million, respectively Table7.3, while the BCRs are 2.4 and 0.51 for the two scenarios, respectively (as indicated in Table 7.3), under a 5% discount rate. Also, when the discount rate was raised to 10%, the NPV of ISM technologies was reduced to ₦851.76 million ($5,257,799). Also, the NPV of ISM technologies at a 12% discount rate, was further reduced to ₦764.19 million. All the NPVs are positive and the BCRs are greater than 1 for the ISM technologies under the three regimes of discounted rates while the NPVs for the local varieties under the three regimes of the discounted rates are all negative and the BCR less than 1. The conclusion is, therefore, that ISM technologies adopted under maize production systems are economically viable. All of the NPVs being positive under the three regimes of the discounted rate, reflect the economic worthiness and the opportunity cost of investment and operating capital in ISM technologies. On the other hand, if farmers continue using local varieties, they will continue experiencing negative return, as reflected by the discounted revenue in Table 7.3. This finding agrees with that of Ellis-Jones *et al.* (2004) and Mignouna *et al.* (2011d; 2013) in their studies of ISC in northern Nigeria and IRM adoption in Nyanza, western Kenya, respectively. The finding indicates that farmers willing to invest in maize production via ISM technologies will gain more benefit when compared to those using the local technology under *Striga* threat. This study reveals that ISM technologies are better than local varieties of maize production. This revelation is based on all the economic indicative factors, including its highest IRR (176%, 163% and 158%) under the three regimes of discount rates, which makes it the most desirable maize production system to undertake. This finding corresponds with many studies in Africa that assessed the economic impact of improved agricultural technologies where both farmers and consumers benefited (Macharia *et al.*, 2012; Mignouna *et al.*, 2015). The finding may be somewhat attributed to tolerance to *Striga* that contributed to higher maize output. Thus, at respective discount rates of 5%, 10% and 12%, the NPV, BCR and IRR indicate the viability of ISM technologies. Detailed information on different economic estimates are presented in Appendix 1 and 2.

Table 7.3: Comparison of investment options in ISM technologies and local varieties

Variable (₦)	ISM technologies	Local varieties	Difference
At 5%			
Discounted revenue ₦	1,935,907,690.10	207,503,645.40	1,728,404,044.70
Discounted costs ₦	6,235,120.45	2,529,764.46	3,705,355.99
Benefit-cost ratio (BCR)	2.40	0.50	1.90
Net present value (NPV) ₦	1,128,148,986.10	-202,318,195.50	1,330,467,181.60
Net present benefit (NPB) ₦	20,032,745.04	5,982,498.00	14,050,247.04
Net benefit per capita ₦	50	18.00	32.00
Internal rate of return (IRR) %	176%	71%	1.05%
At 10%			
Discounted revenue ₦	1,515,748,047.66	163,594,485.00	1,352,153,562.70
Discounted costs ₦	663,984,572.40	343,125,360.30	320,859,212.10
Benefit-cost ratio (BCR)	2.28	0.48	1.80
Net present value (NPV) ₦	851,763,476.88	-179,530,876.98	1,031,294,353.90
Net present benefit (NPB) ₦	20,032,745.04	5,982,498.00	14,050,247.04
Internal rate of return (IRR) %	163%	63%	100%
At 12%			
Discounted revenue	1,382,371,506.90	149,297,819.76	1,233,073,687.10
Discounted costs	618,180,715.08	321,784,935.12	296,395,779.96
Benefit-cost ratio (BCR)	2.24	0.46	1.78
Net present value (NPV)	764,190,791.82	-172,487,113.74	936,677,905.56
Net present benefit (NPB)	20,032,745.04	5,982,498.00	14,050,247.04
Internal rate of return (IRR) %	158%	61%	97%

Source: Authors' calculations

Table 7.3 shows the internal rates of return, as well as the NPVs (at various discount rates) of the two production options. It also presents the economic viability characteristic parameters extracted from Appendix 1 and 2. The net present worth of the 10-year time horizon is ₦1.50 billion, equivalent to more than nine times what is obtained from local maize under a 20% annual yield decrease. This illustrates the profitability of investing in ISM technologies. The results obtained indicate that ISM technology adoption brings higher returns, and that the cost-benefit ratio is reasonably higher than that obtained from local maize. This finding concur with many agricultural technology impact studies across Africa, where many successes were reported regarding the impact of improved sorghum varieties in Sudan (Ahmed *et al.*, 1995); of the improved fallow system in Zambia (Sileshi *et al.*, 2007); and of chickpea adoption in Ethiopia (Macharia *et al.*, 2012). The NPB accrued to farmers who adopted ISM technologies was ₦20.03 for the first year when compared to only ₦5.98 million of farmers who used local maize.

Regarding net benefit income per capita, adopters earned ₦8,100.00 per capita when compared to farmers who used local varieties and earned only ₦2,916.00 per capita, which is far below that of ISM adopters. These returns are a good indicator of income and, hence, poverty reduction because of the employment created through farming. In the poverty income analysis, per capita income indicates the magnitude of a daily income that can be gauged on an absolute poverty thresholds to reflect the depth of poverty. Findings from GMs to net benefit per capita, coupled with the long-term economic viability indicative parameters of ISM technologies, were useful in depicting that ISM is economically more viable in terms of returns on investment when compared to local maize production enterprises, and consequently contribute to poverty alleviation in northern Nigeria that is affected by *Striga*.

7.4 Summary and conclusion

This chapter studies the economic analysis of ISM technologies used by farmers, analysing the performance of these technologies and how it changes along with changes in economic factors. The potential of the different enterprises of maize production in controlling *Striga* and in contributing to productivity and poverty alleviation is also determined. Finally, the chapter concludes by portraying some policy implications and suggesting measures for the way forward. The results demonstrated that both increased yields and productivity (net present benefit – NPB) can be obtained from the use of ISC measures over farmer practice. Also, the GMs, benefit-cost ratio and net benefit per capita for ISM technologies are positive across all locations. Therefore, farmers can recover their costs and remain with a positive return. The highest GMs caused ISM technologies to be a viable, profitable, bankable and potential farming option in *Striga*-prone northern Nigeria. ISM technologies can guarantee significantly higher yields than local varieties. Thus, the long-term economic worth indicators proved that ISM technologies have the potential to increase farm income that can, in turn, help reduce poverty among smallholder maize farmers in northern Nigeria. Its NPV, BCR and net benefits are also attractive. ISM technologies can occupy a central role in the design of *Striga*-eradication campaign initiatives and sustainable management in maize fields and should, therefore, be prioritized, particularly in the *Striga*-infested areas of northern Nigeria. Hence, a significantly positive public-private partnership investment and technology transfer are required to improve the use of ISM technologies. This would, in turn, improve the adaptive capacity of farming households and communities against *Striga* in northern Nigeria. Having discussed the contribution of ISM to farm income as an integral part of ISM technology, the next chapter examines the economic benefit of maize-legume rotation.

CHAPTER 8

AN ASSESSMENT OF INTEGRATED *Striga hermonthica* MANAGEMENT AND ITS ECONOMIC BENEFITS TO MAIZE FARMERS IN NORTHERN NIGERIA[11]

8.1 Introduction

This chapter is aimed at investigating the effect of *Striga*-resistant maize in rotation with improved soya beans varieties under farmer conditions. The chapter presents the experimental evaluation strategy to evaluate the direct contribution of STR maize-soya beans rotation technology to farming households' income in northern Nigeria. This study derives its justification from the general acceptance that *Striga* control can be achieved only by mixing two or more control technologies in the form of ISM technology to provide a more lasting and sustainable *Striga* control over a wide range of socioeconomic and biophysical environments (Berner *et al.*, 1997; Carsky *et al.*, 2000; Dashiell *et al.*, 2000). Developed *Striga* control options already show the potential that ISM technologies can be effectively very high, regarding both increasing grain yields as well as reducing *Striga hermonthica* incidence (Schulz *et al.*, 2003; Ellis-Jones *et al.*, 2004). Results from past studies revealed that *Striga* occurrence was drastically depleted by more than 70% in maize fields due to the rotation between STR maize and a legume as a trap crop. A yield increase of more than 60% was achieved when compared to local maize under the same practice.

This chapter reports on a set of on-farm trials that is expected to complement earlier findings by Carsky *et al.* (2000), Ellis-Jones *et al.* (2004), Kamara *et al.* (2008) and Schulz *et al.* (2003). The study summarizes the effect of STR maize in rotation with soya beans. Also, the chapter reports on the economic benefit of ISM technologies. However, the study was limited to the maize yield data only.

[11] This chapter gave rise to the following manuscript: M.B. Hassan, L.J.S. Baiyegunhi & G.F. Ortmann (under review). An Assessment of Integrated *Striga hermonthica* Management and its Economic Benefits to maize farmers in northern Nigeria. Submitted to *Agro-ecology and Sustainable Food Systems.*

The first set of trials that the chapter reports on were briefly summarized to show the contributions of maize-legume rotation to farm level income. In the remaining parts of the chapter, section 8.2 discusses the materials and methods used in the investigation, section 8.3 itemises the results and discussion, while section 8.4 concludes with some recommendations that can contribute towards the increased use of maize-legume rotation technology.

8.2 Methodology

From 2012-2013, two sets of on-farm trials, involving farmer practice (FP) and an integrated approach to *Striga* management, were conducted and managed by farmers themselves in 81 villages of the Bauchi and Kano States. The on-farms trial fields were located in the northern Guinea and semi/Sudan savannah zone of the Kano State that is characterised by a sub-humid climate. This area has an average daily temperature of 30°C to 33°C between March and May, with a minimum temperature of 10°C observed between September and February. The rainfall pattern is unimodal (only one season) lasting between 4-6 months in a year with an average of 600 mm per annum. The Kano State has a total land mass of 2,076,000 ha of which 1,754,200 ha is arable land and the remaining 75,000 ha reserved for grazing and forest vegetation. The Kano State is within the region of Sahel Savannah of West Africa. The raining season varies from year to year but usually starts in May and ends in October, while the dry season runs from November to April.

The Bauchi State is situated in the north-eastern part of Nigeria (see Appendix 1). It has a total land hectarage of 4,925,900.00 ha, representing about 5.3% of the total national land mass, and has about 3,448,100 ha under cultivation. The average daily temperatures range from 29.2°C in July and August to a maximum of about 37.6°C in March and April. The average minimum daily temperature ranges from 11.7°C in December to January to an average of 24.7°C in April and May. The state enjoys both rainy and dry seasons with a maximum rainfall of about 1300 mm per annum in the south to about 700 mm per annum in the north. These states and communities were selected for the study due to their severe *Striga* infestation.

8.2.1 Experimental design

The method adopted for this experiment followed the one described by Schulz *et al.* (2003). The trials were conducted in 400 farmers' fields, and each farmer's field was used as a replica of the two treatments, namely ISM technology and FP. The ISM technology treatment involved the planting of improved soya beans in the first year, followed by *Striga*-resistant maize in the second year (see Ellis-Jones *et al.*, 2004, for details). The FP treatment consisted of a farmer's best maize variety in the vicinity in the second year, following the soya beans planted in the first year as per the ISM technology. The IITA recommended legume-cereal rotation with soya beans and STR maize as one of the options of *Striga* control for farmers in the *Striga*-infested area, since it is affordable to smallholder farmers.

The farmers managed their own on-farm trials, ranging from land preparations to harvesting with advisory service from other stakeholders such as ABU, Zaria, IITA Nigeria, BUK, BSADP and KNARDA. All the soya beans and STR maize seed materials (Table 8.1) were provided by the IITA. The farmers provided all the other farm inputs for the on-farm trials' STR maize and farmer variety in rotation with soya beans. All trials were carried out on *Striga*-infested fields and concurrently served as technology promotion plots for farmers within and outside the communities to see. Each farmer managed his/her two plots for two cropping seasons and shared his/her experiences with other farmers during field days.

The varieties of maize and soya beans used in the on-farm trials are presented in Chapter 3 and Table 3.4. Only results from the maize grain yield are reported in this study.

8.2.2 Sampling strategies

The multi-stage random sampling procedure was adopted for the study. Only households involved in growing maize were drawn from the maize growing areas of northern Nigeria. The first stage involved the purposive selection of the Bauchi and Kano States, based on the importance of maize production and the level of *Striga* infestation, followed by the selection of five LGAs per state, based on the biophysical survey preceding the baseline survey. A "three-stage sampling technique" comprising:

(i) selection of grid cells on digital maps of target LGAs;
(ii) selection of communities within grid cells; and
(iii) selection of farms within communities and grid cells. Grid cells measuring 10 km × 10 km each were superimposed on the Google maps of the Kano and Bauchi States.

In each LGA, five grid cells were randomly selected. In each grid cell, a community closest to the centre of the cell was selected. The crop fields were systematically sampled at 5km intervals along a transect in each of the four cardinal points of the community. The position of the community and farms sampled were recorded by means of the Global Positioning System (GPS) model. The third stage involved the selection LGAs where maize production was constrained by *Striga* infestation.

All the households within the villages in the surveyed area formed the sampling frame developed by extension officers and some assistance from community heads. In each community, a source list was used and all households were subjected to a random selection using the Microsoft Excel RAND funtion, which generates a random number. Additionally, the following criteria were used in selecting participating farmers for the on-farm ISM technology trial: farmers had to have *Striga*-infested fields; an excellent knowledge of the production of these crops; sufficient resources to manage and maintain the plots; willingness to host and accommodate other farmers to view and learn from the farm; and accessibility of the trial site for on-farm training and field days.

The trial was farmer-managed and successfully conducted in many of the communities in 10 LGAs from the two states (Bauchi and Kano) during 2012 and 2013. The trials were established successfully on 400 farmers' fields across 81 communities in the two states. Due to some logistics and security reasons (*Boko Haram* insurgents prevailing in the north-eastern region), only 40% (160) of the farmers were randomly selected for analyses, but only 148 farmers' logbooks met satisfactory requirements for evaluation across the study locations (Table 8.1).

The villages had similar soil and climatic conditions and were less than 5 km from each other. Every farm had two plots that formed a replica. The total plot area was 800 m^2 and the net size of each of the two sets of trials was 400m^2. In 2012 and 2013, each variety of crop was sown on ridges as a monocrop. Three seeds of maize were sown per hill at a spacing of 75 cm × 20 cm. The maize was thinned to one plant per hill two weeks after planting, while soya beans was drilled at a spacing of 5 cm on ridges with a 75 cm inter-row space. In 2012 and 2013, the same operations were performed. Table 8.1 shows the trial locations and number of sampled participating farmers. Due to the multi-location nature of the trial, we found justification in the trials' evaluations and documentation.

Table 8.1: Trial locations and number of sampled participating farmers, northern Nigeria, 2012/13

Number of sampled farmers in each location			
Kano State	**N=64**	**Bauchi State**	**N=84**
Bebeji	18	Alkaleri	18
Doguwa	8	Bauchi	16
Kiru	11	Dass	20
Rano	20	Ganjuwa	12
Tudun Wada	7	Toro	18

Source: ISMA survey data 2013

8.2.3 Statistical and economic analysis

Data analysis was achieved by using paired t-tests, and farm budgeting techniques by using Microsoft Excel spreadsheets. Parameters used in expressing the performance of maize enterprises under *Striga* infestation included yield in kilogram per hectare and returns to investment in inputs, which is expressed as GM per hectare. Crop yields were multiplied by 2013's average market prices (mean of prices immediately after harvest and at the onset of the new season) to compute revenues. The GM is a straightforward and fast approach of planning changes in farm activity, or in analysing an enterprise. The GM is the difference between the gross farm revenue earned and the incurred VCs. For a farm involved in different enterprises, the total GM is the summation of the individual GM of each enterprise. The analysis by means of GM was used to justify that the selected projects were financially and technically viable to the need of the targeted client (Ghimire, 2003; Gittinger, 1982; Kalash, 2010; Mignouna *et al.*, 2011b; Olukosi & Erhabor, 2005). The basic equation for the GM computation and other economic indicators were the same as the ones earlier presented in section 7.1.

Certain assumptions were made to determine the GM of each production method, namely all the crops were subjected to the same seed quantities, fertilizer rates and agronomic practices. The only difference was the cost of the technology, which was the seed of the *Striga*-resistant maize. This study only focused on the cost-benefit ratio associated with maize production under *Striga* infestation. All crops harvested at the end of the season were priced at the prevailing market price which was an average of ₦60.25k/kg, translated to about US$380/ton of maize grain using the naira exchange rate of ₦162 to US$1[12] at the time of this study.

8.3 Results and discussions

Farmers in northern Nigeria grow several varieties of maize, but the open-pollinated varieties (OPVs) are predominantly common in the communities. The OPVs are highly susceptible to *Striga* attack. Four new varieties that are resistant to *Striga* were introduced, namely: TZL COMP 1SYN, IWD C" SYN, 99EVDT and 2009EVDT. These are the codes given to the varieties by the breeders, and all are open-pollinated (OPV) material and resistant to *Striga*, and their performance compared with the best local variety. The results presented in this study were the sum average of the two-year trials. The gross, maximum and minimum yields, standard deviations (SDs) and the increased productivity of the STR varieties over farmer variety are presented in Table 8.2. The GM, GR, the average rate of return and marginal rate of return (MRR) of the different maize varieties for the Bauchi and Kano States are presented in Tables 8.3 and 8.4.

Table 8.2: Grain yield of improved *Striga*-resistant maize varieties under rotation with soya beans, when compared to farmer variety in the study area, 2012/13

State	No. of farmers	Parameters	Productivity (kg/ha^{-1})		% Yield advantage over farmer control variety
			Improved maize SR	Farmer control variety	
Bauchi	84	Average	3,234	1,972	64
		Maximum	5,000	3,333.33	
		Minimum	2,000	333.33	
		SD	449	596	
Kano	64	Average	3,431	2,031	69
		Maximum	5,000	3,000	
		Minimum	2,667	583.33	
		SD	441	557	

Source: own calculation

The comparison of maize yield difference was carried out between the farmer variety and STR varieties that were grown under the same conditions. The likely source of yield difference was the type of maize seed grown. A paired t-test was conducted on the yields of the STR maize and farmer

[12] ₦162 exchange to a US$1

varieties. The mean yield of the STR maize varieties after soya bean was 3234 kg/ha in the Bauchi State and significantly higher ($P<0.01$) statistically than the mean yield of the farmer variety at 1972 kg/ha. Also, a significant difference was recorded between the mean yield of STR maize at 3431 kg/ha and the variety farmer yield at 2031 kg/ha in the Kano State, the yield difference being statistically significant ($P<0.01$).

The results also show a yield increase of 64% STR maize over the farmer variety in the Bauchi State while the outcome in the Kano State is similar, with a productivity increase of 69% STR maize varieties over the farmer variety. These overall results further indicate a significant difference between the mean yield of STR maize and the farmer variety. The results from using the STR varieties across the two states, Kano and Bauchi, show a statistically significant increase ($P<0.01$) in net benefit, as reflected in Table 8.2.

Estimating the BCR is another way of determining the viability of the technology. According to the Asian Development Bank (2011), the ratio of the present value of the economic benefits stream to the present value of the economic costs stream, each discounted at the economic opportunity cost of capital, should be greater than 1.0 for a project to be acceptable. The BCRs of both STR maize and farmer variety are above 1.0, however, the BCR of the STR maize in Bauchi was 2 as opposed to the 1.41 of the farmer variety. In Kano, the STR maize BCR was 2.04, while the farmer variety was 1.42. This indicates that the STR maize in rotation with soya beans is economically more viable than the farmer variety, as shown in Table 8.3.

The MRR is the ratio of change in benefit over the change in VC by moving from one technology to another. In this case, it is the movement from farmer variety to *Striga*-resistant maize in rotation with soya beans. The results of the MRR clearly indicate a higher return, which is expected, as more resources are taken away from local maize production under *Striga* and invested into STR maize production in rotation with improved soya beans. The results across the two states indicate that the MRR of moving from farmer variety to STR maize are all greater than 5. This suggests that the viability of investment in the STR maize is high when compared to the farmer variety.

Table 8.3: Partial budget (PB) comparing STR maize varieties in rotation with soya and farmer variety in the study areas, 2012/13

	Gross farm gate benefits	Bauchi State		Kano State	
		Maize varieties		Maize varieties	
		Farmer variety	STR in rotation with soya beans	Farmer variety	STR in rotation with soya beans
1	Average yield (kg/ha)	1,972.00	3,234.00	2,031.00	3,431.00
2	Price (₦/kg)	60.25	60.25	59.27	59.27
3	Gross farm gate benefits (₦/ha) (1x2)	118,813.00	194,848.50	120,377.37	203,355.37
	Variable costs (VCs) (₦/ha)				
4	Maize seed	1,205.00	4,400.00	1,205.00	4,400.00
5	Land preparation	8,188.00	8,188.00	8,188.00	8,188.00
6	Planting	2,500.00	2,500.00	2,500.00	2,500.00
7	Fertilizer	41,830.00	41,830.00	41,830.00	41,830.00
8	Fertilizer application	4,080.00	4,080.00	4,080.00	4,080.00
9	Weeding	9,490.00	9,490.00	9,490.00	9,490.00
10	Harvesting	9,465.60	15,523.20	9,748.80	16,468.80
11	Threshing	2,366.40	3,880.80	2437.20	4,117.20
12	Bagging and transportation	4,930.00	8,085.00	5077.50	8,577.50
13	Total variable input costs ₦ (sum: 5-12)	84,055.00	97,977.00	84,556.50	99,651.50
	Net benefit				
14	Net benefit (₦/ha) (3-13)	34,758.00	96,871.50	35,820.87	103,703.87
15	Benefit:costs ratio	1.41	1.99	1.42	2.04
16	Average rate of return %	41.35	98.87	42.36	104.07
17	Change in net benefits between two consecutive treatments (₦/ha)		76,035.50		82,978.00
18	Change in total variable input costs between two consecutive treatments (₦/ha)		13,922.00		15,095.00
	Marginal rate of return				
19	Marginal rate of return (MRR) (17/18)		5.46		5.50

Notes: *** indicates significant difference at 1%.
₦162 = US$1 at time the study was conducted.
Source: Based on survey and own calculations

Table 8.4 shows that the domination in yield by the STR varieties over the farmer variety is not by chance but due to the superiority of the material regarding *Striga* suppression, as indicated by the mean yield obtained and the value of the t-statistics. The STR varieties have higher mean yield with lower SD when compared to the farmer variety across all the locations. This shows a high variability in the farmer variety regarding yield, which means that a high risk of investment is associated with the farmer variety.

Table 8.4: Paired t-test of the two technologies between plots across locations in the study area, 2012/13

Item (kg)	All (n = 148)		Bauchi State (n = 84)		Kano State (n = 64)	
	STR maize	Farmer variety	STR maize	Farmer variety	STR maize	Farmer variety
Mean yield	3,319.36	1,997.5	3,234.14	1,972	3,431.22	2,031.30
Mean yield difference	1,321.85		1,262.33		1,399.97	
SD	455	578	449	596	441	557
P-value	0.0000		0.0000		0.0000	
t-statistics	27.27***		19.83***		18.88***	
Degree of freedom	147		83		63	

Note: *** indicates significant difference at 1%.
Source: Based on survey and own calculations

8.3.1 Net income per hectare from different treatments across locations

The total farm income across the two sites indicates that higher farm income per hectare realized from the STR varieties in rotation with soya bean when compared to the farmer variety, and that the mean income difference is statistically highly significant, as indicated in Table 8.5.

In Bauchi, the highest revenue generated per hectare from STR maize was ₦301,250.00, while the highest revenue from the farmer variety was ₦200,833.00 In Kano, the highest revenue generated per hectare was ₦296,350.00 from STR maize, while the highest revenue from the farmer variety was only ₦177,000.00 (see Figures 8.1 and 8.2). The results show no significant difference between the farmers in Bauchi and Kano in terms of income generated per hectare. As indicated in Figure 8.1, 35 farmers in the Bauchi State received more than ₦200,000.00 per hectare from STR maize, while 32 farmers in the Kano State received more than ₦200,000.00 per hectare.

Table 8.5: Results of the paired t-test for mean income, obtained from the yield per ha between plots across locations in the study area, 2012/13

Location	Observation	Mean income (Naira)	Standard deviation
Kano			
Striga-resistant maize	64	203,370.18***	26,157.82
Farmer variety	64	120,392.18	33,029.46
Bauchi			
Striga-resistant maize	84	194,856.15***	27,059.75
Farmer variety	84	118,802.48	35,938.99
Across all states			
Striga-resistant maize	148	198,365.51***	27,187.13
Farmer variety	148	119,371.94	34,581.64

Notes: *** indicates significant difference at 1%.
₦162 = US$1 at time this study was conducted.
Source: Based on survey and own calculations

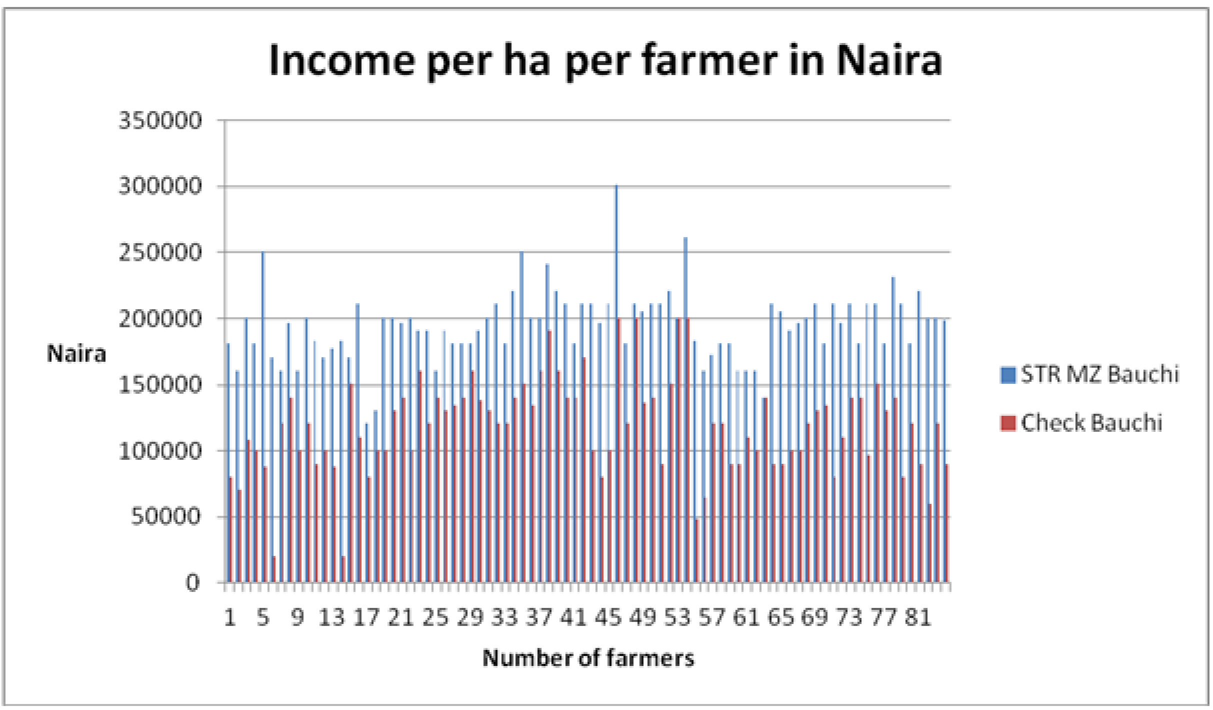

Figure 8.1: Income per ha per farmer in the Bauchi State, northern Nigeria, 2012/13

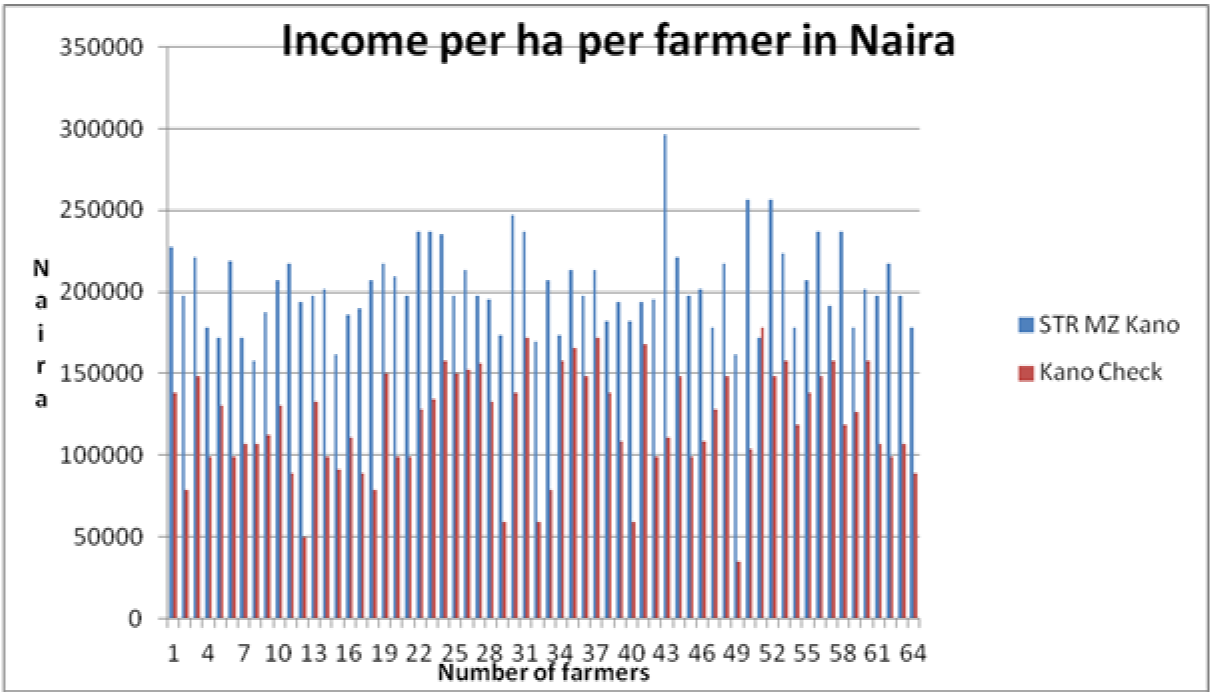

Figure 8.2: Income per ha per farmer in the Kano State, northern Nigeria, 2012/13

All the two-years trials were done by farmers. The results showed that the highest productivity and income were generated from adopting the two ISM technology components (soya beans, followed by the *Striga*-resistant maize variety). The yield increase realised from using *Striga*-resistant maize after soya beans was over 60% across the two states where the study was conducted over the two periods.

The results from this finding indicate a high variability on the maize grain yield among the maize farmers, which led to a different level of income. This could be due to a different response to *Striga* parasitism by the STR maize varieties. Overall, *Striga*-resistant maize produces higher yield and income to farmers. The finding of this study reaffirms the results of Ibrahim, Omotesho & Adewunmi (2010) and Kureh, Kamara & Tarfa (2006) which confirm that STR materials in rotation with trap crops (cowpea and soya beans) has great potential for high yield and adoption by farmers in the study areas. This finding also corresponds with the results of Kuchinda *et al.* (2003) and Kureh *et al.* (2006). Several previous results reveal a significant decrease in *Striga* infestation through adopting production practices that comprise intercropping and rotations of legumes and cereals (Carsky *et al.*, 2000; Ibrahim *et al.*, 2010; Kuchinda *et al.*, 2003; Kureh *et al.*, 2006; Schulz *et al.*, 2003). Some other mechanisms can be suggested to describe the depletion of

Striga when maize is rotated or intercropped with legume trap crops, such as groundnut, Bambara nut, cowpea, green gram and pigeon pea.

Results obtained by Oswald *et al.* (2002) and Gbèhounou and Adango (2003) also show that higher yield was obtained when maize was intercropped with any of the trap legumes, such as Bambara nut, cowpea, soya beans, yellow gram, bean, green gram, and groundnut in western Kenya. The average high yield of maize recorded in the intercrop could be ascribed to the effectiveness of the production practice in decreasing the *Striga* effect. In the case of sole maize, a high *Striga* biomass is observed, which could be responsible for the poor maize yield. The fixation of nitrogen into the soil and reduction in leaching of soil nutrients by the intercrop cover crops could be the reasons for the higher maize yield. Gurney, Press & Scholes (1999) also found the high level of *Striga* biomass in the soil to negatively influence the productivity of the host plant.

The acceptance and suitability of any technology depend on its costs and economic returns associated with the production. It is observed that maize-soya bean rotation gave the highest benefits when compared to the practice of all the farmers across both the seasons of the study in the two states. Many studies (e.g. De Groot, 2007; Jamil *et al.*, 2012) similarly revealed an increase in maize yield and MRR with the use of inorganic fertilizer in plots infested with *Striga*. They believed that soya bean influenced the increased nitrogen level during rotation and also triggered suicidal germination of *Striga.* This finding corroborates the results of Carsky *et al.* (2000), Ellis-Jones et al. (2004), Kamara et al. (2008), Khan et al. (2006a) and Schulz et al. (2003) on the increased productivity of maize in rotation with soya beans.

8.4 Summary and conclusions

The constant planting of maize on the same parcel of land only aggravates *Striga* infestation, which could ultimately lead to maize grain yield reduction. However, rotation of STR maize and grain legumes, such as improved soya bean, can reduce *Striga infestation* and, therefore, increase maize grain yield, thus increasing farmers' income and food security. *Striga*-infested maize fields can be put to productive use if an STR maize variety is rotated with improved soya bean varieties in the second year, followed by STR maize. The results presented in this study demonstrate that both productivity and increased yield can be obtained from the use of ISM technologies over that of farmer variety. Results from this study will be useful in targeting smallholder farmers because of

ISM technologies' low input nature. Legume enhances soil fertility, enriches the diet and neither require herbicide nor pollute the environment. Thus, government policies should promote the adoption of these technologies among farming households in northern Nigeria. This could be achieved by making provision of STR maize as a component of the National Agricultural reform of the Federal Government of Nigeria. The states and local governments should also facilitate the scaling out of these technologies through an innovation platform (IP), where all stakeholders (researchers, extension agents, seed companies, farmer groups and farmers) will be participating in conducting more on-farm trials, demonstrations and field days.

For the last 30 years, global demand for soya beans has increase by 210%, while that of maize increased by only 108%. Evidently, the world has an increased appetite for the protein that is obtainable from soya beans. Therefore, the addition of soya beans into the farming system will help to diversify farmers' enterprise, thereby increasing their income and serving as insurance. At present, there is a considerable market for soya beans in many parts of the world, including Nigeria, where soya beans are used in the preparation of both traditional and modern foods, particularly soya bean cheese that is very popular among rural communities, since it serves as a substitute for animal protein. It is also needed in the preparation of livestock feeds and even foods for human consumption. Since 1993, the price of soya beans in Nigeria and across the globe has doubled that of cereal (FAO, 2013). Currently, soya beans have fewer pests in West Africa. It further carries the additional benefits of decreasing the *Striga* bank in the soil and improving soil fertility through its nitrogen-fixing ability. Carefully chosen soya bean varieties can generate multiple benefits for the farmer and the environment. The next chapter examines the economic benefit of *Striga* management through herbicide-resistant maize and its potential contribution to farm productivity.

CHAPTER 9

STRIGA MANAGEMENT THROUGH HERBICIDE RESISTANT MAIZE AND ITS CONTRIBUTION TO FARM PRODUCTIVITY IN NORTHERN NIGERIA[13]

9.1 Introduction

This chapter presents the results and discussion of the contribution of IRM, otherwise known as herbicide- or Imazapyr-resistant maize, to farm income. As earlier indicated in Chapter 8, only farmers who participated in the on-farm trials were used in the analysis for this chapter. The same empirical approaches used in Chapter 8 were applied to achieve the results presented in this chapter. The question of whether Imazapyr-resistant maize (IRM) technologies have any effects on maize productivity on a *Striga*-infested field, among farmers who participated in the on-farm trials, is answered in this chapter. The rest of the chapter is arranged as follows: section 9.2 provides the background to the study, while section 9.3 outlines the methodology, followed by the empirical results in section 9.4. Section 9.5 concludes the chapter with a summary of the findings and conclusions.

9.2 Background

Maize crop is a staple food in SSA where 95% of the maize produced constitutes a major part of the daily diet (Høgh-Jensen *et al.*, 2007). Likewise, maize is the major cereal consumed and marketed after sorghum and millet in Nigeria (FAO, 2014). In a country like Nigeria, with the majority of its population engaged in farming and residing in rural areas, cereal productivity and food security are interrelated. Consequently, factors that affect cereal production can also impact on food security, as the majority of the poor population are directly dependent on cereals, which is relatively low-priced when compared to other forms of diet (FAO, 2014). Nevertheless, despite the potential for increased productivity, maize production faces many challenges, including low and erratic rainfall, poor soil fertility, drought, *Striga*, and long dry spells (Tambo & Abdoulaye,

[13] This chapter gave rise to the following paper: M.B. Hassan, L.J.S. Baiyegunhi & G.F. Ortmann (under review). *Striga* management through herbicide resistant maize and its contribution to farm productivity in northern Nigeria. Submitted to *Agricultural Systems.*

2012). For the past decades, the IITA, in collaboration with CIMMYT and National Research Institutes, developed some early-maturing maize, and STR technologies that meet the requirement of small-scale farmers were disseminated in northern Nigeria and the West Africa savannah at large.

Maize is highly susceptible to *Striga*, which causes much damage to host crops across the savanna regions of Africa (AATF, 2006). *Striga* has invaded about 2.4 million ha of land under maize cropland, wreaking annual grain losses of about 1.6 million tons with an estimated value of US$383 million (Table 9.1). *Striga* infestation in Nigeria is most severe in the northern part, which covers about 835,000 ha, or arable land with an estimated loss of about 505,308 tons of maize, valued at US$205,660,000 million per annum. Fields in Nigeria affected by *Striga*, account for about 34% of land infested in Africa (Table 9.1).

Table 9.1: *Striga*-distribution yield and economic loss in Africa's maize cropland for selected countries

Area	Coverage x1000 ha	Maize grain loss tons per year	Economic loss US$ per year
Sub-Saharan Africa (SSA)	2,363	1,623,838	383,290,000.00
Southern Africa	589	372,802	69,708,000.00
Malawi	291	208,221	27,900,000.00
West Africa	1,243	790,084	250,095,000.00
Nigeria	835	505,308	205,660,000.00
East Africa	531	460,953	68,487,000.00
Kenya	217	184,227	28,610,000.00

Source: Woomer and Savala (2007)

Striga decreases maize productivity by 20%-100%, at times leaving farmers with little or no grain at harvest. Maize losses in Nigeria from *Striga* alone account for about 100% of its deficit. However, the majority of victims are the millions of small-scale farmers who see their crops wrecked year in year out, unable to produce enough food to feed their families or make some visible progress in their livelihood. The majority of farming households, particularly cereal growers, have developed a defeatist outlook to *Striga*, admitting that it has become part of them, and expected to die with *Striga* in their fields (Woomer & Savala, 2007). According to AATF (2008a) and Manyong (2008), an estimate of the area affected by *Striga spp*. in the world is approximately 44 million hectares of arable land, affecting the livelihoods of more than 100 million smallholder farmers.

The farming community, particularly maize growers, responded to the *Striga* threat in numerous ways. They identified landraces that showed some *Striga* resistance, and these were later improved through traditional maize breeding, resulting in STR maize varieties. Another new method to manage *Striga* is through the planting of vigorous plants which antagonises *Striga*. Studies have identified legumes (cowpea, soya bean, pigeon pea, groundnuts, chickpea and desmodium) that provoke *Striga* and thereby induce it to germinate abortively. This is achieved through a process called push-pull (Khan *et al.*, 2006a). Legumes such as soya bean and groundnut were also shown to asphyxiate *Striga* and induce what is known as suicidal germination, which is achieved either through maize rotation with legumes or through intercropping (Carsky, Singh & Ndikawa, 1994; Ellis-Jones *et al.*, 2004; Woomer *et al.*, 2005). A herbicide called Imazapyr, which kills *Striga* plants while being harmless to maize crops, was also identified (Odhiambo & Ransom, 1993). Mainly commercial farmers used these technologies.

These new technologies worked, even though a part of the land from that used for the main food crop production needed to be sacrificed. Alternatively, it is presumed that farmers gain an advanced understanding of the complex ecology associated with *Striga* (Woomer & Savala, 2007). IRM is achieved through the application of a little quantity of Imazapyr to maize seeds, which is believed to offers many weeks of protection from the action of *Striga* (Kanampiu *et al.*, 2002). The Imazapyr technology is a result of many years of research and development by different organisations. Maize resistance to the herbicide Imazapyr was initially developed by American Cyanamid, a US-based company.

9.2.1 Imazapyr-resistant maize (IRM) trials and dissemination in Africa

In SSA, the first IRM was produced at CIMMYT-Zimbabwe then followed by CIMMYT-Kenya through collaboration with the Agricultural Research Institute (KARI) of Kenya. KARI multiplied maize seeds for Imazapyr testing and breeding. According to Mignouna *et al*. (2011a), "the practicality of covering IRM seeds with the imazapyr herbicide was first demonstrated through the collaborative research at the KARI-Kibos station outside of Kisumu (Kanampiu *et al.*, 2002). In 2004, the IRM was then deployed to farmers for on-farm testing on a large scale, and it was funded by AATF especially the multiplication of *Ua Kayongo* by Western Seed Company. A drive of pre-release testing of IRM was launched by AATF (Otieno *et al.*, 2005), with over 13,000 smallholder farmers and when compared to other *Striga* management technologies across 120 localities in West Kenya (Woomer *et al.*, 2005) with a favorable results. Compared to the recommended commercial hybrid (H513), *Ua Kayongo* improved maize yields by 1,022 kg ha-1, increased farmer's net return by $143 ha-1 (+63%) and reduced *Striga* expression by 81%. (AATF, 2005)."

The success recorded in Kenya triggered the dissemination of IRM maize to other parts of Africa, with the collaboration of many institutions, to reduce *Striga* constraints to maize production, also in northern Nigeria. The ISMA project was funded by the Bill & Melinda Gates Foundation. IITA collaborated with the IAR of ABU and other stakeholders to disseminate the improved agricultural *Striga* management technologies, among which was IRM, to the two states. This paper collected information on socioeconomic characteristics of maize farmers in northern Nigeria that attended the ISMA field days and when compared the productivity of IRM technology with the farmer varieties as control methods.

The development and advancement of IRM can improve the productivity and nutrition of smallholder farmers, particularly women and children in communities where maize form their staple food. Maize is currently the major source of raw material in feed production by livestock industries, particularly for poultry. Therefore, maize has a great potential to augment food insecurity through increased productivity and sustainability of the crop and livestock production system (Alene *et al.*, 2006).

The study reports on two sets of on-farm trials, conducted across the two states, to show the contributions of two hybrid varieties (IRMs: IRM1 and IRM2) to maize productivity and maize farming households income. The study also reported socioeconomic characteristics of farmers who attended farmers' field days. In the remaining parts of the chapter, section 3 discusses the materials and methods, section 4 presents the results and discussion, and lastly, section 5 concludes with a summary and some recommendations that can contribute to the increased use of hybrid IRM technology.

9.3 Methodology

9.3.1 Experimental design

The approach for the trial followed that of Schulz *et al.* (2003) and Ellis-Jones *et al.* (2004).The trial was conducted on 200 farmers' plots, with all plots being replicas of each other and each replica having three treatments, namely IRM1, IRM2 and farmer practice (FP), FP being the traditional best practice of using local open-pollinated maize seed selected from the previous harvest.

9.3.2 Source of data

The study is of two components, that of on-farm trials and a household survey questionnaire. The data ws collected between September and December 2012 by means of a structured questionnaire, by employing a multistage sampling procedure in selecting 518 households from the Bauchi and Kano States of Nigeria. This method ensures a high degree of representativeness, by providing all farmers with equal chances of being selected into the sample (Babbie, 2009). The first stage drew in the purposive selection of the Kano and Bauchi States in northern Nigeria, and five LGAs of each state, based on their importance regarding maize production and high infestation by *Striga.* Then followed selections of five communities from each of the states, one community per local government where a farmers' field day were conducted. In each of the LGAs where a field day was conducted, 39 to 75 farmers per LGA were selected on the spot for the survey, using the field day's attendance register. Large numbers of farmers attended field days. The extension officer and community leaders invited all the neighbouring communities around the farm trial sites. Attendance lists were obtained and names were put in box, shuffled and drawn to ensure each attendee was given equal chance of being selected for the interview. The total sample size for the survey was 518 households with 293 selected from Bauchi and 225 from Kano, as shown in Table 9.2. For on-farm trials, 100 farms were used across 100 selected villages and 50 farms were purposively selected for analysis due to the inaccessibility as a result of insurgents' activities (*Boko Haram*) at the time in the North-East region. Data on yields, costs of production and return from each IRM1, IRM2 and farmer control practice were collected and analysed. The study location and sample size are indicated in Table 9.2.

Table 9.2: Study location and sample size for the survey aspect

State	LGA	Village	Household size
Bauchi	Alkaleri	Marrabar Kirfi	60
	Bauchi	Rijiyan Mallam	60
	Dass	Lussa	65
	Ganjuwa	Kula	54
	Toro	Tilden Fulani	54
Subtotal			293
Kano	Bebeji	Wak	39
	Doguwa	Rufa'i	57
	Kiru	Dangora	53
	Rano	NA	NA
	Tudun Wada	Jammaje	75
Subtotal			225
Total			**518**

Note: NA = Not available
Source: ISMA survey data 2013

9.3.3 Analytical methods

The data was analysed by capturing farm budgeting techniques and paired t-tests on Microsoft Excel spreadsheets, as described in Chapter 8. Parameters used to express maize enterprise productivity under *Striga* infestation included yield (kilogram per hectare) and returns to investment in inputs (GM per hectare). The crop yields and revenues were multiplied by the 2013 average market prices of ₦71.18/kg of maize grain (average harvest price calculated between the lowest and peak price, the latter being close to the beginning of the new harvest), to translate into a yield of about $US357/ton during the period of study, as discussed in Chapter 7 and Chapter 8. The GM is a direct and swift method of planning changes in the activity of a farming business. The GM or profit of a particular farm enterprise is the difference between the GR and the TVCs incurred during production. For a farm undertaking different enterprises, the total GM equals the sum of GM of each enterprise. The GM analysis was used to justify that the selected enterprises are technically and financially viable to the need of the target beneficiaries (Gittinger, 1982; Kalash, 2010; Mignouna *et al.*, 2011c; Olukosi & Erhabor, 2005).

9.4 Results and discussions

9.4.1 Socioeconomic characteristics of households

Table 9.3 shows that the mean age of farmers was 39.42 years, with 58.8% having an education above primary school and only 19% had no formal education. About 90% had to farm as their major occupation. The mean farm size was 5.86 ha with an SD of 10.15 ha; the mean farm size under maize cultivation was 2.62 ha (45%); and the mean farm size under *Striga* infestation was 2.35 ha with an SD of 5 ha. It shows that about 90% of the fields under maize were infested with *Striga*. In the Kano and Bauchi States, about 50% and 59%, respectively, of the field under cultivation was infested with *Striga*. Both states show that farmers possessed farm sizes above the national average of 2 ha.

Table 9.3: Socioeconomic characteristics of sample households

Farmers characteristics	Kano	Bauchi	All
Average age of farmers (standard deviation – SD)	41.68 (11.57)	36.83 (11.94)	39.42 (12.6)
Male (%)	100%	74.48%	85%
Farming as major occupation (%)	90.13%	89.79%	89.94%
Farmers belonging to farmer organisation	35%	32%	33%
Farmers without formal education	14%	22.5%	19.1%
Farmers with secondary school and above	55.4%	61.4%	58.8%
Farm characteristics			
Average total farm size (ha) (Standard deviation – SD)	7.12 (16.05)	5.30 (10.02)	5.86 (10.15)
Mean farm under maize (ha) (Standard deviation – SD)	3.18 (7.12)	2.24 (3.76)	2.62 (5.42)
Mean farm under *Striga* infestation (ha) (Standard deviation – SD)	1.50 (3.70)	3.12 (7.50)	2.35 (5.00)

Source: ISMA Survey data 2012-2013

9.4.2 Cropping patterns, cropped area and traditional methods of *Striga* control

The results in Figure 9.1 show that about 259 hectares of land were devoted to maize and soya bean cultivation, followed by maize and cowpea (188.45 ha), and maize and groundnut (85 ha). It shows that maize is the major staple crop in the study area and that farmers diversify their cropping, never engaged in sole cropping in their parcel of land, except where the farmer have access to *Striga*-resistant maize, which was grown on 24.5 ha of land. This finding also shows that the farmers are aware of the importance of growing legumes in a field that is infected with *Striga*, legumes being known to suppress the *Striga* population (Ellis-Jones *et al.*, 2004; Schulz *et al.*, 2003). Ellis-Jones *et al.* (2004) also found that rotating cereals with legumes produces a higher yield compared to non-rotating farming.

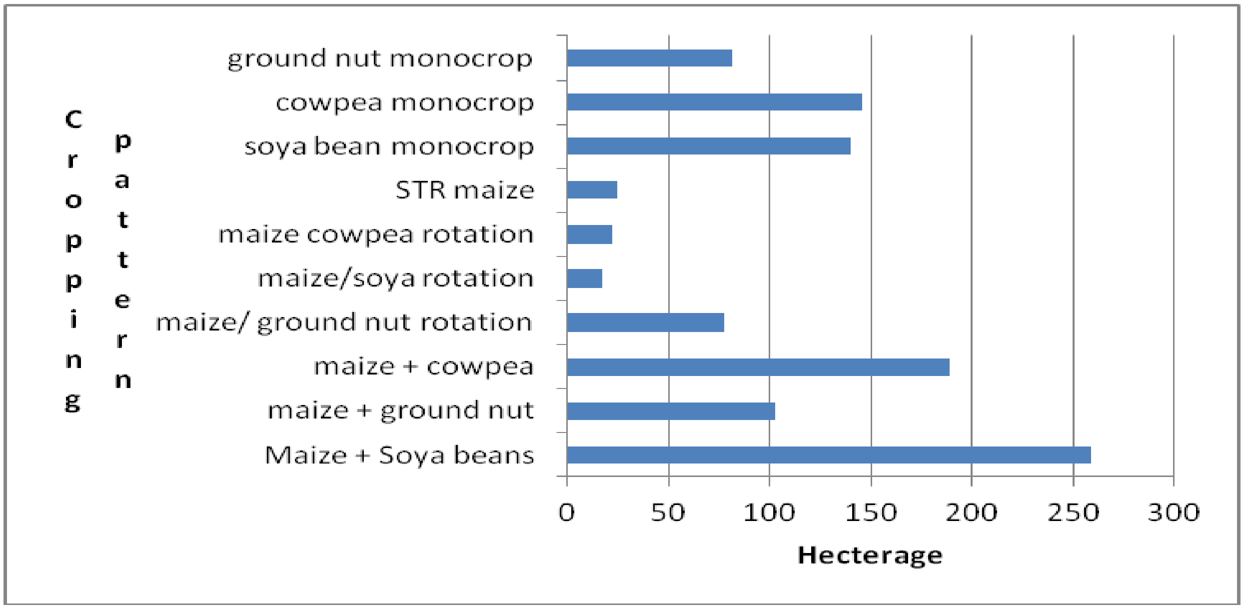

Figure 9.1: Cropping pattern coverage in hectares
Source: ISMA Survey data 2012-2013

The traditional methods of *Striga* control employed by farmers in the study area is presented in Figure 9.2. About 60% of farmers used hand pulling, which is labour intensive but effective; 22% used manure; 12.8% used weeding; and 0.6% verbally cursed the *Striga* (spiritual belief) to control *Striga* in their fields.

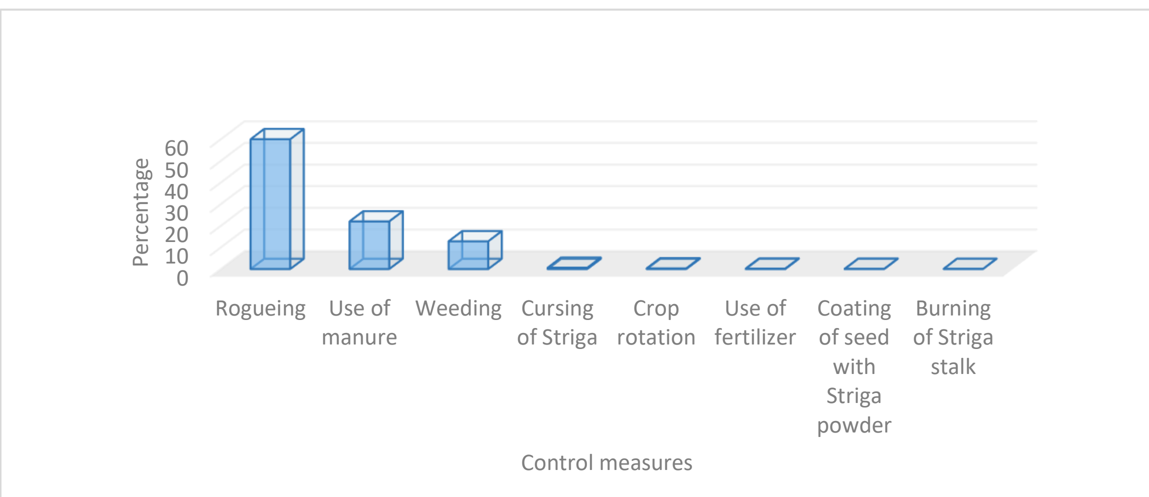

Figure 9.2: The percentage distribution of traditional ways of *Striga* control
Source: ISMA Survey data 2012

Neither of these methods effectively suppress the menace of *Striga* because the *Striga* seed bank in the soil is not adequately being taken care of. As indicated in Table 9.4, the cropped land was increasing annually. This finding concurred with that of De Janvry *et al.*, (2010) , who found that agricultural production in African rose through land expansion rather than productivity. However, although the decline was not significant, the proportion of land under *Striga* infestation reduced from 43.5% in 2010 to 42.34% in 2011.

Table 9.4: Trend of cropped land area and land infested with *Striga*

Production year	Total land cropped (ha)	Land infested with *Striga* (ha)	Percentage affected with *Striga*
2008/2009	2,756	1,199	43.51%
2009/2010	2,828	1,213	42.89%
2010/2011	2,909	1,232	42.34%
2011/2012	3,130	NA	NA

Note: NA = Not available
Source: ISMA Survey data 2012-2013

9.4.3 Distribution of land based on maize under cultivation

The majority (48.7%) of the farmers, as indicated in Table 9.5, believed that *Striga* could cause crop yield loss of between 35% and 64%, while 37% believed that it could cause a yield loss of 65% to 100%, which would aggravate the farmers' poverty and food insecurity situation.

Table 9.5: Distribution of farmers based on perceived level of *Striga* damage

Damage level	Frequency	Percentage
High (65-100%)	187	36.9%
Moderate (35-64%)	247	48.7%
Low (0-34%)	73	14.4%

Source: ISMA Survey data 2012-2013

9.4.4 Economic assessment of the different maize enterprises

Different varieties of maize are grown by farmers in northern Nigeria. However, open-pollinated varieties (OPVs) are most commonly grown and are found across most of the communities. The OPVs are very much susceptible to *Striga*. Two new hybrid varieties were introduced, namely the Imazapyr-resistant hybrid 1 (IRM1) and Imazapyr-resistant hybrid 2 (IRM2), code-named by the breeders. Their performance regarding yield and tolerance to *Striga* were compared to farmer variety. The gross yield, GM and GR of the hybrids and the farmer variety are shown in Tables 9.6 and 9.7 for the Kano and Bauchi States.

The difference in the maize grain yield between IRM varieties and the farmer variety were obtained and compared, the three maize entries having been grown by the same farmer and under the same conditions. The likely yield difference might be due to the kind of maize variety grown. A pair-wise comparison of yield between the two maize varieties indicate that the mean grain yield obtained in the Kano State was 2.83 ton/ha for IRM1, 2.5 ton/ha for IRM2, both significantly higher at ($p<0.01$) and ($p<0.05$) than the yield obtained from farmer variety (1.96 ton/ha). Furthermore, the yield difference in the Bauchi State was also statistically significant at ($p<0.01$) between the yields of 1.92 ton/ha for IRM1 and 1.92 ton/ha for IRM2 when compared to farmer variety of 1.52 ton/ha.

Table 9.6: Results of the on-farm trials across the Kano State

Item N = 25	Calculated difference between the scenarios		
	Farmer variety	**IR Hybrid 1**	**IR Hybrid 2**
1. Average yield (kg/ha)	2,174.50	3,139.50	2,848.00
2. Adjusted yield (1x0.9)	1,957.00	2,825.50	2,563.20
3. Price per kg (US$0.44)	0.44	0.44	0.44
4. Gross farm gate revenue (US$/ha) 2x3	861.08	1,243.22	1,127.81
5. Total variable cost (TVC) (US$/ha)	801.06	892.34	870.65
6. Gross margin (GM) (revenue – total variable costs (TVC)) (US$/ha)	60.02	350.88	257.16
Gross revenue (GR) paired t-test comparison			
Local Vs IRM1: -t = 3.35***	Local Vs IRM2: -t = 2.190**	IRM1 Vs IRM2: t = 0.984 N^S	
Total variable costs (TVCs)			
Local Vs IRM1: -t = 0.00199 N^S	Local Vs IRM2: -t = 0.00509 N^S	IRM1 Vs IRM2: t = 0.0119 N^S	
Gross yield			
Local Vs IRM1: -t = 3.67***	Local Vs IRM2: -t = 2.43**	IRM1 Vs IRM2: -t = 0.957N^s	

Notes: ***Significant difference at 1%, **5%, *10%
US$1 = ₦162 at the time of the survey
Source: ISMA Survey data 2012-2013

In the Kano State, the yield increase between farmer variety and varieties IRM1 and IRM2 was 26.5% and 27%, respectively. A yield increase of about 44.3% from IRM1 and 31% from IRM2 over the farmer variety was also obtained in the Bauchi State. There was no significant difference between the yield obtained from IRM1 and IRM2 in the two states. This finding also agreed with those of Mignouna *et al.* (2011a) and Mignouna *et al.* (2011c) in their studies of *Striga* control in which the IRM that they used in western Kenya also out-performed the farmer variety.

There was a significant increase at ($p<0.01$) in net benefit obtained from IRMs hybrids across the Bauchi and Kano States, as shown in Tables 9.6 and 9.7. However, there was no significant difference in terms of total operational costs incurred between the three varieties across the two states, as shown in Tables 9.6 and 9.7. These results confirm the positive contribution to maize output and the net benefits from using IRM hybrid varieties.

Table 9.7: Results of the on-farm trials across the Bauchi State

Item N = 25	**Calculated difference between the scenarios**		
	Farmer variety	**IR Hybrid 1**	**IR Hybrid 2**
1. Average yield (kg/ha)	1,684.00	2,130.00	2,137.00
2. Adjusted yield (1x0.9)	1,515.70	1,917.00	1,923.00
3. Price per kg ($)	0.43	0.43	0.43
4. Gross farm gate revenue (US$/ha)	651.75	824.31	826.89
5. Total variable cost (TVC) (US$/ha)	561.05	562.21	560.62
6. Gross margin (GM) (revenue – total variable costs (TVCs)) (US$/ha)	90.70	262.10	266.27
Yield kg/ha paired t-test comparison			
Local Vs IRM1: -t = 2.67***	Local Vs IRM2: -t = 3.06***	IRM1 Vs IRM2: -t = N^s	
Total variable costs (TVCs)			
Local Vs IRM1: -t = 0.00286 N^S	Local Vs IRM2: t = 0.00107N^S	IRM1 Vs IRM2: t = 0.003933N^S	
Gross revenue (GR)			
Local Vs IRM1: -t = 3.53***	Local Vs IRM2: -t = 3.18***	IRM1Vs IRM2: -t = 0.957N^s	

Note: ***Significant difference at 1%, **5%, *10%
Source: ISMA Survey data 2012-2013

9.4.5 Economic viability of IRM technologies using dominance analysis

In a dominance analysis, treatment is said to be dominated when a higher total variable input cost is incurred to earn the same or a lower net benefit when compared to other treatments. The treatments are organised in descending order of amount of the TVCs incurred (Badu-Apraku *et al.*, 2012). The results from the Kano State does not indicate any dominating treatment because of the correlation between variable input costs and benefits, while IRM2 in the Bauchi State dominated other treatments as it incurred the least VCs and highest benefit, as shown in Table 9.8. The economic viability parameters extracted from Tables 9.6 and 9.7 is presented in Table 9.8.

Table 9.8: Results of the dominance analysis of the on-farm trials in the Bauchi and Kano States

Net Benefit ($)		Treatment		Variable cost (VC) ($)	
Kano	**Bauchi**	**Kano**	**Bauchi**	**Kano**	**Bauchi**
1243.22	824.31	IRM1	IRM1	892.34	562.21
1127.81	826.89	IRM2	IRM2***	870.65	560.62
861.08	651.75	Farmer variety	Farmer variety	801.06	561.05

Note: *** is dominant over other treatments.
Source: ISMA Survey data 2012

9.4.6 Analysis using residuals of on-farm trials in the Bauchi and Kano States

The change in the net profit and acceptable minimum return produces the residuals of each treatment. Analysis using residuals is used as a decision criterion, which recommends treatment with the highest residual as the best investment, as shown in Table 9.9. In the study area, the average interest rate charge for agricultural purposes per annum was 36% and the production cycle maximum period was six months. Therefore, the farm would pay about 18% interest in using borrowed capital, considering return to management at 50%. Therefore, the acceptable minimum return that farmers can expect to earn from an investment is the acceptable minimum rate of return (AMRR) which covers the cost of borrowing capital and return to management. Any investment that yielded a return below the acceptable minimum render the technology or investment not sustainable. In this study, AMRR, which represents the total cost of capital and returns to management, was 68%.

Decision criterion: The guideline used to make a recommendation is referred to as decision criterion. In this study, the decision criterion is a higher or equal MRR above the acceptable minimum rate of return. For the Kano State, only the IRM1 enterprise should be recommended, because of the residual value being above AMRR. In the Bauchi State, the farmer variety has a residual value below the AMRR, which justifies the rejection of the enterprise, while IRM1 and IRM2 residuals are all above the AMRR (as shown in Table 9.9) and are therefore recommended.

Table 9.9: Results of the on-farm trials using residuals analysis in the Bauchi and Kano States

Item	Treatments					
	Farmer variety		IRM1		IRM2	
	Kano	Bauchi	Kano	Bauchi	Kano	Bauchi
Net benefit (US$)	861.08	651.75	1243.22	824.31	1127.81	826.89
Total variable input US$/ha)	801.06	561.05	892.34	562.21	870.65	560.62
AMRR (%)	68%	68%	68%	68%	68%	68%
AMRR (US$/ha) (2 x 68÷100)	544.72	381.52	606.79	382.30	592.05	381.22
Residuals(US$/ha)	315.10	266.50	634.68	437.27	534.17	441.00

Source: Field trials 2012-13

Table 9.10: Results of the marginal analysis of on-farm trials across the Kano and Bauchi States

	Treatments		
	Farmer variety (variety 1)	IRM2 (variety 2)	IRM1 (variety 3)
KANO			
1. Net benefit (US$/ha)	859.81	1126.23	1241.48
2. Change in net benefit (US$/ha)		266.41	115.25
Change in net benefit between 3 and 1			381.66
3. Total variable input costs (US$/ha)	801.06	870.65	892.34
4. Change in total variable costs (TVCs) (US$/ha)		69.59	3513.88
Change in cost between 3 and 1			91.28
5. Marginal rate of return		383.00	3.28
6. Marginal rate of return from 1 to 3			418.00
BAUCHI			
1. Net benefit (US$/ha)	648.00	819.00	822.00
2. Change in net benefit (US$/ha)		171.57	2.57
Change in net benefit between 3 and 1			174.14
3. Total variable input costs (US$/ha)	561.00	562.00	561.00
4. Change in total variable costs (TVC) (US$/ha)		1.15	1.59
Change in cost between 3 and 1			0.43
5. Marginal rate of return		149.00	161.00
6. Marginal rate of return from 1 to 3			405.00

Source: Field trials 2012-13

As indicated in Table 9.10, IRM1 dominated other treatments in the Kano State, while in IRM2 dominated other treatments in the Bauchi State. Across these two states under *Striga* infestation, the IRM varieties produced higher yield than that of the farmer variety.

9.5 Summary and conclusion

This study focused on three varieties (farmer variety, IRM1 and IRM2) of maize used in the farmers' field under natural *Striga* infestation, analysing the performance of IRM varieties in the study area. The potential of IRMs, regarding both suppressing Striga parasitism and increasing yields in the study area, excelled that of the farmer variety. According to the GMs and AMRRs, the findings also demonstrated that the two IRM varieties have higher productivity under *Striga* infestation across the study areas. The highest GM was recorded from IRM1 in Kano and IRM2 in Bauchi, thus, making these varieties viable and potential options for adoption by farmers in northern Nigeria, whose land is affected by *Striga.*

The result of the dominance, residual and marginal analyses gave a higher return in terms of investment portfolios. IRM hybrid technology will, therefore, be of paramount importance in the strategic plan to eradicate *Striga* in maize fields. It should hence be given priority in northern Nigeria because of it exhibiting an extensive range of variation in growth, production and quality characteristics. However, further investigation and trials need to be carried out to improve the performance of the crop in a manner that is economical and environmentally and socially sustainable within the ambit of increasing farm income and food security. Plant density could also be increased in Kenya, as reported by Illa *et al.* (2010), where the yield of IRM increased by more than double when the plant density was increased from 44,000 to 88,000 plant stands per hectare. Finally, policy should target the strengthening of IRM varieties availability to farming households, since this has the potential of increasing the intensity and the usage of IRM varieties in the study area to attain sustainable maize-based production.

Having achieved the four specific objectives of the research, the next chapter, summarises the empirical findings of the study and elucidates some key policy recommendations. Areas for further research is also included in Chapter 10.

CHAPTER 10

SUMMARY, CONCLUSIONS, RECOMMENDATIONS AND AREAS FOR FURTHER RESEARCH

10.1 A recap of the research

Maize is a major staple food crop grown across agro-ecological zones and production systems in SSA. About 95% of maize is consumed in different food options across many communities of various sociocultural backgrounds. Maize is the major cereal consumed by both livestock and human beings and makes out a major share of everyday food. Maize is also the major cereal marketed after sorghum and millet in Nigeria. Food security and cereal production are interrelated in a country like Nigeria with a vast rural and farming population. Consequently, factors that affect cereal production have a direct impact on food security as the majority of poor population depends on cereals as they are comparatively cheaper than any other form of diet.

However, despite the importance of maize and its potential to increase productivity, maize production is constrained by many challenges, comprising low and erratic rainfall, long dry seasons, poor soil fertility and *Striga*. For the past number of decades, IITA, in collaboration with NARIs, developed some promising early-maturing maize and STR varieties which met the requirements of small-scale farmers and which was disseminated in northern Nigeria and West Africa savannah at large.

Maize is highly susceptible to *Striga* parasite and causes huge damage to the host plant across the main maize producing areas of the continent (AATF, 2006). A collection of available data suggests that *Striga* had invaded 2.4 million ha of land under maize, inflicting yield losses of about 1.6 million tons per annum, which amounts to a total annual value of about US$383 million (AATF, 2006). In Nigeria, *Striga* is most severe in the northern region where it infests 835,000 ha, causing annual maize losses of an estimated 505,308 tons, valued at US$205.66 million per year (AATF, 2006).

Striga depresses maize yield by 20% to 100%, often leaving farmers with little or no food grain at harvest. Losses from *Striga* alone account for about 100% of Nigeria’s deficit in maize. However, the greatest losses are suffered by millions of small-scale farmers, who see their crops destroyed annually, unable to produce enough food to nourish their families or make some obvious improvements in their livelihoods. Too many farmers have developed the attitude toward *Striga*, that they were born and expected to die with *Striga* in their fields, since it follows them everywhere they go.

Small-scale farmers suffer more from parasitic weeds because they do not have the resources to buy inputs and are rigid in their cropping systems. With the growing population pressure in Nigeria and increase in cropping intensities, *Striga* is becoming a serious problem, mostly in areas with poor soil fertility, sandy soils and low rainfall where host plants are too weak to compete for nutrients, water and light (Singh & Emechebe, 1997a). *Striga* plants are hard to manage because their seeds are produced in enormous amounts and their dormancy or mechanisms for adaptation allow the seeds to stay alive in the soil for several years. It is believed that the *Striga* problem cannot be suppressed and solved through a single approach but rather through an integrated approach (Oswald & Ransom, 2004). Therefore, adoption of crop resistance, chemical control, crop rotation, seed treatment, biological control, and other phytosanitary practices were deployed in the Bauchi and Kano States of Nigeria in order to achieve satisfactory and sustainable control through the ISM programme (Singh & Emechebe, 1997a; Singh & Emechebe, 1997b).

IITA, in collaboration with NARIs and some universities, have developed varieties of improved maize that have a high grain yield cum *Striga* tolerant and resistant. However, considering the economic importance of cereal production, maize in particular, in Nigeria and the suitability and volume of investment made towards improving its productivity, there is a need to understand why many farmers are not adopting ISM technologies despite its suitability and ease of application.

There has also been no study so far that explored the prospects of the use of ISM technology adoption and its economic benefits to farmers in northern Nigeria. This study was, therefore, an attempt to explore those knowledge gaps. It also provided an opportunity to arrive at relevant policy and management implications to inform future strategies in the agricultural sector, particularly in maize production. The specific objectives of the study were to:

(i) identify the socioeconomic characteristics of the maize-producing household and their perceptions of ISM technology attributes in the study area;

(ii) determine factors influencing potential adoption and intensity of adoption of ISM technologies by farming households in the study area;

(iii) estimate the potential impact of ISM technology adoption on livelihood improvement, income and food security of maize-farming households in the study area; and

(iv) assess the financial and economic profitability of, and identify the constraints to, adoption of ISM technologies at smallholder farm level in the study area. These specific objectives were addressed by using various conceptual and empirical models.

The first objective was achieved by using descriptive statistics to analyse the data by means of t-tests and chi-square for continuous and categorical variables. In Chapter 3, farmers' socio-economic characteristics between the ISMA project and NPIAs, between ISM technology adopters and non-adopters, and their general perceptions of the technologies were analysed. Adoption rates and indices were employed to measure the penetration and performance indices, which are indicators used to evaluate the acceptability or success levels of the deployed technologies to farmers in the study areas. The performance index indicates the real number of farmers reached from the targeted number of sampled households that should have been reached. The penetration index shows the number of households from the actual number reached, who actually adopted ISM technologies. The data used for this study were collected by using a multi-stage sampling procedure from a cross-section of 643 respondents, selected from 80 communities (353 adopters and 290 non-adopters from both PIAs and NPIAs. The results revealed a significant overall adoption rate of 55% of all the technologies of the targeted population across the two states (multiple responses were considered). In the Bauchi State, a 52% adoption rate was achieved for at least one technology, while the adoption rate reported for the Kano State for at least one technology was 48%. The performance difference in the ISM technology adoption is 11% between project intervention and NPIAs.

Factors influencing adoption and intensity of adoption among smallholder farmers was analysed in Chapter 4. The econometric analysis employed the DH approach, which involved a probit model as the first hurdle and a truncated regression as the second hurdle, to identifying the factors influencing adoption and the intensity of adoption of ISMA technologies among the sample of smallholder farmers. This model assumes that farm households must cross two hurdles in order to adopt the technology. The first hurdle is the decision to adopt or not (probability of adoption) while the second hurdle is sharing the land that allocated for the technology (intensity of adoption), which is conditional on the first decision. The model allows for the probability of adoption and the intensity of adoption (with various explanatory variables). Even variables appearing in both hurdles may have different effects. The results suggest that farmers who are better off in terms of exogenous income and living further away from extension offices are less likely to adopt ISM technologies, while farmers with higher farm income, awareness of the technology, participation in on-farm trials, access to cash remittances and contact with extension agents are more likely to adopt these technologies ($p<0.01$). Marital status, household size, farm size and access to cash remittances are the most significant variables influencing the intensity of adoption. In the study area, maize farmers who adopted ISM technologies were found to attain higher maize yield when compared to non-adopters. This may lead to a positive increase in total farm income.

By controlling the confounding factors such as farm level and farmer characteristics, resource endowments and other factors that are exogenous in nature, the difference in the impact of ISM technology adoption on farm incomes using an ESR model were examined in Chapter 6. The ESR accounts for possible sample selectivity bias as well as for endogeneity. The study compared the expected farm income under real adoption with the counterfactual situations that the household adopted ISM technology or not, and applied this procedure to the household survey data collected in 2014. The findings indicate that ISM technologies have a positive effect on farm income, as measured by farm income levels PAE. Findings further indicate that ISM adoption increased farm income PAE unit by 66%. However, the impact of technology on farm income is smaller for farmers who did adopt the technology than for farmers who did not adopt in the counterfactual situation that they adopted the technology. The FGT approach was employed in Chapter 6 and used to provide a sign of the poverty incidence, poverty depth and severity of poverty in the study area. The treatment procedure determines the impact of ISM technology adoption on farm productivity. The findings in this chapter are critical to both public and private bodies that targeted intervention to reduce poverty and food insecurity in accordance with the proof provided by the ISMA project intervention.

Economic indicator methods were used in Chapter 7 to determine the viability and profitability of ISMA projects by using several financial ratios, including GM analysis, break-even analysis, payback period analysis, NPV, the BCR and IRR.

Finally, Chapter 8 assessed and analysed the economic benefit of some selected ISM technologies from among farmers who participated in the on-farm trials and demonstrations across various communities in the study areas. Estimates of the maize-legume rotations and IRM were compared with estimated GM estimates of the farmer or local practices. Primary data was collected from 148 farmers who tried maize-legume rotations for two years and 50 farmers who tried IRM technologies. These farmers' plots were monitored over the entire production cycle and input-output data was captured. The data was used to estimate income, average cost of production, and other financial analyses.

The remainder of this chapter presents the conclusions (section 10.2), followed by key policy recommendations (section 10.3), the implementation of which could promote ISM technology adoption and intensity of adoption towards eradication of *Striga* on farmers' fields, and enhance household food security in northern Nigeria. Section 10.4 describes the limitations of the study and, finally, section 10.5 concludes the chapter with suggestions for further research.

10.2 General conclusions

This first objective of the study sought to examine the diffusion and adoption rates of ISM technologies in the Bauchi and Kano States of northern Nigeria, since several studies had indicated that *Striga* parasites can only be controlled through an integrated approach. The approaches adopted were maize-legume rotation, *Striga*-resistant maize varieties, herbicide-resistant maize, improved soya bean varieties and cowpea. The adoption rate was greater in the PIAs in comparison with the NPIAs of the project. However, because of the organised field days' effects, farmers from the NPIAs were exposed to the technologies. The adoption rate in the non-project site was excellent, as the performance difference between the two areas was 11%. The results demonstrate the effectiveness of creating awareness through on-farm trial evaluations with farmers in organised field days, which speeds up the adoption of the ISM technologies. Thus, scaling out of the technologies to non-project areas is most likely to help adopters make more informed decisions in eradicating *Striga* in their fields.

Under the second specific objective of this study, it was found that adopters differ significantly from non-adopters in their demographics characteristics. This indicates the existence of variation between the two groups. Thus, using OLS to determine factors influencing the adoption of ISM technologies and adoption intensity would be biased. Therefore, the study applied a DH method to analyse these factors among maize-producing farmers. The results show that farmers with higher exogenous income and located further from extension offices are less likely to adopt ISM technologies. By implication, farmers with other means of income could afford to purchase nitrogenous fertilizer, such as urea, which is also very effective in ameliorating *Striga* damages but which the poor among them could not afford. In addition, households that are located very far from an extension office are less likely to get in touch with extension agents, which reduce or slow their chances of having access to newly introduced technology when compared to those closer to an extension office. Sampled households with higher farm income, polygamous households, past participation in on-farm trials, awareness of the technology, contact with extension agents and access to cash remittances are more likely to influence adoption of ISM technologies positively. The implication is that any policy that will encourage the provision of these factors among smallholder farmers will ultimately encourage ISM technology adoption. Polygamous households, households with a larger family size, households that have access to cash remittances and those with larger farm sizes are more likely to intensify ISM technology adoption. Access to the financial market will offer the needed financial capitals to acquire ISM technologies that can withstand the threat of *Striga*.

Under the third objective of the study, the contributing impact of adoption of ISM technologies was estimated by using TE regression. This helped to estimate the impact of adoption of ISM technologies by controlling the role of selectivity bias on adoption decisions and production. Two major conclusions can be drawn from this study on the effect of ISM technology adoption on farmers' productivity. Firstly, the adopters of ISM technologies have systematically different demographic characteristics in comparison to non-adopters. These dissimilarities could represent sources of variation in productivity between adopters and non-adopters. Therefore, estimation, using an OLS regression model with a dummy variable for adoption, cannot take the variation into account. Secondly, factors influencing the intensity of adoption are different from the factors influencing the decision to adopt, thus justifying the use of the DH approach. These results revealed that maize productivity under *Striga* infestation significantly increased after the adoption of ISM technologies in the PIAs, as well as in the NPIAs prior to project implementation. The adoption of ISM technologies also led to a significant increase in maize productivity under *Striga* infestation, which led to increased income per hectare. Therefore, the ISMA project intervention provide farmers with access to production inputs and, especially *Striga*-resistant maize and improved legumes such as soya beans and cowpea, could potentially be a way forward to reduce poverty among smallholder farmers in *Striga*-infested areas of rural northern Nigeria. The results from the TE regression suggest that adopters of ISM technologies have significantly higher productivity (47% yield per hectare) than non-adopters, which could translate into higher farm income PAE, even after all the confounding factors are controlled. Findings from this study confirm the possible and direct role of ISM technology adoption in improving smallholder farm income, and eventually their livelihood, as a result of the increase in maize productivity obtained from the use of improved *Striga* management technology.

The study also investigated whether there are differences in farm income of sampled households that adopted ISM technologies and those that did not adopt in counterfactual situations. Because technology adoption is not random, the study used ESR to account for the heterogeneity effect in the decision to adopt or not to adopt, and also for unobservable characteristics of the sampled households to address the problem of endogeneity. The findings indicate that ISM technologies have a positive effect on farmers' income, as measured PAE. However, the impact on farm income is smaller for households that did adopt ISM technologies (adopters) when compared to households that did not adopt (non-adopters) in the counterfactual situation that they adopted the technology. This suggests, if non-adopters did adopt, they could likely have higher incomes than adopters could in the non-counterfactual situation. The results show that ISM technologies will be beneficial to all the households from the second (counterfactual) group, had all of them adopted. Also, the result from FGT shows that adopters are less poor the non-adopters regarding income PAE. Therefore, ISM technology adoption seems to be more important to poor households, those who have the least capability to generate minimum income, since it could help them bridge the income gap to non-poor households.

The results of the economic analysis of ISM technologies used by farmers prove that GMs, BCRs, and net benefit per capita for ISM technologies are positive across all locations. Moreover, the results demonstrate that NPB can be obtained from the use of ISC measures over farmer practice. This suggests that farmers can recover costs incurred for adopting the new technologies and generate positive income balances. ISM technologies would occupy a central role in the design of

Striga-eradication campaign initiatives and sustainable management in maize fields and, therefore, it should be prioritised, particularly in *Striga*-infested areas of northern Nigeria.

Results from the selected on-farm trials suggest that continuous cultivation of maize on the same plot will increase *Striga* infestation and reduce maize yield. However, rotation of STR maize and grain legumes, such as improved soya bean, can reduce *Striga* infestation and increase maize grain yield, with a positive impact on farmers' income and food security. Results from the rotation study can be useful in targeting smallholder farmers because of its low input nature. Legumes, especially cowpea and soya bean, enhances soil fertility, enriches the farmer's diet and does not require herbicides or pollute the environment.

The second aspect of the on-farm trial study focused on the three varieties of maize (local variety, Imazapyr-resistant hybrid 1 (IRM1), and Imazapyr-resistant hybrid 2 (IRM2)) that were used on the farmers' *Striga*-infested fields. The study analysed the performance of IRM varieties across the two states. The potential of IRM regarding suppressing *Striga* parasitism and increasing yields and productivity in northern Nigeria exceed that of the farmer variety. Farmers in the villages surrounding the trial sites, who were at the sites for participatory on-farm evaluation during field days, saw the economic merit of the IRMs and showed interest in adopting the technology in the next season. The highest GMs were recorded for IRM1 in Kano and IRM2 in Bauchi, thus making them viable and potential options for adoption by farmers in northern Nigeria. Results from the dominance, residual and marginal analyses gave higher values regarding investment portfolios. IRM hybrid technology will, therefore, be of paramount importance in the strategic plan to eradicate *Striga* in maize fields, meaning that it should be given the due priority in northern Nigeria.

These results would be most useful and effective in policy designs for sustainable *Striga* management in Africa. Public policies, non-governmental organisations and community-based organisation interventions can play a major part in helping farmers adopt ISM technologies. The facilitation of access to extension, establishing on-farm trials and conducting field days are of great importance in defining the execution of ISM for sustainable development in Africa, which could translate into more food security for households, irrespective of their unobservable characteristics. In addition, the accessibility of information on ISM technologies may increase farmers' consciousness and ability to manage *Striga*. Extension services is the backbone of agricultural education and information, for example, delivering information on the cereal-legume rotation practice that can enhance crop productivity gains and trigger suicide germination of *Striga*, resulting in a reduction of *Striga* seed banks on farms.

10.3 Recommendations for policy

The empirical findings in Chapters 3 to 9 suggest that the adoption of ISM technologies among smallholder farmers should be improved and concerted efforts made to intensify awareness creation. The rates of adoption indicated farmers' inclinations to implement maize-legume rotations and maize varieties that are *Striga* resistant. Hence, there is a need for increasing efforts by government agencies and extension organisations, such as ADPs and RBDAs, to promote the deployment of technologies that display good adoption rates among farmers.

The intervention project should liaise with other institutions and private organisations with an obligation for cereal crops to accelerate the adoption of STR maize, for example, millet and sorghum that farmers frequently grow with maize and cowpea as an intercrop. *Striga* management technology intervention will reduce infestation through *Striga*-resistant millet, and sorghum may enhance the adoption of STR maize. This will lead to better *Striga* management in the intervention communities and beyond, since both millet and sorghum are major hosts to *Striga*.

The adoption model results showed factors likely to influence integrated *Striga* management technologies are agricultural information such as extension contact, past participation in on-farm trials, field day attendance and yield increase from adoption. The economic analysis of the different maize enterprises under *Striga* infestation showed higher farm output and return on investment from adopters of ISM technologies, particularly those of *Striga*-resistant maize and the cereal-legume rotation with *Striga*-resistant maize. These technologies are readily available, and effort should be geared towards the scaling out and up of these promising technologies to other communities and regions infested with *Striga,* especially among smallholder farmers.

There is a need for a data-monitoring and evaluation unit within the ISMA project that will facilitate the monitoring and evaluation of the impact of ISM technology adoption through comprehensive data collection and processing, specifically for tracking impact variables for each technology across communities and farm levels. This will help to identify a targeted intervention approach to areas with a high propensity to the adoption of a particular technology. Considering the quantum of achievement after implementing the project over four years, there is a need for an early impact project evaluation to assess the real impact of particular ISM technologies on farmers and communities regarding improved welfare.

This can be achieved through mass public education and awareness programmes, in addition to on-farm trials and field days to improve public knowledge about ISM technologies, training in STR maize seed production and provision of extension services. Currently, ADPs are the only bodies with the capacity to provide training expertise on all newly developed agricultural technologies in the country. However, considering their low complement of staff, it would take time to impart the required skills to a substantial number of farmers and communities. In response to this challenge, the government should consider increasing the number of staff and their facilities, alternatively, establish strong alliances with NGOs to complement its training and extension services. Another option already adopted by the project is the training of lead farmers and community seed production and seed vendors across many locations, and enhancing and scaling it out further.

Henceforward, policies that are intended to increase maize productivity in *Striga*-infested areas through improved *Striga* management need to include ISM technologies as a core component if meaningful results are anticipated. The study also recommends policies that will ease access to production loans from flexible financial institutions such as commercial banks, BOA and other farmer cooperative financing agencies. This will improve farmers' liquidity and thereby increase their potential to adopt improved agricultural technologies, especially ISM technologies. Above all, the most needed action would be an improvement of farmers' access to extension services, as revealed by the findings of this study, since access to extension information is a reliable source of agricultural production information among farmers, particularly those from rural communities. It implies that an integrated approach to *Striga* management is beneficial to smallholder farmers and needs to be scaled out to other areas facing *Striga* infestation.

Therefore, an investment in a significantly positive public-private partnership and technology transfer is required to improve the use of ISM technologies. In turn, this would improve the adaptive capacity of farming households and communities against *Striga* in northern Nigeria. Thus, government policies should promote the adoption of this technology among farming households in northern Nigeria. This could be achieved by making provision of STR maize foundation seeds as a component of agricultural transformation. The states and local governments should also facilitate the scaling out of this technology through an IP in which all the stakeholders (researchers, extension agents, seed companies, farmer groups and farmers) can participate to conduct more on-farm research trials and demonstrations, and attend field days.

The addition of soya beans will be of immense importance in crop production systems as diversification of farmers' investment. Presently, soya beans have minor pests in Nigeria and West Africa in general. There is a great local and international market potential for soya beans, as demand for it almost doubled that of maize over the last decade because of its use in preparing many modern and traditional foods. Additionally, it enhances soil fertility and help reduce *Striga* seed bank triggering through suicidal germination of *Striga* in the soil. Therefore, soya bean varieties that are carefully chosen could yield many benefits to farmers and their livestock.

10.4 Limitations of the study

The study relied on cross-sectional data collected from a single agricultural production season. As such, more research insight could have been gathered if the study had covered more cropping seasons across the country. Also, the use of panel data collected over many years could have improved the understanding and underlying forces of smallholder maize farming. Furthermore, since policy changes impact on agricultural production, analysis over a longer period could have enabled a detailed explanation of the impact of structural changes on the performance of ISM technologies within the PIA and NPIAs.

10.5 Directions for future research

The majority of participants in the surveyed communities are male, especially in the Kano State. This justifies the need for future research to investigate the dynamics behind it and determine the implications of ISM technologies on the empowerment of women and household welfare. It can be hypothesised that ISM technologies positively contribute towards the economic empowerment of men. Furthermore, the importance of social networks in agricultural production systems and collective action also requires further investigation.

More research effort should be focused on the unique role of the different technologies that form part of the ISM and the identification of the most effective ones, particularly the IRM and the Bio-control options in rotation with legumes.

Finally, to understand the full potential impact of adopting ISM technologies, further research is needed to measure and quantify its indirect effects (e.g. on farm wages, employment and food prices as it relates to consumers), its nutritional benefits, the change in *Striga* levels and the severity in the production or cropping systems. The performance and efficiency of community seed producers can also be compared with the private seed companies regarding the cost of production and the accrued benefit, and the development of strategies for market penetration and value chain analysis.

REFERENCES

AATF (African Agricultural Technology Foundation). 2005. A New Bridge to Sustainable Agricultural Development in Africa. Nairobi, Kenya: African Agricultural Technology Foundation.

AATF (African Agricultural Technology Foundation). 2006. Empowering African farmers to eradicate Striga from maize croplands: annual report African Agricultural Technology Foundation, Nairobi, Kenya.

AATF (African Agricultural Technology Foundation). 2008a. Delivering the promise: impacting lives with new technologies. Nairobi, Kenya: African Agricultural Technology Foundation.

AATF (African Agricultural Technology Foundation). 2008b. Striga control in maize - managing a cereal killer, AATF project brief http://www.aatf-africa.org/userfiles/Striga-Project-brief.pdf accessed 21/02/2013. Nairobi, Kenya.

AATF (African Agricultural Technology Foundation). 2009. African Agricultural Technology Foundation : Closer to the promise from lab to field. Nairobi, Kenya. 54pp: African Agricultural Technology Foundation.

Abadie, A. 2003. Semiparametric instrumental variable estimation of treatment response models. *Journal of Econometrics* 113 (2):231-263.

Adegbola, P. and Gardebroek, C. 2007. The effect of information sources on technology adoption and modification decisions. *Agricultural Economics* 37 (1):55-65.

Adesina, A.A. and Baidu-Forson, J. 1995. Farmers' perceptions and adoption of new agricultural technology: evidence from analysis in Burkina Faso and Guinea, West Africa. *Agricultural Economics* 13 (1):1-9.

Adesina, A.A., Mbila, D., Nkamleu, G.B. and Endamana, D. 2000. Econometric analysis of the determinants of adoption of alley farming by farmers in the forest zone of southwest Cameroon. *Agriculture, Ecosystems & Environment* 80 (3):255-265.

Adesina, A.A. and Zinnah, M.M. 1993. Technology characteristics, farmers' perceptions and adoption decisions: A Tobit model application in Sierra Leone. *Agricultural Economics* 9 (4):297-311.

Adetunji, O. 2006. Creating appropriate technology as a means of waste minimization in cassava end products.

African Fertilizer Summit. 2006. Abuja declaration on fertilizer for African Green Revolution.

Ahmed, M.M., Masters, W.A. and Sanders, J.H. 1995. Returns from research in economies with policy distortions: hybrid sorghum in Sudan. *Agricultural Economics* 12 (2):183-192.

Akpan, S., Nkanta, V.S. and Essien, U. 2012a. A double-hurdle model of fertilizer adoption and optimum use among farmers in southern Nigeria. *Tropicultura* 30 (4):249-253.

Akpan, S.B., Patrick, I.V. and Udoka, S.J. 2012b. Stochastic Profit Efficiency of Homestead based Cassava Farmers in Southern Nigeria". *Asian Journal of Agriculture and Rural Development* 2 (3):498-505.

Albert, H. 1999. *Farmers in northern Ghana and the problem of Striga, in Advances in Parasitic Weed Control at On-Farm Level, Joint Action to Control Striga in Africa* Margraf Verlag, Wekersheim, Germany

Alene, A., Manyong, V., Gockowski, J., Coulibaly, O. and Abele, S. 2006. *A framework for conceptualizing impact assessment and promoting impact culture in agricultural research.* IITA.

Alene, A.D. and Manyong, V. 2007. The effects of education on agricultural productivity under traditional and improved technology in northern Nigeria: an endogenous switching regression analysis. *Empirical Economics* 32 (1):141-159.

Alene, A.D., Poonyth, D. and Hassan, R.M. 2000. Determinants of adoption and intensity of use of improved maize varieties in the central highlands of Ethiopia: A tobit analysis. *Agrekon* 39 (4):633-643.

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

Amaza, P., Abdoulaye, T., Kwaghe, P. and Tegbaru, A. 2009. Changes in household food security and poverty status in PROSAB area of Southern Borno State, Nigeria. *International Institute of Tropical Agriculture (IITA) Promoting Sustainable Agriculture in Borno State (PROSAB). IITA, Nigeria*.

Amaza, P., Hassan, M., Abdoulaye, T., Kamara, A. and Oluoch, M. 2014. Mid-Term and Cost–Benefit Study of Smallholder Farmers in Striga-Infested Maize and Cowpea Growing Areas of Northern Nigeria. Ibadan, Nigeria: IITA.

Amaza, P.S., Olayemi, J.K., Adejobi, A.O., Bila, Y. and Iheanacho, A. 2007. Baseline socioeconomic survey report: agriculture in Borno State. Ibadan: International Institute of Tropical Agriculture.

Amudavi, D., Khan, Z., Midega, C., Pickett, J., Lynam, J. and Pittchar, J. Push-pull technology and determinants influencing expansion among smallholder producers in Western Kenya. Proceedings of the 24th Annual Conference, Association for International Agricultural and Extension Education, Costa Rica, 2008. 38-50.

Amusan, I.O., Rich, P.J., Menkir, A., Housley, T. and Ejeta, G. 2008. Resistance to Striga hermonthica in a maize inbred line derived from Zea diploperennis. *New Phytologist* 178 (1):157-166.

Anim, F. 2008. Cattle owners' willingness to pay for extension services in South Africa. *Journal of Extension Systems* 24 (1):31-43.

Antle, J.M. 1987. Econometric estimation of producers' risk attitudes. *American Journal of Agricultural Economics* 69 (3):509-522.

Araar, A. and Duclos, J. 2012. DASP: Distributive Analysis Stata Package. Université Laval PEP.

Arslan, A., McCarthy, N., Lipper, L., Asfaw, S. and Cattaneo, A. 2014. Adoption and intensity of adoption of conservation farming practices in Zambia. *Agriculture, Ecosystems & Environment* 187:72-86.

Asfaw, S. 2010. *Estimating welfare effect of modern agricultural technologies: A micro-perspective from Tanzania and Ethiopia*. Available at: http://www. chronicpoverty. org/uploads/publication_files/asfaw_agricultural_technologie s. pdf [Accessed 23 June 2013].

Asfaw, S., Shiferaw, B., Simtowe, F., Muricho, G., Abate, T. and Ferede, S. 2010. Socio-economic Assessment of Legume Production, Farmer Technology Choice, Market Linkages, Institutions and Poverty in Rural Ethiopia: Institutions, Markets, Policy and Impacts Research Report No. 3. *Field Crops Research* 36 (2):103-111.

Asfaw, S., Kassie, M., Simtowe, F. and Lipper, L. 2012a. Poverty reduction effects of agricultural technology adoption: a micro-evidence from rural Tanzania. *Journal of Development Studies* 48 (9):1288-1305.

Asfaw, S., McCarthy, N., Lipper, L., Arslan, A., Cattaneo, A. and Kachulu, M. 2014. Climate variability, adaptation strategies and food security in Malawi. ESA Working Paper.

Asfaw, S., Shiferaw, B., Simtowe, F. and Haile, M.G. 2011. Agricultural technology adoption, seed access constraints and commercialization in Ethiopia. *Journal of Development and Agricultural Economics* 3 (9):436-477.

Asfaw, S., Shiferaw, B., Simtowe, F. and Lipper, L. 2012b. Impact of modern agricultural technologies on smallholder welfare: Evidence from Tanzania and Ethiopia. *Food Policy* 37 (3):283-295.

Awotide, B.A., Alene, A.D., Abdoulaye, T. and Manyong, V.M. 2015. Impact of agricultural technology adoption on asset ownership: the case of improved cassava varieties in Nigeria. *Food Security* 7 (6):1239-1258.

Awotide, B.A., Diagne, A., Wiredu, A.N. and Ojehomon, V.E. 2012. Wealth status and agricultural technology adoption among smallholder rice farmers in Nigeria. *OIDA International Journal of Sustainable Development* 5 (2):97-108.

Babbie, E.R. 2009. *The practice of social research* 12th Belmont, CA: Wadsworth.

Badu-Apraku, B., Fakorede, M., Menkir, A. and Sanogo, D. 2012. Conduct and management of maize field trials. *IITA, Ibadan, Nigeria*.

Baidu-Forson, J. 1999. Factors influencing adoption of land-enhancing technology in the Sahel: lessons from a case study in Niger. *Agricultural Economics* 20 (3):231-239.

Bandiera, O. and Rasul, I. 2006. Social networks and technology adoption in northern mozambique. *The Economic Journal* 116 (514):869-902.

Becerril, J. and Abdulai, A. 2010. The impact of improved maize varieties on poverty in Mexico: a propensity score-matching approach. *World Development* 38 (7):1024-1035.

Bernard, M., Hellin, J., Nyikal, R. and Mburu, J. Determinants for use of certified maize seed and the relative importance of transaction costs. Joint 3rd African Association of Agricultural Economists and 48 th Agricultural Economists Association of South Africa Conference. Cape Town, South Africa, September, 2010. 19-23.

Berner, D., Winslow, M., Awad, A., Cardwell, K., Mohan Raj, D. and Kim, S. 1997. Sustainable control of S. hermonthica spp. through a focused integrated pest management programme. *Contributing to food selfsufficiency: maize research and development in West and Central Africa. International Institute of Tropical Agriculture (IITA), Ibadan, Nigeria. p*:1-11.

Besley, T. and Case, A. 1993. Modeling technology adoption in developing countries. *The American Economic Review* 83(2) 396-402.

Blundell, R. and Costa Dias, M. 2000. Evaluation methods for non-experimental data. *Fiscal Studies* 21 (4):427-468.

Bokanga, M. 1960. Adoption of new ideas and practices. Iowa State University Press, Ames, IA, USA. 235p.

Bourdillon, M., Hebinck, P., Hoddinott, J., Kinsey, B., Marondo, J., Mudege, N. and Owens, T. 2003. Assessing the impact of high-yielding varieties of maize in resettlement areas of Zimbabwe. *International Food Policy Research Institute, FCND*:161.

BSADP (Bauchi State Agricultural Development Programme). 2003. Annual Report. Bauchi: Bauchi State Agricultural Development Programme

Byerlee, D. and Eicher, C.K. 1997. *Africa's emerging maize revolution.* Lynne Rienner Publishers.

Byerlee, D. and Heisey, P.W. 1996. Past and potential impacts of maize research in sub-Saharan Africa: a critical assessment. *Food Policy* 21 (3):255-277.

Carsky, R., Berner, D., Oyewole, B., Dashiell, K. and Schulz, S. 2000. Reduction of Striga hermonthica parasitism on maize using soybean rotation. *International Journal of Pest Management* 46 (2):115-120.

Carsky, R., Singh, L. and Ndikawa, R. 1994. Suppression of Striga hermonthica on sorghum using a cowpea intercrop. *Experimental Agriculture* 30 (03):349-358.

Carter, D.W. and Milon, J.W. 2005. Price knowledge in household demand for utility services. *Land Economics* 81 (2):265-283.

Casley, D.J. and Lury, D.A. 1982. *Monitoring and evaluation of agriculture and rural development projects.* World Bank Washington DC.

Cavatassi, R., Lipper, L. and Narloch, U. 2011. Modern variety adoption and risk management in drought prone areas: insights from the sorghum farmers of eastern Ethiopia. *Agricultural Economics* 42 (3):279-292.

Cechin, I. and Press, M.C. 1994. The influence of nitrogen on growth and photosynthesis of sorghum infected with Striga hermonthica from different provenances *Weed Research* 34:289-298.

Chikoye, D., Ellis-Jones, J., Tarawali, G. and Lum, A.F.C., 2004.. Reducing Poverty through Improved Striga Control. Proceedings of the second Striga management stakeholders'. 8–9 September 2004, Zaria, Kaduna State, Nigeria. 120.

Chilot, Y., Shapiro, B.I. and Mulat, D. 1998. Factors influencing adoption of new wheat technologies in Walmart and Addis Alem areas of Ethiopia. *Ethiopian Journal of Agricultural Economics* 1 (1):63-64.

CIMMYT. 2004. Striga weed control with herbicide-coated maize seed. Texcoco, Mexico: International Maize and Wheat Improvement Center.

Coelli, T.J. and Battese, G.E. 1996. Identification of factors which influence the technical inefficiency of Indian farmers. *Australian Journal of Agricultural Economics* 40 (2):103-128.

Cornejo, J.F. and McBridge, W.D. 2002. *In Helder Lopes (2010) Adoption of Improved maize and common bean varieties in Mozambique.* Master's, Michigan State University.

Daily Times Newspaper: http://dailytimes.com.ng/article/nigeria-raise-maize-production-12-million-tons-annually accessed on 28/02/2013

Dashiell, K., Di Umba, U., Kling, J., Melake-Berhan, A. and Berner, D. 2000. Breeding for integrated management of Striga hermonthica. *Breeding for Striga Resistance in Cereals* 273281.

De Groot, H. 2007. Striga economicsIn. *In:* Ejeta, G., Gressel, J. (Eds.) (ed.) *Integrating New Technologies for Striga Control.* London, UK: World Scientific Co. Ltd.

De Groote, H., Wangare, L. and Kanampiu, F. 2007. Evaluating the use of herbicide-coated imidazolinone-resistant (IR) maize seeds to control Striga in farmers' fields in Kenya. *Crop Protection* 26 (10):1496-1506.

De Groote, H., Wangare, L., Kanampiu, F., Odendo, M., Diallo, A., Karaya, H. and Friesen, D. 2008. The potential of a herbicide resistant maize technology for Striga control in Africa. *Agricultural Systems* 97 (1):83-94.

De Janvry, A., Dustan, A. and Sadoulet, E. 2010. Recent advances in impact analysis methods for ex-post impact assessments of agricultural technology: Options for the CGIAR. *Unpublished working paper, University of California-Berkeley*.

De Janvry, A. and Sadoulet, E. 2001. Income strategies among rural households in Mexico: The role of off-farm activities. *World Development* 29 (3):467-480.

De Janvry, A. and Sadoulet, E. 2002. World poverty and the role of agricultural technology: direct and indirect effects. *Journal of Development Studies* 38 (4):1-26.

Deininger, K., Ali, D.A. and Alemu, T. 2011. Impacts of land certification on tenure security, investment, and land market participation: evidence from Ethiopia. *Land Economics* 87 (2):312-334.

Deininger, K., Ali, D.A., Holden, S. and Zevenbergen, J. 2008. Rural land certification in Ethiopia: Process, initial impact, and implications for other African countries. *World Development* 36 (10):1786-1812.

Denning, G., Kabambe, P., Sanchez, P., Malik, A., Flor, R., Harawa, R., Nkhoma, P., Zamba, C., Banda, C. and Magombo, C. 2009. Input subsidies to improve smallholder maize productivity in Malawi: Toward an African Green Revolution. *PLoS Biol* 7 (1):e1000023.

Dercon, S. and Christiaensen, L. 2011. Consumption risk, technology adoption and poverty traps: Evidence from Ethiopia. *Journal of Development Economics* 96 (2):159-173.

DFID. 2002. Sustainable Livelihoods Guideline Guidance Sheets. www.livelihoods.org/index.html accessed on17/09/2015

Di Falco, S. and Bulte, E. 2013. The Impact of Kinship Networks on the Adoption of Risk-Mitigating Strategies in Ethiopia. *World Development* 43:100-110.

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

Diagne, A. 2006. Diffusion and adoption of NERICA rice varieties in Côte d'Ivoire. *The Developing Economies* 44 (2):208-231.

Diagne, A., Midingoyi, S.-K.G., Wopereis, M. and Akintayo, I. 2011. Increasing rice productivity and strengthening food security through New Rice for Africa (NERICA). *Yes Africa can: Success stories from a dynamic continent* 253:253.

Diallo, A., Kanampiu, F., Mugo, S., De Groote, H. and Mbogo, P. 2007. Herbicide resistant maize: a novel method to control Striga in Africa. *Demand-Driven Technologies for Sustainable Maize Production in West and Central Africa*:302.

Dorfman, J.H. 1996. Modeling multiple adoption decisions in a joint framework. *American Journal of Agricultural Economics* 78 (3):547-557.

Doss, C.R. 2003. *Understanding farm-level technology adoption: Lessons learned from CIMMYT's micro surveys in eastern Africa.* CIMMYT.

Doss, C.R. and Morris, M.L. 2001. How does gender affect the adoption of agricultural innovations?: The case of improved maize technology in Ghana. *Agricultural Economics* 25 (1):27-39.

Duflo, E., Kremer, M. and Robinson, J. 2008. How high are rates of return to fertilizer? Evidence from field experiments in Kenya. *The American Economic Review* 98 (2):482-488.

Dugje, I.Y., Kamara, A.Y. and Omoigui, L.O. 2006. Infestation of crop fields by Striga species in the savanna zones of northeast Nigeria. . *Agriculture, Ecosystems, and Environment* 116: 251-252.

Durojaiye, B.O. and Olanloye, F.A. 1992. The value of education in small-scale agriculture: Some evidence from Ogun State, Nigeria. *Oxford Agrarian Studies* 20 (2):107-115.

Edmeades, S. and Smale, M. 2006. A trait-based model of the potential demand for a genetically engineered food crop in a developing economy. *Agricultural Economics* 35 (3):351-361.

Ejeta, G. 2007. The Striga scourge in Africa: a growing pandemic. *Integrating new technologies for Striga control: towards ending the witch-hunt*:3-16.

Ejeta, G. and Gressel, J. 2007. *Integrating new technologies for Striga control: towards ending the witch-hunt.* World Scientific.

Ekeleme, F., Jibrin, J., Kamara, A., Oluoch, M., Samndi, A. and Fagge, A. 2014. Assessment of the relationship between soil properties, Striga hermonthica infestation and the on-farm yields of maize in the dry Savannas of Nigeria. *Crop Protection* 66:90-97.

Ellis-Jones, J., Schulz, S., Douthwaite, B., Hussaini, M., Oyewole, B., Olanrewaju, A. and White, R. 2004. An assessment of integrated Striga hermonthica control and early adoption by farmers in northern Nigeria. *Experimental Agriculture* 40 (03):353-368.

Elzein, A. and Kroschel, J. 2003. Progress on management of parasitic weeds. *FAO Plant Production and Protection Paper (FAO)*.

Emechebe, A., Ellis-Jones, J., Schulz, S., Chikoye, D., Douthwaite, B., Kureh, I., Tarawali,G., Hussaini, M., Kormawa, P. and Sanni, A. 2004. Farmers' perception of the Striga problem and its control in northern Nigeria. *Experimental Agriculture* 40 (02):215-232.

Evenson, R.E. and Gollin, D. 2003. Assessing the impact of the Green Revolution, 1960 to 2000. *Science* 300 (5620):758-762.

FAO (Food and Agriculture Organization). 2009. Statistical Yearbook 2009. Rome: FAO.

FAO (Food and Agricultural Organisation). 2014. *FAO Statistical Data Base*. FAO. Available at: http://apps.fao.org/ [Accessed 17 June 2015].

FAO (Food and Agriculture Organization). 2015a. *Food Security Impact of Agricultural Technology Adoption under Climate Change: Micro-evidence from Niger*. Rome, Italy: FAO. Available at: www.fao.org/climatechange/epic [Accessed 5/05/2016 2016].

FAO (Food and Agriculture Organization). 2015b. *The State of Food Insecurity in the World*. Rome, Italy: FAO. Available at: www.fao.org/3/a-i4646e.pdf [Accessed 5/05/2016 2016].

FAO (Food and Agriculture Organization). 2013. Statistical Yearbook 2013: World Food and Agriculture. Rome: FAO.

(FAOSTAT, 2015). Food and Agriculture Organization Statistics.

Feder, G., Just, R.E. and Zilberman, D. 1985. Adoption of agricultural innovations in developing countries: A survey. *Economic Development and Cultural Change* 33:255-298.

Feder, G., Lau, L.J., Lin, J.Y. and Luo, X. 1990. The relationship between credit and productivity in Chinese agriculture: A microeconomic model of disequilibrium. *American Journal of Agricultural Economics*:1151-1157.

Feder, G. and Umali, D.L. 1993. The adoption of agricultural innovations: A review. *Technological Forecasting and Social Change* 43 (3/4):215-239.

Feder, G., Murgai, R. and Quizon, J.B. 2003. *Sending farmers back to school: The impact of farmer field schools in Indonesia.* World Bank Publications.

Feleke, S. and Zegeye, T. 2006. Adoption of improved maize varieties in Southern Ethiopia: Factors and strategy options. *Food Policy* 31 (5):442-457.

Foster, J., Greer, J. and Thorbecke, E. 1984. A class of decomposable poverty measures. *Econometrica: Journal of the Econometric Society*:761-766.

Freeman, H.A., Ehui, S.K. and Jabbar, M.A. 1998. Credit constraints and smallholder dairy production in the East African highlands: application of a switching regression model. *Agricultural Economics* 19 (1):33-44.

Fufa, B. and Hassan, R.M. 2006. Determinants of fertilizer use on maize in Eastern Ethiopia: A weighted endogenous sampling analysis of the extent and intensity of adoption. *Agrekon* 45 (1):38-49.

Fuglie, K.O. and Kascak, C.A. 2001. Adoption and diffusion of natural-resource-conserving agricultural technology. *Review of Agricultural Economics* 23 (2):386-403.

Gbèhounou, G. and Adango, E. 2003. Trap crops of Striga hermonthica: in vitro identification and effectiveness in situ. *Crop Protection* 22 (2):395-404.

Gebremedhin, B. and Swinton, S.M. 2003. Investment in soil conservation in northern Ethiopia: the role of land tenure security and public programs. *Agricultural Economics* 29 (1):69-84.

Gethi, J., Smith, M., Mitchell, S. and Kresovich, S. 2005. Genetic diversity of Striga hermonthica and Striga asiatica populations in Kenya. *Weed Research* 45 (1):64-73.

Ghimire, R. and Huang, W.-C. 2015. Household wealth and adoption of improved maize varieties in Nepal: a double-hurdle approach. *Food Security* 7 (6):1321-1335.

Ghimire, S.R. 2003. *Economic Analysis of Egg Production Agribusiness in Chitwan.* Master's Degree Master's Degree, Tribhuwan University.

Gittinger, J.P. 1982. *Economic Analysis of Agricultural Projects.* 2nd edition. Baltimore, Md: Johns Hopkins University Press.

Green, D.A. and Ng'ong'ola, D. 1993. Factors Affecting Fertilizer Adoption in Less Developed Countries: An Application of Multivariate Logistic Analysis in Malaŵi. *Journal of Agricultural Economics* 44 (1):99-109.

Greene, W.H. 2003. *Econometric analysis.* Upper Saddle River, New Jersey, 07458.: Pearson Education

Gressel, J., Hanafi, A., Head, G., Marasas, W., Obilana, A.B., Ochanda, J., Souissi, T. and Tzotzos, G. 2004. Major heretofore intractable biotic constraints to African food security that may be amenable to novel biotechnological solutions. *Crop Protection* 23 (8):661-689.

Groom, M.J., Gray, E.M. and Townsend, P.A. 2008. Biofuels and biodiversity: principles for creating better policies for biofuel production. *Conservation Biology* 22 (3):602-609.

Gujarati, D.N. 2012. *Basic Econometrics.* New York: Tata McGraw-Hill Education Publishing Company Limited.

Guo, S. and Fraser, W.M. 2015. *Propensity Score Analysis: Statistical Methods and Applications.* 2nd Edition. California, United Kingdom,India and Singapore: SAGE Publications Inc.

Gurney, A., Press, M. and Scholes, J. 1999. Infection time and density influence the response of sorghum to the parasitic angiosperm Striga hermonthica. *New phytologist* 143 (3):573-580.

Hassan, M.B. and Sanni, S.A. Socio-economic analysis of income determinants among small-scale tomato farmers using tin mining ponds in the Jos Plateau, Nigeria. Paper presented at the conference of Agricultural Society of Nigeria. Proceeding of 42nd Annual Conference of Agricultural Society of Nigeria (ASN) 2011 Usman Dan-Fodio University Sokoto ASN.

Hassan, R.M., Onyango, R., Rutto, J.K. and 1998. Determinants of fertilizer use and the gap between farmers' maize yield and potential yields in Kenya. In: Hassan RM (ed), Maize technology development and transfer: A GIS approach to research planning Kenya: CAB International, London.

Hausman, J.A. 1978. Specification tests in econometrics. *Econometrica: Journal of the Econometric Society*:1251-1271.

Heckman, J.J. 1979. Sample selection bias as a specification error. *Econometrica: Journal of the Econometric Society*:153-161.

Heckman, J.J. 2001. Econometrics and empirical economics. *Journal of Econometrics* 100 (1):3-5.

Heckman, J.J. and Vytlacil, E. 2005. Structural equations, treatment effects and econometric policy evaluation. National Bureau of Economic Research.

Heckman, J.J. and Vytlacil, E.J. 2007. Econometric evaluation of social programs, part I: Causal models, structural models and econometric policy evaluation. *Handbook of Econometrics* 6:4779-4874.

Hess, D. and Dodo, H. 2004. Potential for sesame to contribute to integrated control of Striga hermonthica in the West African Sahel. *Crop Protection* 23 (6):515-522.

Høgh-Jensen, H., Myaka, F., Sakala, W., Kamalongo, D., Ngwira, A., Vesterager, J.M., Odgaard, R. and Adu-Gyamfi, J. 2007. Yields and qualities of pigeonpea varieties grown under smallholder farmers' conditions in Eastern and Southern Africa. *African Journal of Agricultural Research* 2 (6):269-278.

Holden, S.T. and Fisher, M. 2015. Subsidies promote use of drought tolerant maize varieties despite variable yield performance under smallholder environments in Malawi. *Food Security* 7 (6):1225-1238.

Holden, S.T. and Shiferaw, B. 2002. Poverty and land degradation: Peasants' willingness to pay to sustain land productivity. *Natural resource management in African agriculture: Understanding and improving current practices.* New York: CABI Publishing.

Hossain, M., Bose, M.L. and Mustafi, B.A. 2006. Adoption and productivity impact of modern rice varieties in Bangladesh. *The Developing Economies* 44 (2):149-166.

Ibrahim, H.I., Omotesho, O.A. and Adewunmi, M.O. 2010 Effect of five Striga hermonthica control methods on input use, Striga counts and maize yield in the northern Guinea Savannah of Nigeria. *Electronic Journal of Environmental, Agriculture and Chemistry* 9 (1): 145-149.

Idrisa, Y.l. 2009. *Analysis of the determinant of soybean production technology adoption by farmers in southern Borno State.* PhD PhD, University of Maiduguri.

IITA (International Institute of Tropical Agriculture). 2013. *Integrated Striga Management in Africa*. Ibadan. Available at: http://www.iita.org/web/isma/about-striga [Accessed 16/06 2014].

IITA (International Institute of Tropical Agriculture). 2015. *www.IITA.org/maize(accessed 6th April, 2015)*.

Illa, A., Odhiambo, G. and Dida, M. 2010. Increasing imazapyr-resistant maize yield by increasing plant density under natural Striga hermonthica infestation. *Agricultural and Biology Journal of North America*.

Imbens, G.W. 2004. Nonparametric estimation of average treatment effects under exogeneity: A review. *Review of Economics and Statistics* 86 (1):4-29.

Jamil, M., Kanampiu, F., Karaya, H., Charnikhova, T. and Bouwmeester, H. 2012. Striga hermonthica parasitism in maize in response to N and P fertilisers. *Field Crops Research* 134:1-10.

Joel, D.M., Hershenhorn, J., Eizenberg, H., Aly, R., Ejeta, G., Rich, P.J., Ransom, J.K., Sauerborn, J. and Rubiales, D.V., Inc.; 2007. pp. 267-349. 2007. Biology and management of weedy root parasites. In: Janick J, editor. Horticultural Reviews. *John Wiley & Sons* 33:267-349.

Johannes, T.A., Vabi, M. and Malaa, D.K. 2010. Adoption of Maize and Cassava Production Technologies in the Forest-Savannah Zone of Cameroon: Implications for Poverty Reduction. *World Applied Science Journal* 11 (2):196-209.

Jones, A.M. 1989. A double-hurdle model of cigarette consumption. *Journal of Applied Econometrics, 4:23-29* 4:23-29.

Jones, K.M. 2005. Technology adoption in West Africa: Adoption and disadoption of soybeans on the Togo-Benin border. (2005). Unpublish MSc thesis submitted to the Graduate Faculty of North Carolina State University in partial fulfilment of the requirements for the Degree of Master of Science

Juma, M., Nyangena, W. and Yesuf, M. 2009. Production risk and farm technology adoption in rain-fed, semi-arid lands of Kenya. *Environment for Development Discussion Paper Series*:09-22.

Just, R.E. and Zilberman, D. 1988. The effects of agricultural development policies on income distribution and technological change in agriculture. *Journal of Development Economics* 28 (2):193-216.

Kaguongo, W., Ortmann, G.F., Wale, E., Darroch, M.A. and Low, J. 2012. Factors influencing adoption and intensity of adoption of orange flesh sweetpotato varieties: evidence from an extension intervention in Nyanza and western provinces, Kenya. *African Journal of Agricultural Research* 7 (3):493-503.

Kalash, R.C. 2010. *Analysis of tomato marketing system in Lalitpur district of Nepal.* Master's Degree Master's Degree, Van Hall Larenstein University of Applied Sciences, Wageningen, the Netherlands

Kaliba, A.R., Verkuijl, H. and Mwangi, W. 2000. Factors affecting adoption of improved maize seeds and use of inorganic fertilizer for maize production in the intermediate and lowland zones of Tanzania. *Journal of Agricultural and Applied Economics* 32 (01):35-47.

Kamara, A., Ellis-Jones, J., Amaza, P., Omoigui, L., Helsen, J., Dugje, I., Kamai, N., Menkir, A. and White, R. 2008. A participatory approach to increasing productivity of maize through Striga hermonthica control in northeast Nigeria. *Experimental Agriculture* 44 (03):349-364.

Kanampiu, F.K., Kabambe, V., Massawe, C., Jasi, L., Friesen, D., Ransom, J.K. and Gressel, J. 2003. Multi-site, multi-season field tests demonstrate that herbicide seed-coating herbicide-resistance maize controls Striga spp. and increases yields in several African countries. *Crop Protection* 22 (5):697-706.

Kanampiu, F.K., Ransom, J.K., Friesen, D. and Gressel, J. 2002. Imazapyr and pyrithiobac movement in soil and from maize seed coats to control Striga in legume intercropping. *Crop Protection* 21 (8):611-619.

Kapalasa, E.G. 2014. Assessing factors influencing farmers adoption of improved soybean varieties in Malawi. *Scholarly Journal of Agricultural Science* 4 (6):339-349.

Kassie, M., Shiferaw, B. and Muricho, G. 2011. Agricultural technology, crop income, and poverty alleviation in Uganda. *World Development* 39 (10):1784-1795.

Katengeza, S., Mangisoni, J.H., Kassie, G.T., Sutcliffe, C., Langyintuo, A., La Rovere, R. and Mwangi, W. 2012. Drivers of improved maize variety adoption in drought prone areas of Malawi. *Journal of Development and Agricultural Economics* 4 (14):393-403.

Katungi, E., Machethe, C. and Smale, M. 2007. Determinants of social capital formation in rural Uganda: Implications for group-based agricultural extension approaches. *African Journal of Agricultural and Resource Economics* 1 (2):167-190.

Katungi, E.M. 2007. *Social Capital and Technology Adoption on Small Farms: The Case of Banana Production Technology in Uganda.* University of Pretoria.

Kebede, Y., Gunjal, K. and Coffin, G. 1990. Adoption of new technologies in Ethiopian agriculture: the case of Tegulet-Bulga district Shoa province. *Agricultural Economics* 4 (1):27-43.

Kenneth, A., Gerald, O., Edilegnaw, W. and Wilberforce, T. Ex-Ante Adoption of New Cooking Banana (Matooke) Hybrids in Uganda Based on Farmers' Perceptions. 2012 Conference, August 18-24, 2012, Foz do Iguacu, Brazil, 2012. International Association of Agricultural Economists.

Khan, Z., Midega, C., Pittchar, J., Pickett, J. and Bruce, T. 2011. Push—pull technology: a conservation agriculture approach for integrated management of insect pests, weeds and soil health in Africa: UK government's Foresight Food and Farming Futures project. *International Journal of Agricultural Sustainability* 9 (1):162-170.

Khan, Z., Pickett, J., Hassanali, A., Hooper, A. and Midega, C. 2008a. Desmodium species and associated biochemical traits for controlling Striga species: present and future prospects. *Weed Research* 48 (4):302-306.

Khan, Z.R., Hassanali, A., Overholt, W., Khamis, T.M., Hooper, A.M., Pickett, J.A., Wadhams, L.J. and Woodcock, C.M. 2002. Control of witchweed Striga hermonthica by intercropping with Desmodium spp., and the mechanism defined as allelopathic. *Journal of Chemical Ecology* 28 (9):1871-1885.

Khan, Z.R., Midega, C.A., Amudavi, D.M., Hassanali, A. and Pickett, J.A. 2008b. On-farm evaluation of the 'push–pull'technology for the control of stemborers and striga weed on maize in western Kenya. *Field Crops Research* 106 (3):224-233.

Khan, Z.R., Midega, C.A., Hassanali, A., Pickett, J.A., Wadhams, L.J. and Wanjoya, A. 2006a. Management of witchweed, Striga hermonthica, and stemborers in sorghum, Sorghum bicolor, through intercropping with greenleaf desmodium, Desmodium intortum. *International Journal of Pest Management* 52 (4):297-302.

Khan, Z.R., Pickett, J.A., Wadhams, L.J., Hassanali, A. and Midega, C.A. 2006b. Combined control of Striga hermonthica and stemborers by maize–Desmodium spp. intercrops. *Crop Protection* 25 (9):989-995.

Khonje, M., Manda, J., Alene, A.D. and Kassie, M. 2015. Analysis of Adoption and Impacts of Improved Maize Varieties in Eastern Zambia. *World Development* 66:695-706.

Kijima, Y., Otsuka, K. and Sserunkuuma, D. 2008. Assessing the impact of NERICA on income and poverty in central and western Uganda. *Agricultural Economics* 38 (3):327-337.

Kim, K. and Chavas, J.P. 2003. Technological change and risk management: an application to the economics of corn production. *Agricultural Economics* 29 (2):125-142.

Kivlin, J.E. and Fliegel, F.C. 1967. Differential perceptions of innovations and rate of adoption. *Rural Sociology* 32 (1):78-91

Kling, J.G., Fajemisin, J.M., Badu-Apraku, B., Diallo, A., Menkir, A., Melake-Berhan, A. and 2000. Striga resistance breeding in maize *In:* Haussman, B.I.G., Hess, D.E., Koyama, M.L., Grivet, L., Rattunde, H.F.W. and H.H., G. (eds.) *Breeding for Striga Resistance in Cereals.* Weikersheim, Germany: Margraf Verlag

Krishna, V.V. and Qaim, M. 2007. Estimating the adoption of Bt eggplant in India: Who Benefits from public–private partnership? *Food Policy* 32 (5–6):523-543.

Krishnan, P. and Patnam, M. 2014. Neighbors and extension agents in Ethiopia: Who matters more for technology adoption? *American Journal of Agricultural Economics* 96 (1):308-327.

Kristjanson, P., Okike, I., Tarawali, S., Singh, B. and Manyong, V. 2005. Farmers' perceptions of benefits and factors affecting the adoption of improved dual-purpose cowpea in the dry savannas of Nigeria. *Agricultural Economics* 32 (2):195-210.

Kuchinda, N.C., Kureh, I., Tarfa, B.D., Shingu, C. and Omolehin, R. 2003. On-farm evaluation of improved maize varieties intercropped with some legumes in the control of Striga in the northern Guinea Savanna of Nigeria. *Crop Protection* 22:533–538.

Kudi, T., Bolaji, M., Akinola, M. and Nasa’l, D. 2011. Analysis of adoption of improved maize varieties among farmers in Kwara State, Nigeria. *International Journal of Peace and Development Studies* 1 (3):8-12.

Kureh, I., Kamara, A. and Tarfa, B. 2006. Influence of cereal-legume rotation on Striga control and maize grain yield in farmers' fields in the Northern Guinea savanna of Nigeria. *Journal of Agriculture and Rural Development in the Tropics and Subtropics (JARTS)* 107 (1):41-54.

Langyintuo, A.S. and Mungoma, C. 2008. The effect of household wealth on the adoption of improved maize varieties in Zambia. *Food Policy* 33 (6):550-559.

Langyintuo, A.S., Mwangi, W., Diallo, A.O., MacRobert, J., Dixon, J. and Bänziger, M. 2010. Challenges of the maize seed industry in eastern and southern Africa: A compelling case for private–public intervention to promote growth. *Food Policy* 35 (4):323-331.

Lee, D.R. 2005. Agricultural sustainability and technology adoption: Issues and policies for developing countries. *American Journal of Agricultural Economics* 87 (5):1325-1334.

Lee, L.-F. 1978. Unionism and wage rates: A simultaneous equations model with qualitative and limited dependent variables. *International Economic Review*: 19 (2): 415-433.

Lendzemo, V.W., van Ast, A. and Kuyper, T.W. 2006. Can arbuscular mycorrhizal fungi contribute to Striga management on cereals in Africa? *Outlook on AGRICULTURE* 35 (4):307-311.

Lin, C.-T.J. and Milon, J.W. 1993. Attribute and safety perceptions in a double-hurdle model of shellfish consumption. *American Journal of Agricultural Economics* 75 (3):724-729.

Lionberger, H.F. 1960. *Adoption of new ideas and practices.* America: IOWA State University Press.

Lockheed, M.E., D.T. Jamison and I.J. Lau 1980. Farmer education and farm efficiency: a survey. *Economic Development and Cultural Change* 29:37-76.

Lokshin, M. and Sajaia, Z. 2004. Maximum likelihood estimation of endogenous switching regression models. *Stata Journal* 4:282-289.

Lopes, H. 2010. *Adoption of improved maize and common Bean varieties in Mozambique.* Michigan State University.

López-Calva, L.F. and Lustig, N. 2010. *Declining Inequality in Latin America: A decade of progress?*: Brookings Institution Press.

Lusty, C. and Smale, M. Assessing the social and economic impact of improved banana varieties in East Africa. Proceedings of an Interdisciplinary Research Design Workshop. INIBAP-IFPRI. November, 2002. Citeseer, 7-11.

Macharia, I., Orr, A., Simtowe, F. and Asfaw, S. Potential Economic And Poverty Impact Of Improved Chickpea Technologies In Ethiopia. Conference, August 18-24, Foz do Iguacu, Brazil, 2012. International Association of Agricultural Economists.

Macías, F.A., Molinillo, J.M., Varela, R.M. and Galindo, J.C. 2007. Allelopathy—a natural alternative for weed control. *Pest Management Science* 63 (4):327-348.

Maddala, G. 1983. Limited dependent and qualitative variables in econometrics. Department of Economics, University of Florida. Cambridge University Press, United Kingdom, 401pp.

Maddala, G.S. and Nelson, F. Switching regression models with exogenous and endogenous switching. Proceedings of the American Statistical Association, 1975. Business and Economics Section, 423-426.

Mansfield, E. 1968. *Industrial research and technological innovation; an econometric analysis* *www.agris.fao.org*. FAO. [Accessed April 2015].

Manski, C.F. 2007. Minimax-regret treatment choice with missing outcome data. *Journal of Econometrics* 139 (1):105-115.

Manyong, V. 2008. *Farmer perceptions of Imazapyr-Resistant (IR) maize technology on the control of Striga in Western Kenya.* African Agricultural Technology Foundation.

Markelova, H., Meinzen-Dick, R., Hellin, J. and Dohrn, S. 2009. Collective action for smallholder market access. *Food Policy* 34 (1):1-7.

Martel, P.V., Bernsten, R.H. and Weber, M.T. 2000. Food markets, policy, and technology: The case of Honduran dry beans. Michigan State University, Department of Agricultural, Food, and Resource Economics.

Mendola, M. 2007. Agricultural technology adoption and poverty reduction: A propensity score matching analysis for rural Bangladesh. *Food Policy* 32 (3):372-393.

Menkir, A. 2006. Assessment of reactions of diverse maize inbred lines to Striga hermonthica (Del.) Benth. *Plant Breeding* 125 (2):131-139.

Mignouna, B.D., Abdoulaye, T., Kamara, A. and Oluoch, M. 2013. Baseline study of smallholder farmers in Striga-infested maize and cowpea-growing areas of northern Nigeria. International Institute of Tropical Agriculture. Ibadan, Nigeria 60 pp.

Mignouna, D., Manyong, V., Rusike, J., Mutabazi, K. and Senkondo, E. 2011a. Determinants of adopting imazapyr-resistant maize technologies and its impact on household income in Western Kenya. *AgBioForum* 14 (3):158-163.

Mignouna, D., Manyong, V., Rusike, J., Mutabazi, K. and Senkondo, E. 2011b. Determinants of adopting imazapyr-resistant maize technologies and its impact on household income in Western Kenya.

Mignouna, D., Mutabazi, K., Senkondo, E. and Manyong, V. 2011c. Imazapyr-resistant maize technology adoption for witch weed control in western Kenya. *African Crop Science Journal* 19 (3):173-182.

Mignouna, D., Mutabazi, K., Senkondo, E. and Manyong, V.M. Contributions Of Agricultural Improved Technologies To Rural Poverty Alleviation In Developing Countries: Case Of Imazapyr-Resistant Maize In Western Kenya. 2011 Conference (55th), February 8-11, 2011, Melbourne, Australia, 2011d. Australian Agricultural and Resource Economics Society.

Mignouna, D.B., Abdoulaye, T., Alene, A., Aighewi, B., Pelemo, O., Manyong, V., Asiedu, R. and Akoroda, M. 2015. Economic Analysis of Yam Seed Tuber Systems in Nigeria. *Journal of Root Crops* 39 (2):221-229.

Minten, B., Singh, K.M. and Sutradhar, R. 2013. Branding and agricultural value chains in developing countries: Insights from Bihar (India). *Food Policy* 38:23-34.

Mittal, S. and Kumar, P. 2000. Literacy, technology adoption, factor demand and productivity: An economic analysis. *Indian Journal of Agricultural Economics* 55 (3):490.

Mmbando, F.E., Wale, E.Z. and Baiyegunhi, L.J. 2015. Determinants of smallholder farmers' participation in maize and pigeonpea markets in Tanzania. *Agrekon* 54 (1):96-119.

Mohamed, H.M., Khan, Z.R., Mueke, J.M., Hassanali, A., Kairu, E. and Pickett, J.A. 2007. Behaviour and biology ofChilo partellus (Swinhoe) on Striga hermonthica (Del.) Benth. infested and uninfested maize plants. *Crop Protection* 26:998-1005.

Moser, C.M. and Barrett, C.B. 2006. The complex dynamics of smallholder technology adoption: the case of SRI in Madagascar. *Agricultural Economics* 35 (3):373-388.

Mosley, P. and Verschoor, A. 2005. Risk attitudes and the ‘vicious circle of poverty’. *The European Journal of Development Research* 17 (1):59-88.

Msambichaka, L.A. 1992. *Methods and Techniques for Agriculture and Rural Development Analysis: A Handbook for Functional Managers.* Economic Research Bureau, University of Dar-es-Salaam.

Murage, A.W., Obare, G., Chianu, J., Amudavi, D.M., Pickett, J. and Khan, Z.R. 2011. Duration analysis of technology adoption effects of dissemination pathways: A case of 'push–pull' technology for control of Striga weeds and stemborers in Western Kenya. *Crop Protection* 30 (5):531-538.

Muyanga, M. 2009. Smallholder adoption and economic impacts of tissue culture banana in Kenya. *African Journal of Biotechnology* 8 (23): 6548-6555.

Mwangi, B., Obare, G. and Murage, A. 2014. Estimating the Adoption Rates of Two Contrasting Striga Weeds Control Technologies in Kenya. *Quarterly Journal of International Agriculture* 53 (3):225-242.

Namara, R.E., Makombe, G., Hagos, F. and Awulachew, S. 2008. Rural poverty and inequality in Ethiopia: Does access to small-scale irrigation make a difference? In: Awlachew SB, Loulseged, M and Yilma AD (eds.) Impact of Irrigation on Poverty and Environment in Ethiopia. . Colombo, Sri Lanka.: International Water Management Institute (IWMI).

NBS. 2013. General household survey panel data 2010/11-2012/13 post planting and post harvesting. *Press briefing by the Director General of NBS February* *http://tribune.com.ng/index.php/front-page-news/35947-nigerias-poverty-level-rises-hits-715-sokoto-niger-top-list-of-poorest-states*.

Ndjeunga, J. and Bantilan, M.C.S. 2005. Uptake of improved technologies in the Semi-arid Tropics of West Africa: Why is agricultural transformation lagging behind? *Electronic Journal of Agricultural and Development Economics* 2 (1):85-102.

Neill, S.P. and Lee, D.R. 2001. Explaining the adoption and disadoption of sustainable agriculture: the case of cover crops in Northern Honduras. *Economic Development and Cultural Change* 49 (4):793-820.

NEPAD (New Partnership for Africa's Development). 2004. Comprehensive Africa Agriculture Development Programme (CAADP):TCP/NIR/2905. Nigeria: New Partnership for Africa's Development (NEPAD)

Nkonya, E., Schroeder, T. and Norman, D. 1997. Factors affecting adoption of improved maize seed and fertiliser in northern Tanzania. *Journal of Agricultural Economics* 48 (1-3):1-12.

NPC (National Planning Commission). 2009. Nigeria Vision 20: 2020 Economic Transformation Blueprint. Abuja: NPC.

NPC (National Population Commission). 2006. National Population commission Census Report. Abuja: National Population Commission.

O'Mara, G. 1980. The Microeconomics of Technique Adoption by Small-holding Mexican Farmers. Washington, D.C: World Bank Development Research Center, 1980.

Odhiambo, G. and Ransom, J. 1993. Effect of Dicamba on the Control of Striga hermonthica check for this species in other resources in Maize in Western Kenya. *African Crop Science Journal* 1 (2): 105-110

Oladele, O. and Rantseo, K. 2010. Determinants of cattle farmers' perceived relevance of livestock technologies in Botswana. *Livestock Research for Rural Development* 22 (5).

Olukosi, J.O. and Erhabor, P. 2005. Introduction to farm production and management 66-67.

Oswald, A. and Ransom, J. 2004. Response of maize varieties to Striga infestation. *Crop Protection* 23 (2):89-94.

Oswald, A., Ransom, J., Kroschel, J. and Sauerborn, J. 2002. Intercropping controls Striga in maize based farming systems. *Crop Protection* 21 (5):367-374.

Otieno, H., Maina, J., Omare, M., Omanya, G. and Woomer, P. Field testing imazapyr-resistant maize to control striga in Western Kenya. African Crop Science Conference Proceedings, 2005. 461-465.

Padel, S. 2003. Conversion to organic farming: A typical example of the diffusion of an innovation? *Sociologia Ruralis* 41 (1):40-61.

Pageau, K., Simier, P., Naulet, N., Robins, R. and Fer, A. 1998. Carbon dependency of the hemiparasite Striga hermonthica on Sorghum bicolor determined by carbon isotopic and gas exchange analyses. *Functional Plant Biology* 25 (6):695-700.

Parikh, A. and Bernard, A. 1988. Impact of risk on HYV adoption in Bangladesh. *Agricultural Economics* 2 (2):167-178.

Parker, C. 2009. Observations on the current status of Orobanche and Striga problems worldwide. *Pest Management Science* 65 (5):453-459.

Parker, C. and Riches, C.R. 1993. *Parasitic weeds of the world: Biology and Control.* CAB International.

Parvan, A. 2012. Agricultural technology adoption: Issues for consideration when scaling-up. *The Cornell Policy Review: Journal of the Cornell Institute for Public Affairs, 1*.

Pfeffer, M.J. 1992. Labor and Production Barriers to the Reduction of Agricultural Chemical Inputs1. *Rural Sociology* 57 (3):347-362.

Phillip, D., Nkonya, E., Pender, J. and Oni, O.A. 2009. Constraints to increasing agricultural productivity in Nigeria: A review. International Food Policy Research Institute (IFPRI).

Phillips, J.M. 1994. Farmer education and farmer efficiency: a meta-analysis. *Economic Development and Cultural Change* 43:1439-1465.

Polson, R.A. and Spencer, D.S. 1991. The technology adoption process in subsistence agriculture: The case of cassava in Southwestern Nigeria. *Agricultural Systems* 36 (1):65-78.

Puhani, P. 2000. The Heckman correction for sample selection and its critique. *Journal of Economic Surveys* 14 (1):53-68.

Ramírez, H.G., Bernsten, R.H. and Gallegos, J.A.A. 2003. Economic evaluation of bean research investment in northern México.

Rank, C., Rasmussen, L.S., Jensen, S.R., Pierce, S., Press, M. and Scholes, J. 2004. Cytotoxic constituents of Alectra and Striga species. *Weed Research* 44 (4):265-270.

Ravallion, M. 2006. Looking beyond averages in the trade and poverty debate. *World Development* 34 (8):1374-1392.

Rich, P.J. and Ejeta, G. 2008. Towards effective resistance to Striga in African maize. *Plant Signaling & Behavior* 3 (9):618-621.

Richards, M., Davies, J. and Yaron, G. 2003. *Stakeholder incentives in participatory forest management: a manual for economic analysis.* ITDG Publishing.

Rogers, E.M. 1995. Diffusion of Innovations: modifications of a model for telecommunications. *Die Diffusion von Innovationen in der Telekommunikation* 17:25-38.

Roling, N. 1988. *Extension science: Information systems in agricultural development.* CUP Archive.

Rosenbaum, P.R. 2002. *Observational studies.* Springer.

Rubiales, D., Pérez-de-Luque, A., Fernández-Aparico, M., Sillero, J.C., Román, B., Kharrat, M., Khalil, S., Joel, D.M. and Riches, C. 2006. Screening techniques and sources of resistance against parasitic weeds in grain legumes. *Euphytica* 147 (1-2):187-199.

Rubin, D.B. 1974. Estimating causal effects of treatments in randomized and nonrandomized studies. *Journal of Educational Psychology* 66 (5):688.

Samson, P.K., Julius, H.M., Girma, T.K., Chloe, S., Langyintuo., A., Roberto., L. and Wilfred, M. 2012. *Journal of Development and Agricultural Economics* 4(14): 393-403.

Sanginga, P., Adesina, A., Manyong, V., Otite, O. and Dashiell, K. 1999. Social impact of soybean in Nigeria's southern Guinea savanna.

Sauerborn, J., Ransom, J., Musselman, L., Worsham, A. and Parker, C. The economic importance of the phytoparasites Orobanche and Striga. Proceedings of the 5th international symposium of parasitic weeds, Nairobi, Kenya, 24-30 June 1991. organised by CIMMYT (International Maize and Wheat Improvement Center), 137-143.

Schulz, S., Hussaini, M., Kling, J., Berner, D. and Ikie, F. 2003. Evaluation of integrated Striga hermonthica control technologies under farmer management. *Experimental Agriculture* 39 (01):99-108.

Shakya, P.B. and Flinn, J. 1985. Adoption of modern varieties and fertilizer use on rice in the Eastern Tarai of Nepal. *Journal of Agricultural Economics* 36 (3):409-419.

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

Shiferaw, B., Obare, G., Muricho, G. and Silim, S. 2009. Leveraging institutions for collective action to improve markets for smallholder producers in less-favored areas. *African Journal of Agricultural and Resource Economics* 3 (1):1-18.

Shiferaw, B.A., Kebede, T.A. and You, L. 2008. Technology adoption under seed access constraints and the economic impacts of improved pigeonpea varieties in Tanzania. *Agricultural Economics* 39 (3):309-323.

Shiyani, R., Joshi, P., Asokan, M. and Bantilan, M.C.S. 2002. Adoption of improved chickpea varieties: KRIBHCO experience in tribal region of Gujarat, India. *Agricultural Economics* 27 (1):33-39.

Sileshi, G., Akinnifesi, F.K., Ajayi, O.C., Chakeredza, S., Kaonga, M. and Matakala, P. 2007. Contributions of agroforestry to ecosystem services in the Miombo eco-region of eastern and southern Africa. *African Journal of Environmental Science and Technology* 1 (4):68-80.

Simtowe, F., Asfaw, S., Diagne, A. and Shiferaw, B.A. 2010b. Determinants of Agricultural Technology adoption: the case of improved groundnut varieties in Malawi: September *Paper presented at the Contributed paper presented at the joint 3rd African Association of Agricultural Economists (AAAE) and 48th Agricultural Economists Association of South Africa (AEASA)* Cape Town, South Africa,

Simtowe, F., Kassie, M., Asfaw, S., Shiferaw, B., Monyo, E. and Siambi, M. Welfare Effects of Agricultural Technology adoption: the case of improved groundnut varieties in rural Malawi. Selected Paper prepared for presentation at the International Association of Agricultural Economists (IAAE) Triennial Conference, Foz do Iguaçu, Brazil, 2012. 18-24.

Simtowe, F., Kassie, M., Diagne, A., Silim, S., Muange, E., Asfaw, S. and Shiferaw, B. 2011. Determinants of Agricultural Technology Adoption: The Case of Improved Pigeonpea Varieties in Tanzania. *Quarterly Journal of International Agriculture 50* (4):325-345.

Singh, B. and Emechebe, A. 1997a. Advances in research on cowpea Striga and Alectra. *Advances in cowpea research. International Institute of Tropical Agriculture (IITA), Ibadan, Nigeria*: 215-224.

Singh, B. and Emechebe, A. Increasing productivity of millet-cowpea intercropping systems. Pearl millet in Nigeria agriculture: Production, utilization and research priorities. Proc. of the Pre-season Planning Meeting for the Nationally Coordinated Research Programme for Pearl Millet, Maidiguri, 1997b. 21-24.

Singh, I., Squire, L. and Strauss, J. 1986. *Agricultural household models: Extensions, applications, and policy.* The World Bank.

Sinyolo, S., Mudhara, M. and Wale, E. 2014. The impact of smallholder irrigation on household welfare: The case of Tugela Ferry irrigation scheme in KwaZulu-Natal, South Africa. *WaterSA* 40 (1):145-156.

Smale, M., Bellon, M.R. and Aguirre Gómez, J.A. 2001. Maize diversity, variety attributes, and farmers' choices in Southeastern Guanajuato, Mexico. *Economic Development and Cultural Change* 50 (1):201-225.

Smith, J., Weber, G., Manyong, M. and Fakorede, M. 1997. Fostering sustainable increases in maize productivity in Nigeria. *Africa's emerging maize revolution*. Published in the United States of America by Lynne Rienner Publishers. Inc. 1800 30th Street, Boulder Colorado.

Solís, D., Bravo-Ureta, B.E. and Quiroga, R.E. 2007. Soil conservation and technical efficiency among hillside farmers in Central America: a switching regression model. *Australian Journal of Agricultural and Resource Economics* 51 (4):491-510.

Stutely, R. 2007. *The Definitive Guide to Business Finance: What Smart Managers Do with the Numbers.* Pearson Education.

Tambo, J.A. and Abdoulaye, T. 2012. Climate change and agricultural technology adoption: the case of drought tolerant maize in rural Nigeria. *Mitigation and Adaptation Strategies for Global Change* 17 (3):277-292.

Taylor, A., Martin, J. and Seel, W. 1996. Physiology of the parasitic association between maize and witchweed (Striga hermonthica): is ABA involved? *Journal of Experimental Botany* 47 (8):1057-1065.

Teklewold, H., Dadi, L., Yami, A. and Dana, N. 2006. Determinants of adoption of poultry technology: a double-hurdle approach. *Livestock research for rural development* 18 (3):(http://www.cipav.org.co/lrrd/lrrd18/13/tekl18040.htm).

Teklewold, H., Kassie, M., Shiferaw, B. and Köhlin, G. 2013. Cropping system diversification, conservation tillage and modern seed adoption in Ethiopia: Impacts on household income, agrochemical use and demand for labor. *Ecological Economics* 93:85-93.

Uaiene, R.N., Arndt, C. and Masters, W. 2009. Determinants of agricultural technology adoption in Mozambique. *Discussion papers* (67E):1-29.

UNAIDS. 2014. The gap report: Joint United Nations Programme on HIV/AIDS.

Unicef. 2015. Committing to child survival: a promise renewed. eSocialSciences.

UNSD (United Nations Statistical Division) 2008. *Designing household survey samples: practical guidelines.* United Nations Publications.

USDA (United States Department of Agriculture) 2014. United States Department of Agriculture: Statistic of maize production country by country. http//www.usda.gov/ accessed 28 August 2015.

Vanlauwe, B., Kanampiu, F., Odhiambo, G., De Groote, H., Wadhams, L. and Khan, Z. 2008. Integrated management of Striga hermonthica, stemborers, and declining soil fertility in western Kenya. *Field Crops Research* 107 (2):102-115.

Voh, J.P. 1982. A study of factors associated with the adoption of recommended farm practices in a Nigerian village. *Agricultural Administration* 9 (1):17-27.

Wale, E. and Yalew, A. 2007. Farmers' variety attribute preferences: implications for breeding priority setting and agricultural extension policy in Ethiopia. *African Development Review* 19 (2):379-396.

Wang, J., Wailes, E.J. and Cramer, G.L. 1996. A shadow-price frontier measurement of profit efficiency in Chinese agriculture. *American Journal of Agricultural Economics* 78:146-156.

Wanjiku, J., Ackello–ogutu, C., Kimenye, N. and Place, F. Socioeconomic factors influencing the intensity of use of bio mass transfer in food crop production in western Kenya. African Crop Science Conference Proceedings, 2003. 661-667.

WDR. (World Development Report). 2008. Agriculture for Development Washington, DC: The World Bank, p32.

Welch, F. 1970. Education in production. *Journal of Political Economy* 78 (1):35-59.

Wooldridge, J. 2012. *Introductory econometrics: A modern approach.* Cengage Learning.

Wooldridge, J.M. 2003. Introductory Econometrics: A Modern Approach. Thomson South-Western, Mason, Ohio.

Wooldridge, J.M. 2009. On estimating firm-level production functions using proxy variables to control for unobservables. *Economics Letters* 104 (3):112-114.

Woomer, P., Tungani, J., Odhiambo, G. and Mwaura, F. Striga management options in western Kenya. African Crop Science Conference Proceedings, 2005. 479-484.

Woomer, P.L. and Savala, C.N. Striga Management through Herbicide Resistance: A Public-Private Partnership in Action. AAAE Conference Proceedings, 2007. 489-496.

World, Bank. 2015. World Development Indicators. Washington, DC: The World Bank.

World Bank 2008. World Development report. *Agriculture for development.* Washington D.C: World Bank.

World Bank. 2013. Turn down the heart: Climate extremes, regional impacts and the case for resilience. Washington, DC.: USA.

Yamauchi, F., Yohannes, Y. and Quisumbing, A.R. 2009. Natural disasters, self-insurance and human capital investment: evidence from Bangladesh, Ethiopia and Malawi. *World Bank Policy Research Working Paper Series, Vol*.

Yang, D.T. 1997. Education in production: measuring labor quality and management. *American Journal of Agricultural Economics* 79 (3):764-772.

Zahran, E., Sauerborn, J., Abbasher, A.A., Ahmed, E.A., Mohukker, R., Karlovsky, P., Mohamed, E. and Müller-Stöver, D. 2008. "Pesta" and alginate delivery systems of Fusarium spp. for biological control of Striga hermonthica (Del.) Benth. under Sudanese field conditions. *Biological Control* 44 (2):160-168.

Zeller, M., Diagne, A. and Mataya, C. 1998. Market access by smallholder farmers in Malawi: implications for technology adoption, agricultural productivity and crop income. *Agricultural Economics* 19 (1/2):219-229.

APPENDIX 1**:** Cash Flow Analysis of integrated *Striga* management technologies in northern Nigeria

Items	**Year 0**	**Year 1**	**Year 2**	**Year 3**	**Year 4**	**Year 5**	**Year 6**	**Year 7**	**Year 8**	**Year 9**
Household adopted the technology [1]	353	353	353	353	353	353	353	353	353	353
Average houshold size (with 2.7 growth rate) [2]	7.0	7.2	7.4	7.6	7.8	8.0	8.2	8.4	8.7	8.9
Total number of beneficiaries [3=1x2]	2471	2538	2606	2677	2749	2823	2899	2978	3058	3141
OUTPUT AND BENEFITS										
Area under ISMA technologies [4]	734	734	734	734	734	734	734	734	734	734
Average yield of ISMA(ton/ha)[5]	2	3	5	7	7	7	7	7	7	7
Average price in US$/ton[6]	366	366	366	366	366	366	366	366	366	366
Total annual output in tons[7] (4x5)	1618	2427	3640	5460	5432	5432	5432	5432	5432	5432
Total annual revenue (US$) [8=6x7]	592091	888137	1332206	1998308	1987966	1987966	1987966	1987966	1987966	1987966
Gross revenue (US$) [9=8]	**592091**	**888137**	**1332206**	**1998308**	**1987966**	**1987966**	**1987966**	**1987966**	**1987966**	**1987966**
OVERHEAD AND PRODUCTION COSTS										
Land rent (US$) [10]	12686	12686	12686	12686	12686	12686	12686	12686	12686	12686
Maize seed (US$) [11]	19936	19936	19936	19936	19936	19936	19936	19936	19936	19936
Land preparation (US$)[12]	37099	37099	37099	37099	37099	37099	37099	37099	37099	37099
Planting (US$)[13]	11327	11327	11327	11327	11327	11327	11327	11327	11327	11327
Fertilizer (US$)[14]	190183	190183	190183	190183	190183	190183	190183	190183	190183	190183
Fertilizer application (US$)[15]	18486	18486	18486	18486	18486	18486	18486	18486	18486	18486
Manure	40370	40370	40370	40370	40370	40370	40370	40370	40370	40370
Weeding (US$) [16]	53464	53464	53464	53464	53464	53464	53464	53464	53464	53464
Harvesting (US$) (4800 per ton)[17]	47933	71899	107849	161774	160936	160936	160936	160936	160936	160936
Thresing (US$) (N1200per ton)[18]	11983	17975	26962	40443	40234	40234	40234	40234	40234	40234
Bagging and transportation per ton(N2500) (US$)[1	24965	37448	56171	84257	83821	83821	83821	83821	83821	83821
Total variable input costs (US$)[20= 10+----+19]	468432	510873	574534	670025	668543	668543	668543	668543	668543	668543
Net benefit (US$)[21= 9-19]	123659	377264	757672	1328283	1319423	1319423	1319423	1319423	1319423	1319423
Discounted revenue (US$)[22]	11950047									
Discounted cost (US$)[23]	4986165									
Benefit cost ratio [24=22÷23]	2.4									
Net benefit per capita (US$)[25=21÷2]	50.04408	148.66276	290.715	496.2569	479.987	467.36812	455.080935	443.116782	431.467168	420.124
Net Present value at 5% discount rate (US$) (26)	6963883									
Internal rate of return (27)	176%									
Net Present value at 10% discount rate (28)	5257799									
Benefit cost ratio at 10% discount rate (29)	2.28									
IRR (30)	163%									
Net Present value at 12% discount rate (31)	8533157									
BCR at 12 % discount rate (32)	2.23									
IRR (33)	158%									
*Exchange rate 1 US$ = 162 NGN										

APPENDIX 2: Cash Flow Analysis of Local maize production under *Striga* in northern Nigeria (annual yield decrease of 10%)

Items	Year 0	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Year 7	Year 8	Year 9
Household using local practice [1]	290									
Average houshold size (with 2.7 growth rate) [2]	7.0	7.2	7.4	7.6	7.8	8.0	8.2	8.4	8.7	8.9
Total number of beneficiaries [3=1x2]	2030	2084.8	2141.1	2198.9	2258.3	2319.3	2381.9	2446.2	2512.2	2580.1
OUTPUT AND BENEFITS										
Area under local maize [4]	779	779	779	779	779	779	779	779	779	779
Average yield of local(ton/ha)[5]	1.283	1.155	1.039	0.935	0.842	0.758	0.682	0.614	0.552	0.497
Average price in US$/ton[6]	366	366	366	366	366	366	366	366	366	366
Total annual output in tons[7] (4x5)	999	900	810	729	656	590	531	478	430	387
Total annual revenue (US$) [8=6x7]	365801	329221	296299	266669	240002	216002	194402	174962	157465	141719
Gross revenue (US$) [9=8]	**365801**	**329221**	**296299**	**266669**	**240002**	**216002**	**194402**	**174962**	**157465**	**141719**
OVERHEAD AND PRODUCTION COSTS										
Land rent (US$) [10]	13464	13464	13464	13464	13464	13464	13464	13464	13464	13464
Maize seed (US$) [11]	5700	5700	5700	5700	5700	5700	5700	5700	5700	5700
Land preparation (US$)[12]	39373	39373	39373	39373	39373	39373	39373	39373	39373	39373
Planting (US$)[13]	12022	12022	12022	12022	12022	12022	12022	12022	12022	12022
Fertilizer (US$)[14]	98577	98577	98577	98577	98577	98577	98577	98577	98577	98577
Fertilizer application (US$)[15]	10002	10002	10002	10002	10002	10002	10002	10002	10002	10002
Manure	40551	40551	40551	40551	40551	40551	40551	40551	40551	40551
Weeding (US$) [16]	56742	56742	56742	56742	56742	56742	56742	56742	56742	56742
Harvesting (US$) (480 per bag of 100kg)[17]	29614	26652	23987	21588	19429	17486	15738	14164	12748	11473
Thresing (US$) (N120per bag of 100kg)[18]	7403	6663	5997	5397	4857	4372	3934	3541	3187	2868
Bagging and transportation (US$)[19]	15424	13881	12493	11244	10120	9108	8197	7377	6639	5975
Total variable input costs (US$)[20= 10+----+19]	**328872**	**323628**	**318908**	**314661**	**310838**	**307397**	**304301**	**301514**	**299005**	**296748**
Net benefit (US$)[21= 9-19]	36929	5593	-22609	-47992	-70836	-91395	-109899	-126552	-141540	-155029
Discounted revenue (US$)[22]	1280887									
Discounted cost (US$)[23]	2529764									
Benefit cost ratio [24=22÷23]	0.5									
Net benefit per capita (US$)[25=21÷2]	18	3	-11	-22	-31	-39	-46	-52	-56	-60
Net Present value at 5% discount rate (US$) (26)	-1248878									
Internal rate of return (27)	71%									
Net Present value at 10% discount rate (28)	-1108215									
Benefit cost ratio at 10% discount rate (29)	0.48									
IRR (30)	63%									
Net Present value at 12% discount rate (31)	-1064735									
BCR at 12 % discount rate (32)	0.46									
IRR (33)	61%									
*Exchange rate 1 US$ = 162 NGN										

APPENDIX 3: List of states, LGA and Communities where farmers were interviewed

1. KANO STATE					**2. BAUCHI STATE**		
1	***KIRU***	***5***	***RANO***	**9**	***DASS LGA***	***13***	***ALKALERI LGA***
	Lamin Kwari=1		*Saji Saji=21*		*Dot=41*		*Gar=61*
	Kyarana=2		*Rurum=22*		*Gwaltukurwa=42*		*Gwarum=62*
	Kiru=3		*Kundu=23*		*Tak Bundili=43*		*Tumuru=63*
	Sabuwar Badafi=4		*Gazobi Tsohuwa=24*		*Dajin=44*		*Bajoja=64*
	Baure=5		*Babuha=25*		*Bundott=45*		*Alkaleri=65*
2	***BEBEJI***	6	***KARAYE LGA***	10	***TORO LGA***	14	***TAFAWA BALAWA LGA***
	Kofa=6		Kafin Dabga =26		*Dababe=46*		*Shirtawa -66*
	Danmako=7		*Yan Nedi =27*		*Rishi=47*		*Wuro Jibam = 67*
	Kuki=8		*Dederi = 28*		*Unguwar Gulawa=48*		*Yala = 68*
	Gajale=9		*Kumbuga =29*		*Tilden Fulani=49*		*Tamajira = 69*
	Bebeji=10		*Kadafa =30*		*Rinji=50*		*Gaso = 70*
3	***TUDUN WADA***	7	***KIBIYA LGA***	11	***GANJUIWA LGA***	15	***WARJI LGA***
	Gimbawa=11		*Kibiya =31*		*Ganjiwa=51*		*Muda Lallam = 71*
	Dagulau=12		*Tarai = 32*		*Gali=52*		*Muda Kwata =72*
	Yaryasa=13		*Kahu = 33*		*Durum=53*		*Kadale = 73*
	Sumana=14		*Nariya = 34*		*Zalanga=54*		*Baima =74*
	Kyangaram=15		*Saya Saya =35*		*Dasha=55*		*Bachuwa = 75*
4	***DOGUWA***	8	***SUMAILA LGA***	12	***BAUCHI LGA***	16	***KIRFI LGA***
	Shuburu=16		*Garfa = 36*		*Gubi=56*		*Kafin Maigarei = 76*
	Falgore=17		*Gala = 37*		*Bishi=57*		*Badara = 77*
	Burji=18		*Rumo = 38*		*Buzaye=58*		*Badawaire = 78*
	Ragada=19		*Riyi = 39*		*Kutaru=59*		*Kaloma = 79*
	Katakau=20		*Kargo = 40*		*Yamrat=60*		*Maimari = 80*

APPENDIX 4: Household survey questionnaire

Identification number of the questionnaire:___________________
FARM HOUSEHOLD SURVEY QUESTIONNAIRE
SMALLHOLDER LIVELIHOODS IN THE *STRIGA* INFESTED MAIZE AND COWPEA GROWING AREAS IN NORTHERN NIGERIA
EX-ANTE SURVEY OF KANO AND BAUCHI STATES.

Basic Information State: ---------LGA....................Village: ....

Enumerator's Name________________________

A. Interview and Household Details

A1 DATE			A2 TIME START		A3 INTERVIEW END	
Dd	Mm	Yr	Hr	Min	Hr	Min

GPS Coordinates: Latitudes______________________; Longitudes____________________________; Altitudes(elevation)___________________

A4 Interview Information

A4.1 Name of the Respondent (farmer)	
A4.2 Age of the farmer	
A4.3 Gender of the Respondent (1=male; 0= Female	
A4.4 Name of Household Head	
A4.5 Marital status: 1= single; 2= monogamous; 3= polygamous; 4=widowed; 5=divorced	
A4.6 Farming Experience in Years	
A4.7 Highest level of formal Education (None=0 , Primary=1, JSS=2,; SSS=3; NCE/OND=4, degree and above=5 ,others=6	
A4.8 What is the distance in(km) to the nearest weekly grain market from your home?	
A4.9 What is the distance in (km) to the nearest Agricultural Extension Office from your home?	
A4.9 Have you participated in the ISMA on-farm trial;(*Gwajin Koran wuta-wuta, soki, makasa*)	
A4.10 Have you ever attended a farmers' field day? 1= Yes; 0=No	
A4.11 What is your major occupation? Farming =1, trader=2; civil servant=3; technical skills=4,	
A4.12 Do you have another occupation other than the farming 1=Yes; 0=No. If yes answer A4.13	
A4.13 What is that occupation?	

B. HOUSEHOLD DEMOGRAPHIC CHARACTERISTICS

B1. What is your total household size including you? ………
B2. Household socio-demographics

Age	<2 yrs		2-10 yrs		11 – 20		21-30		30 -40		40-50		>50	
	M	F	M	F	M	F	M	F	M	F	M	F	M	F
Going to school														
Working on the farm														

B2. Intrahousehold decision making

B2.1. Please who makes decisions in your household on the following? (Use table below)

Item	Who makes decision Head alone=1 Spouse alone=2 jointly=3	Reason for making decision
Crops to plant		
Varieties to grow		
Planting new crop		
Purchase of farm inputs/household assets		
Food security coping mechanisms to be used		
Farm operations		
New agricultural technology to be adopted		

C. Productive Resources Endowment

C1. Land Tenure and Use Structure

C1.1. Please provide information on land tenure and use

Variables	Number of hectare
1. Inherited	
2. Purchased	
3. Rent in	
4. Borrowed	
5. Sharecropped land	
6. Rent out	
7. Loaned	
Total farm land (1+2+3+4+5) – (6+7)	

1 hectare= 2.47 acres; 1 acre= 0.405 hectares

C.1.2 If rent in (or rent out), how much do you pay (or receive) as rent for land per ha?________________

C.1.3. Do you practice fallow in your farms? 1=Yes 2=No, if yes how much _________ha

C1.4. How do you grade your operational farm land in terms of fertility? 1= high; 2= medium; 3= low; 4= poor; 5= too poor

C1.5. What can you say about your farm gradient. 1= level; 2= sloppy; 3= undulating, 4= hilly.

C2. Household Workforce

C2.2. Please provide information on household workforce

Age category (years)	**Total in the household**		**Number of household members who work full time on**		**Number of household members who work part time on the**		**Number of household members who work off farm**		**Number of able bodied household members doing nothing**		**Number of disabled members** (too young, too old, physically impaired)	
	M	F	M	F	M	F	M	F	M	F	M	F
0 – 6 years												
7 – 12												
13 – 17												
18 – 40												
41 – 60												
Over 60												

M=Male; F=Female

C3. Productive Assets

C3.1. Please provide information on the following key productive assets

Functioning asset	**Number Owned**	**Price per unit** (Current price if liquidated)	**Total value**
Hand hoe			
Machete (cutlass)			
Axe			
Shovel			
Ox plough			
Ox cart			
Wheelbarrow			
Work bull			
Donkeys			
Sprayer			
Irrigation pump			
Others (Specify) …………………			
Others (Specify) …………………			
Others (Specify) …………………			

D. Gender issues

D1 Membership and headship of social group

D1.1 Are you a member of any social group? ….. (Yes=1, No=2)
D1.2 If No to D1.1 above, please move to D2
D1.3 If yes to D1.1 above, are women members of the group? ……… Yes=1; No=2
D1.4 If yes to D1.3 above, what is the number of women compared to men in the group?

Number	**Women**	**Men**
Membership		
Headship		

D2. Access to resources

D2.1 According to you, do women as well as men have equally access to resources in your community? Please fill in below

No	**Resources**	**Access** 1=Accessible 2=Inaccessible	**If accessible, what is the level of accessibility** 1-More than men 2-Equally with men 3-Less than men
1	Natural capital (land area size and tenure)		
2	Human capital (labour)		
3	Financial capital (cash, credit)		
4	Physical capital (housing quality and consumer durables)		
5	Social capital (social networks and associations)		

E. Production inputs

E1. Land allocation and inputs in relation to maize and cowpea during last season of 2013.

Crop enterprise involved in	**Area (Ha)**	**Extent of *Striga* infestation?** 1=Not infested 2=Mild 3=Severe	**Intercropped with: 1=Sorghum 2=Millet 3=maize 4=Cowpea 5=G/nuts 6=Other**	**Proportion of maize** (%)	**Proportion of cowpea** (%)	**Seed source****	**Quantity of seed pla…**	Cost Naira	**Organic fertilizer**	Cost Naira	**Inorganic fertilizer 50 (Kg) bag**			**Seed (only for all intercrops so**(Kg)	**Insecticides** (liters)	**Herbicides** (liters)
											NPK	**UREA**	**SSP**			
Local maize, sole																
Hybrid maize, sole																
Improved OPV maize, sole																
Local maize intercropped																
Hybrid maize intercropped																
Improved OPV maize intercropped																
Local cowpea, sole																
Improved cowpea, sole																
Local cowpea intercropped																
Improved cowpea intercropped																
Others (Specify) ………….																

1 hectare= 2.47 acres; 1 acre= 0.405 hectares

** **Code:** 1= Own saved seed; 2=Another farmer; 3=Informal seed market; 4= ADPs; 5=. Cooperative, 6= Research Institute; 7=Private seed company; 8. Other, specify

****Measurement unit codes***: 1 = Kilogram, 2 = Litre, 3 = Bag (Specify in kgs) _________, 4 = Others (Specify in kgs)

*** Organic fertilizer: 1= Donkey load (*mangala);* 2= Ox-cart; 3= tractor trailer; 4= Pick up load; 5= Jumbo bag; 6= others (specify in kg)

E1.1 If you obtained your maize seeds from off-farm why did you needed the seed? 1. New variety, 2. Lost own seed,3. Early maturity, 4. *Striga* tolerant, 5. Advice by experts; 6. Other specify

E1.2 If you obtained seeds from own saved seed, in how many years do you plan to change your maize seed? 1. Every year 2. Every two years 3. Every three years 4. It depends, specify

E1.3 If you obtained cowpea seeds from on-farm why do you needed the seed? 1. New variety, 2. Lost own seed,3. Early maturity, 4. *Striga* tolerant, 5. Advice by experts; 6. Other specify

E1.4 In how many years do you plan to change your cowpea seed? 1. Every year; 2. Every two years; 3. Every three years 4. It depends, specify

E1.5 Please give the unit price of NPK ₦_____________; Urea ₦ __________; SSP ₦ ______________, Insecticide per litre ₦ ___________; Herbicide per litre ₦ ______________

E2. Production costs and labour inputs for last season 2012

Crop enterprise you engaged in.	**How do you rate the season with regard to rainfall/soil moisture in your farms?** 1=Very good	**How much did you harvest in 2012 (IN KG**	**Direct costs and family labour input** FAMILY LABOUR: PEOPLE (AE) X EFFECTIVE DAYS X EFFECTIVE HOURS AE = Adult Equivalents (1 Adult = A person of 15 and above years of age; A child of 10-14 years of age will be equated to 0.5 0f an adult equivalent)												
			Land rented if rente	Land preparation (clearing, ploughing,		Planting (Seed)		Fertiliser/chemical application		Weeding (all)		Harvesting and transport ation		Storage(shelling + storag	
			Cost	Cost	Labou	Cost	Labou	Cost	Labou	Cos	Labo	Cost	Labo	Cost	Labour
Local maize, sole															
Hybrid maize, sole															
Improved OPV maize, sole															
Local maize intercropped															
Hybrid maize intercropped															
Improved OPV maize intercropped															
Local cowpea, sole															
Improved cowpea, sole															
Local cowpea intercropped															
Improved cowpea															
Others (Specify) …………															

E2.1 from your last harvest (2012), how did you share your farm produce among the following?

Crop name	Yield obtained in bags of 100Kg	Quantity to be consume (bags of 100kg)	Quantity given out as zakat (charity) or gift	Quantity sold (bags of 100kg)
1.				
2.				
3.				
4				

E2.2 Production costs and labour inputs for current season 2013

Crop enterprise you engaged in.	**How do you rate the season with regard to rainfall/soil moisture in your farms?** 1= Very goo	**How much did you harvest in 201314 (IN KG PLEA**	**Direct costs and family labour input** FAMILY LABOUR: PEOPLE (AE) X EFFECTIVE DAYS X EFFECTIVE HOURS AE = Adult Equivalents (1 Adult = A person of 18 and above years of age; A child of 10- 17 years of age will be equated to 0.5 0f an adult equivalent)												
			Land rented if rente	Land preparation (clearing, ploughing,		Planting (Seed)		Fertiliser/chemical applicatio n		Weeding (all)		Harvesting and transport ation		Storage(shelling + storage equipment)	
			Cost	Cost	Labou	Cos	Labo	Cost	Labo	Cos	Labo	Cos	Labo	Cost	Labour
Local maize, sole															
Hybrid maize, sole															
Improved OPV maize, sole															
Local maize intercropped															
Hybrid maize intercropped															
Improved OPV maize intercropped															
Local cowpea, sole															
Improved cowpea, sole															
Local cowpea intercropped															
Improved cowpea															
Others (Specify)															

E2.3 from your current harvest (2013/14), how did you share your farm produce among the following?

Crop name	Yield obtained in bags of 100Kg	Quantity to be consume (Bags of 100kg)	Quantity given out as zakat (charity) or gift (Bags of 100kg)	Quantity sold or to be sold (Bags of 100kg)
1.				
2.				
3.				
4				

E2.4. In your own view, what is the acceptable minimum return on every naira invested in farm production in your community: 1= 100%; 2=50%; 3= 25%, 4=<25%; 5=>100%

E3. Crop marketing aspects for the last season 2013

Name of the crops you eted	Quantity stored in 100kg bag	Quantity sold Bags (100 kg)	Month most of the produce were sold	Average unit sale price during a		Market place where most of the produce were sold[1]	Who bought most the produce [2]	What is the most limiting marketing constraint [3]	Does this market constraint limit your willingness to adopt productivity enhancing technologies 1=Yes 0=No	Mention any technologies you have not adopted because of lack of market incentives[4]
				2012	2013					
Local maize, sole										
Hybrid maize, sole										
Improved OPV maize,										
Local maize intercropped										
Hybrid maize intercropped										
Improved										
Local cowpea, sole										
Improved cowpea, sole										
Local cowpea										
Improved cowpea										
Others (Specify)										

[1]*Market place*: 1=Village, 2=Neighbouring village/location/road/junction, 3=Nearby township, 4=Distant township, 5=Regional market, 6=Others (Specify) ………………
[2]*Trader typology*: 1=Local consumer, 2=Small trader/broker (bicycle, motorcycle or on foot), 3=Larger trader (vehicle), 4=Institution (school, prisons, etc), 5= Others (Specify) ....
[3]*Constraint*: 1=Low producer price, 2=Poor road to the market, 3=Poor access to information, 4=Lack of reliable transport, 5=Others (Specify) ……………………[4]**Technologies:** 1= improved maize, 2= improved cowpea, 3=improved soybean, 4=improved groundnuts, 5=improved rice, 6= other (specify)

F. *Striga* extent, severity and control technologies

Crop	Production constraints	A constraint 1=Yes 2=No	If yes, what is the level of severity 1=Highly severe 2=Severe 3=Less severe	If yes, to *Striga* when did it start to be a major constraint in your farm? Number of years
Maize	*Striga*			
	Stemborer			
	Termites			
	Storage insects			
	Low and erratic rainfall			
	Water logging (flooding)			
	Lack of improved seeds			
	Lack of fertiliser			
	Lack of herbicide			
	Lack of pesticide			
	Others weeds (Specify) …………			
Cowpea	*Striga*			
	Alectra			
	Diseases			
	Storage insects			
	Low and erratic rainfall			
	Water logging (flooding)			
	Lack of improved seeds			
	Lack of fertiliser			
	Lack of herbicide			
	Lack of pesticide			
	Others weeds (Specify) …………			

F1. What are the most important maize and cowpea productions' constraints?

F2. What is the extent and dimension to the *Striga (wuta-wuta, soki, makasa) problem* in your maize and cowpea plots?

Crops	**Proportion of land infested by *Striga*** (%)		
	Now (Hecterage)	Past two years	Control measures used (multiple answer possible)*
Local maize, sole			
Hybrid maize, sole			
Improved OPV maize, sole			
Local maize intercropped			
Hybrid maize intercropped			
Improved OPV maize intercropped			
Local cowpea, sole			
Improved cowpea, sole			
Local cowpea intercropped			
Improved cowpea intercropped			

Codes for Striga control measures: 1=Uprooting, 2=Burning, 3=Manuring, 4=crop rotation, 5=Intercropping, 6=Others (Specify) ……………………………………

F3. Use of integrated *Striga* control technologies (ISMA)

S/No	**Technology**	(a) Do you know it? 1=Yes 0=No	(b)Have you ever used it? 1=Yes 0=No
1.	Maize legume rotation		
2.	Maize legume intercropping		
3.	*Striga* resistant maize monocrop		
4.	Imazapyr herbicide resistant maize (IR) monocrop		
5.	Biocontrol technology monocrop		

F4. Which of the specific ISMA technologies are you using, and what is your current use status?

Striga* control Technology** ;(*Dabarun Koran wuta-wuta, soki, makasa*) **Code**	**What is the estimated farm size under specific technology?** (ha)	**What is the associated yield for Soybean**	**What is the associate d yield for Maize (kg)**	**What is the associate d yield per hectare yield for cowpea**	**What is the associate d yield for Groundnuts**	**Since when did you start to using it** (year)	**What is your perception of the technology in term of *Striga* control? See code Code****	**If you are practic ing it, who demon strated it to you?***
Striga resistant maize without legumes (1)								
Striga resistant maize intercropped with legumes (soybean (2), cowpea (3), groundnuts) (4)								
Striga resistance Maize in crop rotation with								
Striga resistant Cowpea (6)								
Cowpea in crop rotation with *Striga* resistant Maize (7)								
Maize + Biocontrol of *Striga* (8)								
Imazapyr-resistant hybrid maize (9)								
Other integrated management control								

Codes for the source of information and technology demonstration: 1=Farmers in the village, 2=Farmers in other villages, 3=Mass media (radio, newspapers), 4=Extension workers, 5=Local NGOs, 6=Research institutes, 8=Farmer Community Based Organisations (CBOs), 9= Field days/visits, 10=Others (Specify) ………………………

****Codes for perception of *Striga* control measures**: 1= very effective; 2= effective; 3=Fair; 4= not effective; 5= worse than without the technology.

***** 1**-10

F5. If you are aware of any modern *Striga* control technologies mentioned in here, how would you rank them relative to your own traditional control practices?

Type of Crop	***Striga* control Technology**	**Rank in each type of crop based on**				
		Yield (Most yield enhancing to the least) 1=Most yield 2=Moderately yield 3=Least yield	**Technical simplicity** (Simplest to most complex) 1=Simplest 2=Simpler 3=Complex	**Labour demand** (Least demanding to the most demanding) 1=Least demanding 2=Moderately 3=Most	***Striga* population** (Most *Striga* reducing to the least) 1=Most *Striga* reducing 2=Moderately 3=Least	**Soil fertility** (Most fertility enhancing to the least) 1=Most fertility enhancing 2=Moderately 3=Least
Maize	Use of farm yard manure					
	Hand-pulling					
	Use of inorganic fertilizer					
	Cursing of *Striga* verbally					
	Use of *Striga* ash to dressed seed					
	Striga resistant maize without legumes					
	Striga resistant maize intercropped with legumes					
	Local Maize in crop rotation with legumes					
	Imazapyr-resistant maize					
	Other integrated management control approach (Specify) ……….					
Cowpea	Use of farm yard manure					
	Hand-pulling					
	Use of inorganic fertilizer					
	Striga resistant cowpea					
	Cowpea in crop rotation with *Striga* resistant Maize					
	Other integrated management control approach (Specify) ……………………… …..					

F6. If you are aware of any *Striga* control technology but have not adopted any, what is the most important reason for non-adoption? (Multiple answers possible)

	Reason for non-adoption	***Reason status*** *(Yes=1, No=0)*	***Ranking*** *(1^{st} being the most important reason)*
1	*Lack of adequate information about the technology*		
2	*Traditional control practice is better*		
3	*Fear of technology failure*		
4	*High cost of technology*		
5	*Non-availability of improved seed (Striga resistant varieties)*		
6	*Non-availability of improved IR maize seed*		
7	*Non-availability of improved cowpea Striga resistant seed*		
9	*Others (eg cultural factors) (Specify) …………*		

F7. Perceptions about ISMA technologies (circle the number corresponding to the response). To what extent do you agree with each of the following statements? Please indicate your answer using the following 5-point scale. where: (5) Strongly Agree, (4) Agree,
(3) Disagree, (2) Strongly Disagree, (1) Don't Know

Statement	**Strongly disagree**	**Disagree**	**Undecid ed**	**Agree**	**Strongly agree**
ISMA varieties have higher yield compared to your local varieties	1	2	3	4	5
ISMA varieties are more tolerance to *Striga* than local varieties.	1	2	3	4	5
ISMA maize varieties mature early than local	1	2	3	4	5
ISMA varieties are more resistance to insects and diseases than your local varieties.	1	2	3	4	5
ISMA varieties are more resistance to storage weevil	1	2	3	4	5
ISMA varieties are more resistance to wind and lodging than your local varieties.	1	2	3	4	5
ISMA varieties have better taste when cooked than your own local varieties.	1	2	3	4	5
ISMA varieties have bigger and multiple ears than local varieties.	1	2	3	4	5
ISMA varieties are more tolerant to drought	1	2	3	4	5
ISMA varieties have taller stalk than local	1	2	3	4	5

F8. Perception of farmers about seed quality obtained under ISMA project.

	Excellent	Very Good	Good	Fairly Good
How do you rate the purity of seed as compared to your own maize, cowpea and soybean seed				
How do you rate the germination percentage of the varieties				
How was the resistance of the varieties to *Striga*				

1=Fairly good; 2=good; 3=Very Good; 4= Excellent

F9. How satisfied are you with the performance of ISMA technologies?

Very Dissatisfied (1)		Somewhat Dissatisfied(2)		Neutral(3)		Somewhat Satisfied(4)		Very Satisfied(5)	

F10. Have you ever encountered crops yield lost due to *Striga*? 1=Yes; 0= No

F11. if yes to F10. How many times in the last 5 years_______________?

What are the coping strategies you employed in order to cushion the effect of *Striga*? List them

i.____ ii. ____

iii.____ iv. ____

v.____ vi. ____

F12. Improved Maize, cowpea and soybean seed distribution.

			2013			2012		
			1. Y 0. N	Variety Code C	Amount (kg)	1. Y 0. N	Variety Code C	Amount (kg)
1. Did you distribute/give improved maize, cowpea or soybean seeds in the last two years?								
2. If Yes, how many farmers did get your seed?								
3. On what terms you did give the seed.	Sale (price)							
	Gift							
	Exchange	Code A-Crop						
		Code B-Amount						
	Loan							
	Labor exchange							

CODE A: 1. same crop, 0. Different crop;
CODE B. 1. Same amount 2. More amount, 3. Less amount

Code C: 1. *Striga* resistance; 2. Imazapyr-resistant hybrid1; 3 Imazapyr-resistant hybrid2; 4. Hybrid maize; 5. Improved OPV maize;7= *Striga* resistance cowpea; 8= improved soybean variety; 9= others (specify)

G. Vulnerability, capital assets and livelihoods

G1 Household Food Security

G.1.1. Number of months that harvest lasted

In 2012/13 season, how long did your harvest of main cereal and legume lasted?

	(a) Crop	(b) Name of crop	How long did the harvest last?(No. Of months out of 12 months)	How long do you think your harvest will last this time 2013/14)
1	Main cereal			
2	Main legume			
3	Main root/tuber			

G.1.2. in the past 12 months, were there months in which you did not have enough food to meet your family needs.

1= Yes; 0= No if No go to G.1.3

b) If yes, which were the months in the last 12 months that you did not have enough food to meet your family needs.

	Month	(a) Did you have enough food to meet your family's needs 1=Yes; 0=No			(a) Did you have enough food to meet your family's needs 1=Yes; 0=No
1	January		7	July	January
2	February		8	August	February
3	March		9	September	March
4	April		10	October	April
5	May		11	November	May
6	June		12	December	June

G.1.3. Coping with food shortages.
If you faced any food shortage in the last 12 months, what coping strategies did you used? (Tick appropriate)

Coping mechanism	(a) Did it happened 1=Yes 0= N0	If you used strategy how often did you use it?*
Borrowed money to buy food or got food on credit		
Reduced the number of meals		
Father ate less		
Children ate less		
Substituted commonly bought food with cheaper kind		
Mortgage or sold asset to buy food		
Borrowed from neighbours		

*How often: 1=Very few time (seldom0; 2=occasionally; 3=regularly; 4=All the time

G2. Financial Capital

G2.1 Please indicate the types of your financial capital and livestock that the household owns

Financial capital	Do you have access to such a financial capital? 1=Yes 0=No	Livestock owned		
		Type	**Number**	**Average price/unit**
Cash savings at bank		Cattle		
Cash savings at home/pocket		Goats		
Claim on your good debtors		Sheep/ ram		
Jewellery		Chicken		
Formal credit*		Rabbits *(zomo)*		
Informal credit*		Pigeon *(Tattabaru*)		
Cash remittances from relatives/friends		Donkeys		
Others (Specify) …………..		Horses		
1		Guinea fowl		
2		Ducks		
3		Tolotolo		
4		Pigs		
5		Others (Specify)		

*The question needs to be addressed as whether the household can get formal/informal credit when needed.

G2.2 Access to credit
Did you receive any cash and/or in-kind input (formal and informal) credit for maize/cowpea production?
1= Yes 0= No
If No, please say why:
1 = N/A 2 = No source of credit in vicinity 3 = Did not look for credit 4 = No collateral to guarantee credit, 5= High interest rate 6=Other (specify): ________________________

IF YES provide information on the cash and input credit you received during the last cropping season

Item	Cash amount (local currency)/ quantity (kg)	Source **(Code 1)**	Who received it? **(Code 2)**	Form of repayment **(Code 3)**	Cash amount/quantity reimburse	Was credit received on time? *Yes =1 No=2*
Production cash credit						
Consumption cash credit						
In-kind Input credit seeds (List crops)						
1.						
2.						
3.						
In-kind Input credit- Fertilizer and chemical						
NPK, Urea, SSP						
Organic manure						
Chemical pesticides						
Botanicals						
Other: (specify)						

Code 1: Source of credit: 1= Commercial banks,2= Bank of Agriculture; 3=Farmers Cooperatives 4= Money lender, 5= Neighbours, 6= Relative, 7= Government program, 8= NGO;
Code 2: Beneficiary: 1= Male spouse, 2= Female spouse, 3= Joint beneficiary, 4= Other male adult, 4= Other female adult; **Code 3: Repayments**: 1= Seeds, 2= Cash, 3= Other1____________, 4= Other 2_______________

G3. Physical capital

G3.1. Please indicate the physical infrastructure you have access to

Physical capital	**Codes for responses**	**Responses** (more than 1 response allowed)
Water supply	1=Piped, 2= Public Tap, 3= Borehole, 4= well/spring, 5=Rain water, 6=Vendor/tanker truck, 7=River/lake/stream, 8=Others	
Toilet facility	1 =Flush toilet, 2= Pit latrine, 3=Bush, 4=Others (Specify)	
Type of lighting for house	1=Electricity, 2=Paraffin or kerosene lantern, 3=Candle wax, 4=torch, 5=Firewood, 6=Solar or gas, 7=Others (Specify)	
Cooking fuel	1=Firewood, 2=Charcoal, 3=Electricity, 4=Paraffin or kerosene,	
Health center/hospital	Yes=1;	
Own vehicle	Yes=1;	
Own motorcycle	Yes=1;	
Own bicycle	Yes=1;	
Telecommunication (mobile phone, others)	Yes=1; No=2	
Own a house	Yes=1;	
Renting a house	Yes=1;	
House roof	1=Thatched, 2Corrugated iron sheets, 3=Asbestos, 4=Tiles, 5=Aluminum, 6=Cement, 7=Mud, 8=Others (Specify)	
House wall	1=Thatched, 2=Mud and poles, 3=Raw bricks, 4=Burnt bricks with mud, 5=Cement blocks, 8=Stone, 9=Others (Specify)	

G4. Human capital

G4.1 Please provide the following information on the types of agricultural technologies introduced

Agricultural technology	Have you ever been in contact with extension agents from different sectors on improved technologies? 1=Yes 2=No		Number of extension visits you received in last year	
	Public (ADP/Ministry, etc.)	NGO/Projects (IITA, Sasakawa etc.)	Public	NGO/Projects
Improved maize varieties				
Improved cowpea varieties				
Control of *Striga*				
Control of other weeds				
Soil fertility management				
Improved food grain storage				
Collective product marketing				
Livestock management				

G5 Social capital

G5.1 Please provide the following information if you or any member of your household belongs to any local association/group. Yes=1; No=0

If yes, which type of association/grouping?

Type of associations **(Code 1)**	What was your motivation to join the association? **(Code2)**	How long have you been a member (years)?	Status of membership 1=Simple member 2=responsible	Is the association still functioning? *1=Yes 0=No*	What benefits do you get for being a member of association/grouping? **(Code 2)**

Code 1: 1= Farmer organization; 2= Platform; 3= Cultural association; 4= Political association; 5= Religious association; 6= NGO; 7= others (specify)

Code 2: 1= Easy access to credit, 2= the association supplies maize, 3= Collective freight transportation of maize, 4= Group selling of farm produce, 5= Easy access to inputs, 6=Others (please specify)

G5.2 In the past one year, how many people have you interacted with in exchange of information on development issues?

Different wealth status	[ ]	Same wealth status	[ ]
Different ethnic/tribe	[ ]	Same ethnic/tribe	[ ]
Different age category	[ ]	Same age category	[ ]
Different occupation	[ ]	Same occupation	[ ]
Different religious faith	[ ]	Same religious faith	[ ]
Different political denomination	[ ]	Same political denomination	[ ]

Codes: 1=none, 2=less ten people, 3= ten people, 4=More than 10 people

H. Livelihood strategies and outcomes

H1. Please provide information on farm and non-farm income sources, the family members involved, the average income per year, and the seasonal stability of income generated

Income source	**Were all members involved?** 1=Yes 2=No	**Amount per year Naira**	**How stable is this source of income?** 1=Stable 2=Somewhat stable 3=unstable
Farm income			
Maize production			
Cowpea production			
Soybean			
Other crops' production			
Livestock keeping			
Agricultural wage employment			
Total farm income			
Non-farm income			
Non-agricultural wage employment			
Petty trade*			
Handicrafts			
Transport service			
Grain mills			
Fishing			
Hunting and gathering of wild food			
Selling fuel wood and charcoal			
Selling prepared foods/drinks			
Professional work**			
Traditional medicine			
Rent income			
Remittances			
Other non-farm income (Specify) …………………………………..			
Total non-farm income			
Total income			

*Includes manufactured goods, food grains, fruits and vegetables, cotton, and livestock and livestock products *Includes teachers, health workers, vets, etc.

J. Household expenditure

J1; Average Household Expenditure on food

Expenditure items	**Average weekly expenditure (Naira)**	**Number of weeks of expenditure/year**
Food and beverages		
Maize		
Others Cereals		
Cowpea		
Other legumes		
Roots and tubers		
Other foods/snacks		
Fruit and vegetables		
Meat, poultry and fish		
Grocery food (bread, milk, egg, oils, food additives and condiments, nuts, snakes)		

Non-alcoholic beverages (coffee, tea, water, juices)		
Alcoholic/ tobacco		
Others (Specify) 1		
Total food expenditure		

J2: Household Expenditure on Non-food items
Please indicate how much your household spend on the following items in the **past 12 months?**

S/N	**Non-food Expenditure**	**Average annual Expenditure (Naira)**
1	Clothing/ footwear	
2	Fuel- wood, paraffin, generators, etc.	
3	Housing (rent, water and light) and household services (wages for servants)	
4	Transport and communications	
5	Education	
6	Health expenses	
7	Repairs (bicycle, motorcycles, car, etc.)	
8	Recreation, entertainment and cultural activities	
	Total Non-Food Expenditure	

Thank you for your co-operation in responding to this questionnaire.

APPENDIX 5: Checklist for community surveys

<u>INTEGRATED *STRIGA* MANAGEMENT IN AFRICA</u>
<u>COMMUNITY SURVEY INSTRUMENT</u>

CHECKLIST:

1. Farmers' world view and descriptions: perceptions, indigenous taxonomies, criteria, classificatory system, predictive and forecasting skills, know-how and knowledge on incidences of *Striga*.

2. Trends and experiences of *Striga* occurrence: associated causes, degree and magnitude of severity.

3. Consequences of *Striga* incidence: effects and outcomes on farm environment (resources, crops, livestock), decision-making process, health (nutritional status and well-being), relationships and social responsibilities (between and among family, groups and community members), conflicts and disputes, income generation (profits, savings, expenditure patterns, prices and markets).

4. Changes due to *Striga* incidence: types and patterns, adaptations, rate and levels

5. Mitigations: *Striga* management and coping strategies (indigenous practices, modern practices and complementary practices, institutional interventions, farmers' opinions and future strategies.

Interview and Village Details

Name of village: ________________ longitude_____________latitude

LGA

State

What are major sources of livelihood in this community?
What are the major tribes?
What is the rough estimate of the community population?

Type of group: Men_______ women_________________

Number of participants:

Interviewer

B. Village infrastructure (transect trekking would be conducted with the community members)

Infrastructure	Availability Available=1 Not available=2	If not available, distance to nearest (km)
Primary school		
Secondary school		
Health centre/hospital		
Pipe borne water		
Community centre		
Bore hole/well water		
Latrine facilities		
Electricity		
Telecommunication		

C. Crops grown

C1. List the 5 most important crops grown in this village for household food and cash income (starting with the most important in each case)

Rank	Food crop	Cash crop
1		
2		
3		
4		
5		

C2 What are the varieties of maize, cowpea and soybean grown in your village?

Type of crop	Varieties	Mostly grown by	
		Men	Women
Maize			
Cowpea			
Soybean			

C3. Please provide information on cropping calendar for the following crops.

Crop Name	Crop operation month(s)			
	Land preparation	Planting	Weeding	Harvesting
Maize				
Cowpea				

D. Access to inputs

D1. Do you have access to the following in your village? Fill in

Opportunities	Easy access Yes= 1, No=2	If No, what is the distance to the nearest dealer/outlet (in
Fertilizer dealer/outlet		
Insecticide dealer/outlet		
Herbicide dealer		
Improved seed dealer		

D2. What is the wage rate for hired labour in this village? (____Naira/day) E. *Striga* and *Striga* control technologies

E1. Does *Striga* a major constraint to crop production in your village? .... (Yes=1, No=2) E2. If yes to E1, what are the crops the most affected? Cite them:

E3. Since when has *Striga* been a major constraint to crop production in your village?

____

E4. What traditional practice(s) are used to control *Striga*?

____

____

E5. What are the per hectare yields in years of

	Yield per Hectare
1.Little *Striga* infestation	
2. Moderate *Striga* infestation	
3. High *Striga* infestation	
4. Very high *Striga* infestation	

E6. Which *Striga* control technologies are mostly used in your village and what are the associated per hectare maize yields?

Striga control technology	*Yield per hectare*

E7. What are your perceptions of the Striga control technologies with respect to yield, technical simplicity, labour demand, appropriateness for men/women farmers and rich/poor farmers relative to the traditional control practice?

Striga control technology	*Perceptions*				
	Maize yield *Better=1* *Same=2* *Poor=3*	*Technical simplicity* *Simpler=1* *Same=2* *More complex=3*	*Labour demand* *Less labour=1* *Same=2* *More labour=3*	*Men/women farmers* *Equally appropriate =1* *Less appropriate*	*Rich/poor farmers* *Equally appropriate =1* *Less appropriate for the poor=2*

E8. Which month(s) of the year do villagers encounter serious food shortage? ----------------------

F. Food security

F1. How often are serious food shortages encountered in this village? Every ------year(s)

F2. What is the major cause of the food shortage in your village? Please rank only those that apply

Cause	Rank
Low production due to *Striga* infestation	
Low production due to drought (crop + livestock)	
Low production due to pest infestation (e.g. army worm, locust, etc.)	
Low production due to a failed improved technology	
Low production due to declining soil fertility (trend)	
Low production due to progressive land shortage (trend)	
Low production due to a health shock reducing labour availability	
Low real (off-farm) wages due to rising food prices (Price shock)	

F3. What are the three most common coping strategies used by villagers to mitigate the shock?

F4. Are there differences in coping strategies by gender (Men, Women, Youth)? ------ by socio-economic class (Rich/poor)? -----------(Yes=1; No=2)
If Yes, what are the most important strategy pursued by the different categories?

Gender	Coping strategy
Men	
Women	
Youth	

F5. Are there differences in coping strategies by socio-economic class (Rich/poor)? Yes=1; No=2)
If Yes, what are the most important strategy pursued by the different categories?

Socio-economic class	Coping strategy
Rich	
Poor	

G. Assets
G1. Please provide the following information on the natural capital the villagers have access to.

Natural capital	Size (Hectares)	Ownership Communal=1 State=2	Conservation investment High=1 Low=2 No investment=3	Who has access? Men only=1 Women only=2 Men and women=3	Type of access Restricted=1 Open access=2
Cropland					
Pasture/grazing land					
Forestland					
Fishponds					
Irrigation water					
Others: Specify					

G2. Have individual members of the community been educated? --------(Yes=1; No=2)

G3. Are girls sent to school? ------------ (Yes=1; No=2)
G4. Have individual members of the community received skills training? --------(Yes=1; No=2) G5. Have members of the community received literacy training? --------(Yes=1; No=2)

G6. Please indicate the associations and groups in this village and their associated benefits.

G7. Do government extension services assist the community? --------(Yes=1; No=2) G8. If there are government extension services, what do they cover?

____

G9. What agricultural technologies have extension services, NGOs, and other organisations introduced to this village? When were these first introduced? Have villagers adopted these?

Agricultural technology	Year technology was first introduced	Have villagers adopted the technology? Adopted=1

APPENDIX 6: Survey instrument administer at field days

Farmers perceptions and Economic Assessment of Sustainable *Striga* Control Technologies for Poor farmers in Northern Nigeria

QUESTIONNAIRE ON *STRIGA* MANAGEMENT TECHNOLOGIES

Date……………………………… GSM No: ....Enumerators name______________________

SECTION A

1. State________________: LGA: ____________________
2. Village/community/…………………………………………………
3. Type of *Striga* management in the field: ____
4. Name of respondent: ……………………………………………………
5. Gender of respondent: *Male=1;) Female=2*
6. Family size including you_______________
7. Age of respondent (in years): _______________
8. Highest education level?

1= No formal education ( ); 2=Primary Sch. ( ); 3 = Secondary. sch. ( ); 4 = Post. Sec. ( );
5= Adult education ( ); 6= others (specify)………………………………………………

9. Major occupation ………………………………………
10. Other sources of livelihood ……………………………………………………………………
11. List three major crops from which you derive the highest income (in order of importance)

……...................................

12. How long have you been a farmer? ....……….
13. Do you belong to any producer's association? ***1** = yes* ***0** = No ………………………*
14. If yes, what are the benefits you derived from the associations?

……………………………………………………………...

15. Are you currently participating in the ISMA on-farm trial? Yes=1; No=0

SECTION B

1. Where did you hear about this field day/demonstration? *(tick all that apply)*

[ ] Invited by the host farmer; [ ] Other farmers told me about it
[ ] Heard about it from extension or community based organisation
[ ] Read about it in the newspaper; [ ] Heard about it through radio/ television
[ ] Heard about it from my church/mosque
[ ] Other *(Please explain)* .....…………………………………………………

2. Why did you come to this field day/demonstration? *(tick all that apply)*

[ ] Know the host farmer
[ ] I am generally interested in the technologies, but I know little about them
[ ] I am interested in trying these technologies on my farm
[ ] I want to meet with other farmers using these technologies
[ ] Other *(Specify)* ……………………………………………………………

3. Did you attend last year's ISMA field day? Yes=1; No=0. If No go to question 8
4. If yes to question 3, which technology did you preferred most? _____________
5. Are you currently using it? Yes=1; No=0
6. What was your source of the technology? ___________________________

7. How many hectares of your land is under this technology? ____________________

8. What is the estimated trekking time from your home to the field day site? ____________ in minutes

9. How far is your home from the nearest weekly market? ……………Kilometers

10. Is *Striga* a problem on your farm? Yes=1; No=0

11. If yes, what is the level of *Striga* damage?
    (a) High (*65 – 100%*)______ (b) moderate (*35 – 64%*)_______ (c) Low (*0 to 34%*)_______
12. How many hectares of land do you owned currently in 2013? ………………………. Hactares

13. Total farm size and area affected by *Striga* in the last three years?

Year	Total farm size	Area affected by *Striga* (ha)
2011		
2012		
2013		

14. How many hectares of your farm are currently under any of the following practice?
    a. Maize Local Variety …………
    b. Maize Hybrid Variety ………….
    c. Maize + Soybean Intercropping ………….
    d. Maize + Groundnut Intercropping ……………
    e. Maize + Cowpea intercropping …………..
    f. Maize + Soybean rotation ……………
    g. Maize + Groundnut rotation ……………
    h. Maize + Cowpea rotation ……………
    i. IR Maize or MSM Maize ……………
    j. *Striga* resistant maize ……………
    k. Soybean monocrop ....
    l. Cowpea monocrop ....
    m. Groundnut monocrop ....

15. If applicable, how long have you been using any of the following technologies to control *Striga* (*wuta wuta ko kuduji*)?
    a. Maize +Soybean intercropping …………...Years
    b. Maize + Groundnut Intercropping …………... Years
    c. Maize + Cowpea intercropping …………... Years
    d. Maize + Soybean rotation ………….. .Years
    e. Maize + Groundnut rotation ………….. .Years
    f. Maize + Cowpea rotation ………….. .Years
    g. IR or MSM Maize monocrop ....…….. .Years
    h. *Striga* resistant maize monocrop ………….. . Years
    i. Maize + Biocontrol Technology .... Years
    j. Maize + Desmodium Intercrop (*push –pull technology*) .... Years

16. Which of these practices would best be the most practical method on your farm to control *Striga* weed? <u>*Rank the best three in order of importance 1= best*</u>

Hand pulling	Maize + Cowpea Intercrop	Maize + Soybean Intercrop	Maize + Groundnut Intercrop	Maize + Soybean Rotation	Maize + Cowpea Rotation	Maize + Groundnut Rotation
IR Maize	*Striga* Resistant Maize	Soybean monocrop	Cowpea monocrop	Groundnut monocrop	Maize + Biocontrol	Maize + Desmodium (*push pull*)

For the best ranked method, Why?
…………………………………………………………………………………….

17. Do you have any reservation or reason why you cannot use the technologies demonstrated today?
Yes [ ] No [ ]

If yes, state the reasons
………
…………………………………………………………………………………

18. Which of the ISMA technologies would you like to learn more about in the future?
a) ………………………………………………………………………………………
b) ………………………………………………………………………………………
c) ....

19. How many hectares of your farm do you hope to put under these technologies in the future? ____________

20. In your own way *i.e. Traditionally* how do you control *Striga* problem? ------------------------------ --------------------
....
....

21. List three constraints that will hinder you from adoption of improved production technologies:
....
....
....

22. On-Farm demonstration and field days really help farmers in adopting new technologies

Strongly agree = 1	Agree = 2	Undecided = 3	Disagree = 4	strongly disagree = 5

23. Please rate the Demonstration/field day on the following items. (*circle one number for each item*)

a) Content	*Of little use*	1	2	3	4	5	*Useful*
b) Organisation	*Poor*	1	2	3	4	5	*Excellent*
c) Involvement of farmers	*Poor*	1	2	3	4	5	*Excellent*

24. Did you find today's Demonstration/field day useful? Yes [ ] No [ ]

25. What should be improved in the future field days?
……
……
……
……

26. Is there any other comment?
....
....
....

Thank you for responding to the questions.

APPENDIX 7: Simplified survey questionnaire for on-farm trials for integrated *Striga* control

STATE:____________________

LOCAL GOVERNMENT AREA:_______________________________________

FARM LOCATION:____

NAME OF TECHNOLOGY (Tried):____

NAME OF VARIETY:____

DATE OF PLANTING:____

DATE OF HARVESTING:____

PLOT SIZE:_____________________

YIELD PER PLOT:____

YIELD PER HECTARE

COST OF LABOUR IN NAIRA

Item			
COSTS OF OPERATIONS	Labour wage in 2012	Labour wage in 2013	Labour wage in 2014
LAND RENT/HA/YEAR			
LAND PREPARATION /HA			
1. LAND CLEARING			
2. PLOUGHING			
3. HAROOWING			
4. RIDGING			
OTHERS(SPECIFY)			
Herbicide application where applicable			
Insecticide application where applicable			
Planting/ha			
1st weeding/ha			
1st fert. Application/ha			
2nd weeding/ha			
2nd fert. Application/ha			
moulding/ha			
harvesting, threshing and storage cost/ 100kg bag			
transportation to the market /100kg bag including loading and offloading			

COST OF INPUTS IN NAIRA

Items	2012			2013
	UNIT PRICE	QUANTITY USED	TOTAL NAIRA	UNIT PRICE
Improved seed /kg				
NPK fertilizer ₦/ 50kg bag				
Urea fertilizer ₦ / 50kg bag				
Herbicide ₦ /lit or Kg				
Insecticide ₦ /lit				
100 kg empty bag				

SELLING PRICES OF FARM PRODUCE PER 100 KG BAG IN NAIRA

Items	At harvest 2012	Peak 2012	Harvest 2013	Peak 2013
Maize				
Soybeans				
Cowpea				