Adoption and Impact of Climate-smart Agriculture Technologies in Integrated Crop-Livestock Farming Systems

By

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Dedication

To my children (Anesuishe, Anotidaishe, Anogonaishe, Aitaishe and Anoonaishe) and my Loving parents (Grace and Stephen Chisvino)

DECLARATION 1

I, Angeline Mujeyi, declare that,

1. The research reported in this thesis, except where otherwise indicated, is my original research,

2. This thesis has not been submitted for any degree or examination at any other university,

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As the candidate's main supervisor, I, Professor. M. Mudhara, agree to the submission of this thesis.

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DECLARATION 2: PUBLICATIONS

The following manuscripts (published and under review) form part of the research presented in this thesis

Manuscript 1- Chapter 3 *(Under review)*

Adoption patterns of Climate-Smart Agriculture in integrated crop-livestock smallholder farming systems. *Under review in Journal:* Climate and Development

Manuscript 2 - Chapter 4 (*Published)*

Mujeyi, A., Mudhara, M., and Mutenje, M.J., 2019. "Adoption Determinants of Multiple Climate-smart Agricultural Technologies in Zimbabwe : Considerations for Scaling-up and Out." *African Journal of Science, Technology, Innovation, and Development* 0 (0). 1–12. https://doi.org/10.1080/20421338.2019.1694780.

Manuscript 3 - Chapter 5 *(Published)*

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Manuscript 4- Chapter 6 (*Published book chapter*)

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Manuscript 5- Chapter 7 *(Under review)*

Optimal Enterprise Mix in Crop-Livestock Integrated Farming Systems of Zimbabwe: Implications for Heterogeneous Climate-smart Agriculture Technology Adoption. *Under review in Journal*: Technology in Society.

Conference contributions

Mujeyi A, Mudhara M and Mutenje M.J. A Review of Current Climate-smart Agriculture Technologies: Adoption and Impact in Integrated Smallholder Farming Systems of Zimbabwe. Review selected for presentation at the Biennial Climate-smart Agriculture Stakeholders conference on 1-2 December 2020. Hosted by The Forum for Agricultural Research in Africa *(*FARA*)* and conducted virtually.

ABSTRACT OF THESIS

In Zimbabwe, smallholder farmers who rely on rain-fed crop-livestock systems for their livelihoods face multiple constraints which include a shortage of labour, inadequate capital to purchase inputs, low soil fertility, pests, disease outbreak, and low productivity as a result of climate change and variability. Climate change has caused prolonged droughts, reduced rainfall amounts and changing rainfall patterns, threatening the welfare of agriculture-based households. Climate-smart agriculture (CSA) technologies have been promoted as a panacea to address the negative effects of climate change. To date, the adoption of CSA has been low and on small land sizes. However, to ensure maximum benefits from CSA and scale up adoption, a better understanding is required regarding smallholder farmer adoption patterns. This study mapped adoption patterns, analysed common CSA technology bundles, measured the impact of CSA on household welfare and modelled optimal enterprise mix for farmers adopting CSA. Data was collected through a cross-sectional household survey of 386 multi-stage randomly selected respondents from four districts in Zimbabwe. Analysis was done using multivariate statistical techniques of principal component analysis and cluster analysis as well as the Cragg double hurdle model, multinomial logistic regression model, endogenous Switching Regression model, Cost-Benefit Analysis, stochastic profit frontier model and multi-objective goal programming.

The findings based on the PCA-Clustering analysis showed that patterns of CSA varied across the household typologies. Resource endowed and experienced farmers have a high use of technologies such as crop rotation and minimum tillage that require more resources while resource-constrained clusters avoided resource-intensive CSA technologies. The Cragg double hurdle model results showed that the adoption of CSA is significantly affected by distance to the tarred road, access to weather information, livestock income share, and ownership of transport assets. Adoption intensity is significantly affected by factors such as sex of household head, labour size, frequency of extension contact, access to credit, access to weather forecasts, off-farm income, distance to input and output markets, number of traders and asset ownership. In light of these findings, policies that ensure access to weather forecasts information, coupled with frequent access to extension officers by farmers and access to credit will go a long way in encouraging farmers to scale up the use of CSA. Additionally, government efforts should be directed towards input markets decentralization which can be done through policy incentives to the private sector which brings markets closer to farmers. Also, the establishment of tarred

roads in rural areas will incentivise farmers to increase the adoption intensity of CSA while on the other hand attracting more traders to the rural areas. The multinomial logistic selection model results reveal that observable household and market access characteristics influence the likelihood of a farming household adopting three identified prominent technology bundles/combinations. The results highlight that household characteristics (gender of household head, labour size), farm characteristics (soil type), and institutional factors (market access, information access and access to credit) are the main factors that determine the adoption of various CSA technology combinations. The results encourage the government to design policies aimed at improving farmers' knowledge with regards to CSA. These should include early warning systems and programs that enhance access to information, markets and credit. The econometric results of the Endogenous Switching Regression model showed that the soil fertility status of the fields and access to weather forecasts had a significant impact on the farmer's decision to adopt CSA. The Average Treatment effect of the Treated and Average Treatment effect of the Untreated was positive and significant for adopters and non-adopters indicating that CSA adoption had resulted in a significant positive impact on the welfare of the farmers. Analysis of outcomes revealed that farmer and farm characteristics as well as market factors significantly affected household welfare. Household income with reference to adoption was significantly affected by factors such as education of household head, labour size, TLU, off-farm income and asset index. Food security was influenced by factors such as education of household head, TLU, access to safe water, access to sanitation, access to inputs and output markets. Results from the cost-benefit analysis revealed that maize performs best under CSA technologies. The cost-benefit analysis results point to the potential of CSA in positively influencing profitability as a result of reduced costs and improved productivity. The profit inefficiency model showed that extension contact, number of traders locally and adoption of CSA had significant negative coefficients implying that as these variables increase, profit inefficiency among maize growing farmers then decreases. The findings call for development practitioners to incorporate market linkages that bring buyers closer to the farmers and support for extension staff to be able to have frequent contacts with farmers. Results of the multi-objective goal programming model suggest a reduction in the area committed to field crops and point towards concentrating on high-value crops such as horticulture and larger ruminants such as cattle.

LIST OF ACRONYMS

ACSA	Africa Climate-smart Agriculture
AGRA	Alliance for a Green Revolution in Africa
ATT	Average Treatment effect of the Treated
ATU	Average Treatment effect of the Untreated
BCR	Benefit-Cost ratio
BMI	Body mass index
CA	Conservation Agriculture
CBA	Costs Benefits Analysis
CIAT	International Center for Tropical Agriculture
CIMMYT	International Maize and Wheat Improvement Centre
C-L	Crop-Livestock
CSA	Climate-smart agriculture
CSPM	Climate-Smart Pest Management
DDS	Dietary Diversity Score
DFID	Department for International Development
DRSS	Department of Research and Specialist Services
DT	Drought Tolerant
DTM	Drought Tolerant Maize
DTMA	Drought Tolerant Maize for Africa
ESR	Endogenous Switching Regression
FAO	Food and Agricultural Organization of the United Nations
FAOSTAT	Food and Agriculture Organization of the United Nation Statistics
FGDs	Focus Group Discussions
FGP	Fuzzy Goal Programming
GDP	Gross Domestic Product
GHG	Greenhouse gas
GOZ	Government of Zimbabwe
GP	Goal programming
HDDS	Household Dietary Diversity Score
ICIPE	International Centre of Insect Physiology and Ecology
ICRAF	International Centre for Research in Agroforestry

IFPRI	International Food Policy Research Institute
IITA	International Institute for Tropical Agriculture
ILRI	International Livestock Research Institute
IPCC	Intergovernmental Panel on Climate Change
IRM	Imazapyr-Resistant maize
LER	Land Equivalent Ratios
LFSP	Livelihoods and Food Security Programme
LP	Linear programming
LU	Livestock units
MCDM	Multi-Criteria Decision Modelling
MGLP	Multiple Goal Linear Programming
MNL	Multinomial logit
MNP	Multinomial Probit
MOP	Multiple objective-programming
NGOs	Non-governmental Organisations
OFSP	Orange Fleshed Sweet Potato
PABRA	Pan Africa Bean Research Alliance
PCA	Principal Component Analysis
QPM	Quality Protein Maize
ROI	Return on investment
SLM	Sustainable Land Management
SSA	Sub-Saharan Africa
TLU	Total Livestock Units
UKZN	University of KwaZulu-Natal
UMP	Uzumba Maramba Pfungwe
UNCCS	United Nations Common Coding System
ZAGP	Zimbabwe Agriculture Growth Program
ZimCLIFS	Zimbabwe Crop Livestock Integration for Food Security
ZIMSTAT	Zimbabwe National Statistics Agency
ZimVAC	Zimbabwe Vulnerability Assessment Committee
ZRBF	Zimbabwe Resilience Building Fund

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CHAPTER 1: INTRODUCTION

1.1 Background

The Intergovernmental Panel on Climate Change (IPCC) has highlighted that Africa is facing rising temperatures (at a rate of about 0.03 °C per year since 1975) and more extreme weather such as heat waves, droughts and floods (Rosenstock et al., 2019). Farmers are badly affected due to their reliance on rain-fed agricultural systems. Climate-smart Agriculture (CSA) can provide important benefits to farmers who are facing these climate-induced-agriculture impacts such as prolonged droughts, reduced rainfall amounts and changed rainfall patterns which have adversely affected crop and animal productivity (FAO, 2018; IPCC, 2018; Ouédraogo et al., 2019; Zougmoré et al., 2016). The concept of Climate-smart Agriculture was introduced by the Food and Agricultural Organization of the United Nations (FAO) in 2010 to define a set of technologies necessary for increasing productivity in the context of national food security and development goals. CSA technologies refer to agriculture practices that sustainably increase productivity, build resilience (adaptation) and reduce or remove greenhouse gases (mitigation) (Lipper and Campbell, 2014; FAO, 2013; Steenwerth et al., 2014). CSA consists of three pillars namely adaptation, mitigation, and increasing food security through increased agricultural productivity. CSA examples include drought-resistant or shorter maturing varieties (Martey et al., 2020; Tesfaye et al., 2018), integrated soil fertility management which includes rotation or intercropping cereals with legumes (Vanlauwe et al., 2015), agroforestry with legume fodder trees, choosing adapted animal types and breeds (Vanlauwe et al., 2015) and conservation agriculture (Thierfelder et al., 2017a; Rosenstock et al., 2019) among others. Climate-smart agriculture helps farmers to meet the growing demand for food despite the changing climate and fewer opportunities for agricultural expansion on to additional land and contribute to the achievement of food security, economic development, and poverty reduction (Steenwerth et al., 2014). These CSA technologies can increase the productivity of crops and livestock while enhancing the welfare of farmers and minimizing resource degradation in the face of climatic threats (Lipper and Campbell, 2014).

The adoption of improved agricultural technologies is vital for attaining the development goals of improving welfare and food security of smallholder farming households relying on rain-fed agriculture and who own 42% as reported by the Zimbabwe National Statistics Agency

(ZIMSTAT, 2019) of total cultivated land in Zimbabwe. In Zimbabwe, agriculture plays an important role in promoting economic growth and development. This is evidenced by reports from the Government of Zimbabwe (GOZ) that show that its share in Gross Domestic Product (GDP) is significant (9.9 per cent of GDP between 2012 and 2016), national export earnings (29% in 2020), raw material provision (60%) (GOZ, 2012), and direct and indirect employment generation (60-70%) (GOZ, 2021; ZIMSTAT, 2019). Furthermore, 70% earn their livelihood from this sector. Agricultural productivity has been emphasized in all the country's development policies to address constraints faced by smallholder farmers. Agricultural production under smallholder farming systems in Zimbabwe, quite often, takes place on small landholdings averaging 1.8 hectares (ZIMSTAT, 2019) including marginal land (Andersson and Souza, 2014) under rain-fed conditions and predominantly relying on family labour and draught power. Smallholder farmers practice low-input – low-output agriculture which is sometimes tantamount to subsistence farming. They use input levels and obtain yields that are far below the recommended averages. For instance, smallholder farmers apply a sub-optimal fertiliser rate of less than 10 kg nutrients per hectare which is far below the recommended target of 50 kg nutrients per hectare that was set at the Abuja Fertiliser Summit in Nigeria by African Heads of State and Government (Gotosa et al., 2019). Yields for staple crops such as maize are below one tonne per hectare against a yield potential of more than 5 tonnes per hectare (ZIMSTAT, 2019). Productivity is also low for livestock. Livestock among smallholder farmers is usually grazed on native natural pasture that is usually in short supply and of poor nutritive value during the prolonged dry season. The rangelands and pastures have been depleted by the effects of climate change through changes in legume and grasses ratios. In addition, the digestibility of feed has been reduced, leading to low nutrients available for productivity. This has caused reduced meat and milk, reduced cow fertility, reduced fitness of draft animals and even reduced longevity of livestock (Thornton et al. 2009). Thus, in a nutshell, the interaction between genotype, environment and local farming practices have affected the yields in smallholder farming conditions. In addition to poor soil fertility, the farmers have also had limited investments in fertilisers and improved seeds necessary to intensify production, limited labour leading to late planting and experienced erratic rains and recurrent droughts (Kanyenji et al., 2020; Nezomba et al., 2018). Climate-smart agriculture can therefore provide important benefits to farmers to reduce the negative effects of climate change. The government of Zimbabwe in partnership with research, private sector and development partners have been promoting CSA technologies such as drought-tolerant maize varieties, conservation agriculture, fodder production (fodder crops and agroforestry fodder trees) among smallholder farmers to improve food security through increased productivity (Mujeyi, 2018).

Despite the potential of these technologies and efforts to promote them among farmers, adoption has been on smaller pieces of land, i.e., 0.1 to 1 ha of land by less than 3% of the smallholder farmers (Sebata, 2018) for fodder, and approximately between one to five per cent of the area allocated to Conservation Agriculture (CA) in Southern Africa (Mugandani and Mafongoya, 2019). Economic assessments of the varied adoption of CSA technologies in smallholder farming communities is therefore important to farmers, researchers and policymakers so that impacts (Issahaku and Abdulai, 2020; Fentie and Beyene, 2019; Sain et al. 2017; Martey et al., 2020; Ogada et al., 2020b; Siziba et al., 2019; Mango et al., 2020) are known and drivers of adoption (Mujeyi et al., 2019; Aryal et al., 2018; Abegunde et al., 2019; Beyene et al., 2017) for different household typologies are also identified to inform strategies of scaling up adoption.

1.2 Justification

Rain-fed agriculture is the main livelihood source for smallholder farmers in developing countries. The farmers are confronted with a complexity of bio-physical and socio-economic challenges that lead to low agricultural productivity, which in turn leads to low incomes and reduced household food and livelihood security. The low yields are a result of abiotic (declining soil fertility, drought, heat, temperature changes) and biotic stresses (leaf blight, grey leaf spot, leaf rust, maize lethal necrosis, Striga, pests, and diseases) (Pandey et al., 2017; Raza et al., 2019). Other factors that cause reduced productivity include poor varieties, poor farming practices such as mono-cropping and dependency on rain-fed agriculture in the face of climate change and population growth. The debilitating effects of climate change add to the challenges already facing smallholder farming systems. The Alliance for Green Revolution in Africa (AGRA) has highlighted that climate change is worsening the situation of the already resource-constrained smallholder farmers, with more erratic weather patterns and extreme weather events, decreasing the already low agricultural productivity (AGRA, 2014). A range of climate risks confronts smallholder agriculture to the extent of posing far-reaching consequences for future food production. Rapid and uncertain changes in rainfall and temperature patterns increase the vulnerability of smallholder farmers, threaten food production, and accentuate rural poverty (Ibid). Annual precipitation in Southern Africa is projected to decline by 30% between 2071 and 2099 under a 3°C warming scenario, a situation that could lead to an increased risk of drought (Lawal et al., 2019). These projected negative effects of climate change call for options that will reduce their impact on farmers.

CSA practices have been identified as a possible strategy for increasing productivity. Despite all the benefits proven by agricultural research organisations over the years through on-station and on-farm trials showing technologies that increase farm productivity, researchers note that there is low adoption of such technologies by farmers (Amadu et al., 2020). Given the scientific prediction that countries like Zimbabwe will experience further warming (Lawal et al., 2019), farmers must consider adopting CSA technologies that have the potential to maintain or enhance household food security. Without the adoption of CSA technologies, food, income and livelihood insecurity will worsen particularly among smallholder farmers. This reality precipitates the need to understand factors that are constraining the adoption of CSA technologies, their impact on household welfare indicators such as food security and income.

The actual nature and magnitude of the effects of adopting CSA technologies are not well explored, particularly for Zimbabwe. One reason for this is that most researchers address single CSA technologies without recognizing that households can adopt several technologies simultaneously. A second research gap is that the effects of CSA technologies on the whole farm system (crop-livestock interactions) have not been studied as most studies focused on the impact of single technologies on crop production. Likewise, there is a lack of information on the effects of CSA technologies on crop-livestock integrated systems for households that are heterogeneous in terms of resource endowments. Thirdly, a number of studies examining various CSA technologies estimated adoption as being a dichotomous variable with two options i.e. adoption or non-adoption. Existing studies on the impact of agriculture technologies on household food security in Zimbabwe are marred by univariate analysis (Makate et al., 2016; Mango et al., 2017; Mango et al., 2014) of single climate agriculture technologies and the single dimension of food security. Research can however move beyond the dichotomous dependent adoption variable to explore the diverse combinations of CSA being adopted by farmers. Various factors affecting the probability of adoption were examined. The reality, however, shows that decision-making processes concerning innovation adoption involve a multi-stage procedure encompassing when to adopt, level of adoption (intensity), for which enterprise as well as whether or not to replace the conventional technologies (Yigezu et al., 2018). Thus, the contribution of this study to the existing literature is the provision of a hybrid model for CSA technology adoption that considers different factors affecting the adoption of multiple CSA technologies at two levels i.e. decision to adopt and level of adoption. CSA technologies are likely to be adopted when farmers attain benefits in terms of e.g. higher and more stable incomes and improved consumption prospects. The benefits of CSA technologies has mostly been measured in biophysical terms such as yields, soil fertility (Thierfelder et al., 2014; Thierfelder et al., 2016; Mupangwa et al., 2017) and less attention has been given to the welfare implications e.g. impact on farm household income and food security. The study thus investigates the welfare implications of CSA technology adoption. Lastly, given the scarcity of resources, trade-offs existing between crop and livestock enterprises in achieving household goals, it is therefore also important to investigate the optimal enterprise combinations that are ideal for farmers when adopting diverse CSA technology combinations.

1.3 Objectives

The broad and primary objective of the research is to analyse and evaluate the adoption of CSA technologies by smallholder farmers in crop-livestock (C-L) integrated farming systems.
Specifically, the research objectives of the project are:

1. To establish the extent of adoption of CSA technologies among smallholder farmers in crop-livestock integrated farming systems across different household typologies,
2. To identify CSA technology adoption patterns and determinants at the farm level,
3. To analyse the effect of CSA technologies on household welfare, measured by household income and food security,
4. To quantify the costs and benefits of CSA technologies, and
5. To determine optimal enterprise mix for farmers adopting different CSA technology bundles.

1.4 Significance of the study

Given the reliance of the huge majority of smallholder farmers on agriculture for food, income, and livelihood security, and the relative role of this sector to national income, it is apparent that the key to the economic development of Zimbabwe lies in the growth of the agriculture sector. As mentioned earlier, given the challenge of climate change in addition to other biotic and abiotic constraints, the key to growth lies in the adoption of climate-smart agriculture technologies by farmers which can increase agriculture productivity. It is thus worthwhile to investigate the nature and extent of adoption to date to inform policy.

The study seeks to contribute to adoption studies by assessing the patterns of adoption of CSA technologies for rural households who are confronted with climate change. Findings from this study will be key in identifying technology combinations being adopted by farmers and reasons for such choices. The study will benefit researchers through the characterisation of adopters and non-adopters and mapping the CSA technologies currently under use. The results will help researchers through the refinement of technologies to suit farmer's socio-economic and biophysical realities and policymakers by identifying which CSA technology combinations to promote.

There is also no relevant literature that links household typology, adoption, productivity enhancement and food security in crop-livestock integrated farming systems. This study thus seeks to bridge the gap. The study contributes to the existing literature in two ways. Firstly, the analysis uses comprehensive cross-sectional data across household typologies. This study discusses CSA technologies adopted by farming households. Secondly, the study further clusters adoption into popular technology bundles. Recent studies have used adoption as a binary variable (Khonje et al., 2015; Kassie et al., 2012) which does not show the extent of adoption. This study, therefore, used the double hurdle model which is run at two levels i.e. adoption decision and intensity of adoption. Also, the study measures the impact of the adoption on household welfare (household income, food security). The study winds up by modelling the optimal enterprise mix suitable for different technology bundles. Findings from this study will help inform policymakers on the current impact of CSA practices on welfare and inform farmers on which technologies save more on costs of production or increase revenue. The research findings also provide feedback to research programs on the technologies which they are promoting.

1.5 Structure of the research thesis

The thesis uses a research paper format. Each chapter is mostly autonomous with sections on abstract, introduction, analysis, results with discussion and conclusion. Chapter 1 is an introductory chapter that presents the research problem, the rationale for the study and the research gap that this study addresses. The chapter also outlines the specific objectives. Chapter 1 is then followed by Chapter 2, which provides an overview of climate change and variability and how it has negatively affected smallholder agriculture in integrated farming systems in southern Africa. It goes on to discuss CSA that has been promoted in the study sites. The chapter also reviews studies that have been conducted on the components of adoption and impacts thereof, and help in deriving methods that were then used in addressing research objectives. Chapters 3 up to 7 discuss the findings to address the stated objectives and presented them in paper format. The methodology section of all these chapters has been discussed in Chapter 3 under Section 3.4 only. This is so given that it cuts across all the empirical chapters (i.e. Chapter 3 through Chapter 7). Chapter 8 gives a summary of key findings, conclusion, and policy recommendation and suggest future research focus.

References

Abegunde, V. O., Sibanda, M. and Obi, A., 2019. 'Determinants of the Adoption of Climate-Smart Agricultural Practices by Small-Scale Farming Households in King Cetshwayo District Municipality, South Africa', Sustainability, 12 (195), 1–27.

AGRA, 2014. Africa Agriculture Status Report: Climate change and smallholder agriculture in sub-*Saharan Africa. Nairobi, Kenya.*

Amadu, F. O., McNamara, P. E., and Miller, D. C., 2020. Understanding the adoption of climate-smart agriculture: A farm-level typology with empirical evidence from southern Malawi. *World Development*, *126*, 104692, 1-22. https://doi.org/10.1016/j.worlddev.2019.104692

Andersson, J. A., and Souza, S. D., 2014. Agriculture, Ecosystems and Environment From adoption claims to understanding farmers and contexts : A literature review of Conservation Agriculture (CA) adoption among smallholder farmers in southern Africa. *"Agriculture, Ecosystems and Environment," 187*, 116–132. https://doi.org/10.1016/j.agee.2013.08.008

Aryal, J. P., Rahut, D. B., Maharjan, S., and Erenstein, O., 2018. Factors affecting the adoption of multiple climate-smart agricultural practices in the Indo-Gangetic Plains of India. *Natural Resources Forum*, *42*, 141–158. https://doi.org/10.1111/1477-8947.12152

Beyene, A. D., Mekonnen, A., Kassie, M., Falco, S. Di, and Bezabih, M., 2017. Determinants of Adoption and Impacts of Sustainable Land Management and Climate Smart Agricultural Practices (SLM-CSA): Panel Data Evidence from the Ethiopian Highlands. *Environment for Development*. www.efdinitiative.orgorcontactinfo@efdinitiative.org.

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

FAO, 2018. Climate-Smart Agriculture: Building Resilience to Climate Change. In *Natural Resource Management and Policy* (Vol. 52). https://doi.org/10.1007/978-3-319-61194-5

Fentie, A., and Beyene, A. D., 2019. Climate-smart agricultural practices and welfare of rural smallholders in Ethiopia: Does planting method matter? *Land Use Policy*, *85*(May 2018), 387–396. https://doi.org/10.1016/j.landusepol.2019.04.020

Gotosa, J., Kodzwa, J., Nyamangara, J., and Gwenzi, W., 2019. Effect of Nitrogen Fertiliser Application on Maize Yield Across Agro-Ecological Regions and Soil Types in Zimbabwe : A Meta-analysis Approach. *International Journal of Plant Production*, (0123456789). https://doi.org/10.1007/s42106-019-00045-9

GOZ, 2012. Comprehensive agricultural policy framework (2012-2032). *Government of Zimbabwe*.

GOZ, 2021. National Development Strategy. *Government of Zimbabwe.*

IPCC, 2018. Global Warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change. *In Press*.

Issahaku, G., and Abdulai, A., 2020. Household welfare implications of sustainable land management practices among smallholder farmers in Ghana. *Land Use Policy*, *94* (December 2019), 104502, 1-14. https://doi.org/10.1016/j.landusepol.2020.104502

Kanyenji, M. G., Oluoch-kosura, W., Onyango, M. C., and Ng'anga, K. S., 2020. Heliyon Prospects and constraints in smallholder farmers ' adoption of multiple soil carbon enhancing practices in Western Kenya. *Heliyo*n, 6 (3) E03226, 1-10 2019). https://doi.org/10.1016/j.heliyon.2020.e03226

Kassie, M., Jaleta, M., Shiferaw, B., Mmbando, F., and Muricho, G., 2012. Plot and Household-Level Determinants of Sustainable Agricultural Practices in Rural Tanzania. 1-45. *Environment for Development*. http://www.jstor.org/stable/resrep14956

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). 706-706. https://doi.org/10.1016/j.worlddev.2014.09.008

Lawal, S., Lennard, C., and Hewitson, B., 2019. Response of southern African vegetation to climate change at 1 . 5 and 2. 0 ° global warming above the pre-industrial level. *Climate Services*, *16*(November), 100134, 1-16. https://doi.org/10.1016/j.cliser.2019.100134

Lipper, L., and Campbell, B., 2014. Climate-Smart Agriculture for Food Security. *Nature Climate Change*, (r). 4(12), 1068-1072. https://doi.org/10.1038/nclimate2437

Makate, C., Wang, R., Makate, M., and Mango, N., 2016. Crop diversification and livelihoods of smallholder farmers in Zimbabwe : adaptive management for environmental change. *SpringerPlus*. 5 (1135), 1-18. https://doi.org/10.1186/s40064-016-2802-4

Mango, N., Makate, C., Tamene, L., Mponela, P., and Ndengu, G., 2020. Impact of the adoption of conservation practices on cereal consumption in a maize-based farming system in the Chinyanja Triangle, Southern Africa. *Sustainable Futures*, *2* (December 2019), 100014, 1-9. https://doi.org/10.1016/j.sftr.2020.100014

Mango, N., Siziba, S., and Makate, C., 2017. The impact of the adoption of conservation agriculture on smallholder farmers ' food security in semi-arid zones of southern Africa. *Agriculture and Food Security*, 4–11. https://doi.org/10.1186/s40066-017-0109-5

Mango, N., Zamasiya, B., Makate, C., Nyikahadzoi, K., and Siziba, S., 2014. Factors influencing household food security among smallholder farmers in the Mudzi district of Zimbabwe. *Development Southern Africa*, *31*(January 20154), 37–41. https://doi.org/10.1080/0376835X.2014.911694

Martey, E., Maxwell, P., Abdoulaye, T., and Tl, P. O. B., 2020. Land Use Policy Welfare impacts of climate-smart agriculture in Ghana : Does row planting and drought-tolerant maize varieties matter ? *Land Use Policy*, *95*(December 2019), 104622, 1-10. https://doi.org/10.1016/j.landusepol.2020.104622

Mugandani, R., and Mafongoya, P., 2019. Behaviour of smallholder farmers towards adoption of conservation agriculture in Zimbabwe. *Soil Use and Management*, (September). https://doi.org/10.1111/sum.12528

Mujeyi, A., 2018. Policy and Institutional Dimensions in Climate-Smart Agriculture Adoption : Case of Rural Communities in Zimbabwe. In W. Leal Filho (ed.) (Ed.), *Handbook of Climate Change Resilience*. https://doi.org/10.1007/978-3-319-71025-9_66-1

Mujeyi, A., Mudhara, M., and Mutenje, M. J., 2019. Adoption determinants of multiple climate-smart agricultural technologies in Zimbabwe : Considerations for scaling-up and out. *African Journal of Science, Technology, Innovation and Development*, *0*(0), 1–12. https://doi.org/10.1080/20421338.2019.1694780

Mupangwa, W., Mutenje, M., Thierfelder, C., Mwila, M., Malumo, H., Mujeyi, A., and Setimela, P., 2017. Productivity and profitability of manual and mechanized conservation agriculture (CA) systems in Eastern Zambia. *Renewable Agriculture and Food Systems*. 1-15. https://doi.org/10.1017/S1742170517000606

Nezomba, H., Mtambanengwe, F., Rurinda, J., and Mapfumo, P., 2018. Field Crops Research Integrated soil fertility management sequences for reducing climate risk in smallholder crop production systems in southern Africa. *Field Crops Research*, *224*(May), 102–114. https://doi.org/10.1016/j.fcr.2018.05.003

Ogada, M. J., Rao, E. J. O., Radeny, M., Recha, J. W., and Solomon, D., 2020. Climate-smart agriculture, household income and asset accumulation among smallholder farmers in the Nyando basin of Kenya. *World Development Perspectives*, (June 2019), 1-11. https://doi.org/10.1016/j.wdp.2020.100203

Ouedraogo, M., Houessionon, P., Zougmoré, R. B., and Partey, S. T., 2019. Uptake of climate-smart agricultural technologies and practices: Actual and potential adoption rates in the climate-smart village site of Mali. *Sustainability (Switzerland)*, *11*(17), 1-19. https://doi.org/10.3390/su11174710

Pandey, P., Irulappan, V., Bagavathiannan, M. V, and Sanchez, L. E., 2017. Impact of Combined Abiotic and Biotic Stresses on Plant Growth and Avenues for Crop Improvement by Exploiting Physio-morphological Traits. *Frontiers in Plant Science*, *8*(April), 1–15. https://doi.org/10.3389/fpls.2017.00537

Raza, A., Razzaq, A., Mehmood, S. S., Zou, X., Zhang, X., and Lv, Y., 2019. Impact of Climate Change on Crops Adaptation and Strategies to Tackle Its Outcome : A Review. *Plants*, *8*(34), 1-29. https://doi.org/10.3390/plants8020034

Rosenstock, T. S., Nowak, A., and Girvetz, E., 2019. *The Climate-Smart Agriculture Papers: Investigating the Business of a Productive, Resilient and Low Emission Future*. https://doi.org/10.1007/978-3-319-92798-5 Library

Sain, G., Loboguerrero, A. M., Corner-Dolloff, C., Lizarazo, M., Nowak, A., Martínez-Barón, D., and Andrieu, N., 2017. Costs and benefits of climate-smart agriculture: The case of the Dry Corridor in Guatemala. *Agricultural Systems*, *151,* 163–173. https://doi.org/10.1016/j.agsy.2016.05.004

Sebata, A., 2018. An Insight into Current and Future Production of Forage Crops in Zimbabwe. In *New Perspectives in Forage Crops, Ricardo Loiola Edvan and Leilson Rocha Bezerra, IntechOpen*. https://doi.org/10.5772/intechopen.71997

Siziba, S., Nyikahadzoi, K., Makate, C., and Mango, N., 2019. Impact of conservation agriculture on maize yield and food security : Evidence from smallholder farmers in Zimbabwe. *African Journal of Agricultural and Resource Economics*, *14*(2), 89–105.

Steenwerth, K. L., Hodson, A. K., Bloom, A. J., Carter, M. R., Cattaneo, A., Chartres, C. J., … Jackson, L. E., 2014. Climate-smart agriculture global research agenda : scientific basis for action. *Agriculture and Food Security*, *2*(11), 1–39.

Tesfaye, K., Kruseman, G., Cairns, J. E., Zaman-Allah, M., Wegary, D., Zaidi, P. H., … Erenstein, O., 2018. Climate Risk Management Potential benefits of drought and heat tolerance for adapting maize to climate change in tropical environments. *Climate Risk Management*, *19*(April 2017), 106–119. https://doi.org/10.1016/j.crm.2017.10.001

Thierfelder, C., Chivenge, P., Mupangwa, W., Rosenstock, T. S., Lamanna, C., and Eyre, J. X., 2017. How climate-smart is conservation agriculture (CA)? – its potential to deliver on adaptation, mitigation and productivity on smallholder farms in southern Africa. *Food Security. , 9(3), 537–560.* https://doi.org/10.1007/s12571-017-0665-3

Thierfelder, C., Matemba-Mutasa, R., Bunderson, W. T., Mutenje, M., Nyagumbo, I., and Mupangwa, W., 2016. Evaluating manual conservation agriculture systems in southern Africa. *Agriculture, Ecosystems and Environment*, *222*(February), 112–124. https://doi.org/10.1016/j.agee.2016.02.009

Thierfelder, C., Rusinamhodzi, L., Ngwira, A. R., Mupangwa, W., Nyagumbo, I., Kassie, G. T., and Cairns, J. E., 2014. Conservation agriculture in Southern Africa : Advances in knowledge. *Renewable Agriculture and Food Systems*, 1–21. https://doi.org/10.1017/S1742170513000550

Thornton, P. K., Steeg, J. Van De, Notenbaert, A., and Herrero, M., 2009. The impacts of climate change on livestock and livestock systems in developing countries : A review of what we know and what we need to know. *Agricultural Systems*, *101*, 113–127. https://doi.org/10.1016/j.agsy.2009.05.002

Vanlauwe, B., Descheemaeker, K., Giller, K. E., Huising, J., Merckx, R., Nziguheba, G., Zingore, S., 2015. Integrated soil fertility management in sub-Saharan Africa: Unravelling local adaptation. *Soil*, *1*(1), 491–508. https://doi.org/10.5194/soil-1-491-2015

Yigezu, Y. A., Mugera, A., El-shater, T., Aw-hassan, A., Piggin, C., Haddad, A., Loss, S., 2018. Technological Forecasting and Social Change Enhancing adoption of agricultural technologies requiring high initial investment among smallholders. *Technological Forecasting and Social Change*, *134* (November 2017), 199–206. https://doi.org/10.1016/j.techfore.2018.06.006

ZIMSTAT., 2019. *Zimbabwe Smallholder Agricultural Productivity Survey 2017 Report* (pp. 1–100). Harare, Zimbabwe: Zimbabwe National Statistics Agency.

Zougmore, R., Partey, S., Ouédraogo, M., Omitoyin, B., Thomas, T., Ayantunde, A., … Jalloh, A.,2016. Toward climate-smart agriculture in West Africa: A review of climate change impacts, adaptation strategies and policy developments for the livestock, fishery and crop production sectors. *Agriculture and Food Security*, *5*(1), 1–16. https://doi.org/10.1186/s40066-016-0075-3

CHAPTER 2: LITERATURE REVIEW

2.1 Abstract

Climate-smart Agriculture (CSA) is increasingly being promoted by governments, research and development institutions to increase productivity, adapt to climate variability and change and improve the resilience of livelihoods and farming systems. This review synthesized knowledge on climate change and the prospects of climate-smart agriculture (CSA) in addressing the negative effects of climate change and variability. The findings show that Sub-Saharan Africa is vulnerable and the smallholder farmers are mainly affected because they rely on rain-fed agriculture production. From the basket of CSA technologies, the review found that Conservation Agriculture for Zimbabwe is the dominant option promoted in addition to drought-tolerant crop varieties and fodder production for livestock. Secondly, adoption varies across farmer typologies and thus there can never be a one-size-fits-all approach when promoting adoption in farming communities. Thirdly the involvement of all actors along value chains from input suppliers to buyers of agriculture commodities is key in spearheading adoption. Furthermore, the review showed that the government has played an important role as evidenced by the policy framework that supports CSA initiatives. Lastly existing empirical research is limited to the discussion of adoption and impact patterns of individual technologies with limits on measuring such for a combination of technologies and modelling of optimal enterprise mix for farmers adopting different CSA technology combinations.

Keywords: *climate change; climate-smart agriculture; Zimbabwe*

2.2 Introduction

This chapter reviews the current literature on climate-smart agricultural technologies, including adoption and their impact. Climate change is expected to act as an effective barrier to agricultural growth in many regions, especially in developing country contexts that are heavily dependent on rain-fed agriculture. Climate change impacts food security negatively and is affecting the livelihoods of millions of smallholder farmers in sub-Saharan Africa. Climate change projections for the Sub-Saharan Africa region point to a warming trend, characterised by the frequent occurrence of extreme heat waves (temperatures 3 and 5 standard deviations above the historical norm), increasing aridity and changes in rainfall (a 50 to 100% increase in very wet days in eastern tropical Africa and a decrease in wet days of 15-45% for Southern Africa 2016). Agriculture is also a major part of the climate problem, currently generating 19–29% of total greenhouse gas (GHG) emissions. These changes have negative effects on crop yields with worst-case projections indicating potential losses of 27 to 32 % for cereals (i.e. maize, millet and sorghum) and legumes (e.g. groundnut and beans) for more than 2^0C warming. (IPCC, 2018; Serdeczny et al., 2016). The incidence of pests has also been on the increase as a result of climate change. Worldwide, 40% of the world's food supply is lost to pests (Heeb et al., 2019). Zimbabwe has experienced the emergence of crop pests such as fall armyworm, tomato leaf miners, and cotton mealy bug during the 2016/2017 season. These pests can cause 100% crop losses if not managed. The effectiveness of certain pesticides has further been reduced by rising temperatures associated with climate change. This has thus increased vulnerability of water stressed crops from pest attack.

Livestock production is not spared either in Sub-Saharan Africa due to the reliance on pasture for feed. When there is a drought, grazing and water are scarce, resultantly exerting pressure on household labour. This may increase labour time needed in the search for grazing and water and ultimately reducing time for other farming operations (e.g. crop production activities) and household activities (household care, food preparation, leisure, etc.) (Hadush, 2018). Also, heat stress on livestock has negative impacts on a variety of productive parameters including reproduction, milk yield, carcass traits and growth (Baumgard et al., 2012). Heat stress leads to reduced feed intake by animals and resultantly leads to a decline in these productive parameters. Warmer temperatures also lead to increased disease incidence and higher parasite abundance. The higher temperatures promote shorter development rates and survivability of insects such as ticks and mosquitos as well as transmission of pathogenic micro-organisms. Zimbabwe lost more than 50 000 cattle to tick-borne diseases (theileriosis, babesiosis, heartwater, and anaplasmosis) during the 2017-2018 agriculture seasons (Munjenjema, 2019). All these changes will therefore negatively impact household food security and incomes. The effects of this will be felt on agricultural production and the incomes of rural households, food prices and markets and in many other parts of the food system (e.g., storage, food quality, and safety). Reducing the vulnerability of agricultural systems to extreme weather events and climate change as well as strengthening the agricultural systems' adaptive capacity are important priorities that need to be addressed if agriculture is to fully play its role in ensuring food security. Reducing emissions that contribute to global warming is also crucial to securing global wellbeing, and the agricultural sector has considerable potential to reduce emissions while at the same time playing its important role in ensuring poverty reduction and food security. Considering that the impacts of climate change are felt differently within regions, context-specific adaptation measures are required to reduce risks and build the adaptive capacity of smallholder farmers. Climate-smart agriculture has therefore been promoted in smallholder farming communities to mitigate and adapt to climate change and variability. This review provides up-to-date knowledge of CSA in Sub Saharan Africa and Zimbabwe. It discusses its adoption and impact on household welfare. Furthermore, it discusses how adoption and impact have been measured. The key research questions addressed in this review are:

i. Which CSA technologies have been promoted as a solution to climate change?
ii. How has been the adoption of the various CSA and what is the impact on household welfare?

The literature review explored existing information in Sub-Saharan Africa and Zimbabwe about climate change status, its effects and how CSA is promoted and its adoption patterns. Furthermore, the review discusses theoretical models for measuring technology adoption and the impact found in literature. It also discusses how new studies can use and improve upon some of these models. Methodologies and analytical techniques used in these articles were reviewed and gaps were identified to inform future research. The review acts as a foundation in the designing of the conceptual framework which depicts how adoption and food security concepts are interrelated. The literature thus provides evidence of previous studies and the gaps thereof.

2.3 Review Methodology

Peer-reviewed journals and book chapters published between 2010 and 2020 were reviewed on CSA. 2010 was considered because it was the year when the term “CSA” was first coined by FAO. Other literature review focussed on how adoption and impact have been measured empirically by other researchers. Review articles were extracted from reputable electronic databases such as

Springer, Science Direct and Taylor and Francis. Key search terms and words used were CSA, adoption, impact, sub-Saharan Africa and Zimbabwe.

2.4 Review Findings

The findings of the review are presented according to the following: i. the CSA concept and its role in addressing impacts of climate change; ii. CSA technologies promoted in Zimbabwe (adoption patterns and impacts) and iii. a Discussion on how adoption and impact have been measured by other researchers.

2.4.1 Climate-smart Agriculture defined

With a view to better integrate agricultural development and climate-responsiveness, climate-smart agriculture, CSA is an integrated approach to managing landscapes such as cropland, livestock, forests and fisheries that aims to achieve increased and sustainable productivity, enhanced resilience and reduced emissions. Eradicating poverty, ending hunger and taking urgent action to combat climate change and its impacts are three objectives the global community has committed to achieving by 2030 by adopting sustainable development goals. Agriculture, and the way we manage it in the years leading up to 2030, will be a key determinant of whether or not these objectives are met. Agriculture has been, and can further be used as an important instrument in eradicating hunger, poverty and all forms of malnutrition.

The CSA is an approach to agricultural development that aims to address the intertwined challenges of food security and climate change (Lipper and Campbell, 2014; Steenwerth et al., 2014). It is a set of agriculture practices aimed at increasing productivity, building and improving resilience to various shocks, and mitigating the devastating impact of climate change. The CSA has three interlinked pillars i.e. sustainably increasing productivity, building capacity to adapt, and reducing greenhouse gas (GHG) emissions. The climate-smartness nature of technology is therefore based on the impact on these three pillars. Interventions ranging from climate information services to field management have the potential to accomplish these goals (Khatri-Chhetri et al., 2017). The CSA interventions can deliver two or three climate-smart benefits. For example, agroforestry system trees can help farmers adapt and at the same time contribute to carbon sequestration. Similarly, drought-tolerant crop varieties can improve productivity in years of drought while improving the adaptation of farming households. It should also be noted that there is no one-size-fits-all CSA solution. The CSA implementation is most effective when it goes beyond the farm plot level and is applied in an integrated way that considers competing for sectoral priorities, the cumulative effect of combined CSA technologies, and the potential for transformational change. Smallholder adoption of farming technology is necessary to speed the transition to CSA. While CSA is diverse, an analysis has shown that just five technology clusters i.e. crop tolerance to stress ,water management, intercropping, conservation agriculture and organic inputs account for almost 50% of all CSA technologies identified by experts as climate-smart across the 33 countries covered by the climate-smart profiles (Sova et al., 2018). Despite the potential benefits, the adoption of CSA-relevant technologies is still generally low, especially in sub-Saharan Africa (SSA). For example, the adoption of maize-legume rotation in Tanzania, minimum tillage in Malawi and soil water conservation (ridges and soil bunds) in both Kenya and Tanzania is adopted by less than 10% of farmers (Tesfaye et al., 2017).

2.4.2 CSA technologies in integrated crop-livestock farming systems

Smallholder farming systems in SSA are characterised by low productivity attributed to overall poor management systems which are typified by the application of low inputs, insufficient control of weeds, pests, diseases and inadequate labour (Dahlin and Rusinamhodzi, 2019), and lack of resilience mechanism against the devastating effects of climate change-induced rainfall and extreme temperature stress. Climate change is worsening the situation of the already resource-constrained smallholder farmers, with more erratic weather patterns and extreme weather events decreasing the already low agricultural productivity (Harvey et al., 2018; Misra, 2014). A range of climate risks confronts smallholder agriculture to the extent of posing far-reaching consequences on sustainable food production. Rapid and uncertain changes in rainfall and temperature patterns increase the vulnerability of smallholder farmers, threaten food production, and accentuate rural poverty (Ibid). Annual precipitation in Southern Africa is projected to decline by 30% under a 4°C warming scenario, a situation that could lead to an increased risk of drought (Rosenstock et al., 2019; Lawal et al., 2019). These projected climate change scenarios point towards limited diversification options for smallholder farmers due to the reduced carrying capacity of crop and livestock productivity. Agriculture is one of the principal contributors to climate change, accounting for 24% of global greenhouse gas emission through carbon dioxide (CO_2) emitted from the decomposition of soil organic carbon (SOC), methane (CH_4) from enteric fermentation and nitrous oxide (N_2O) from synthetic fertilizer and manure (AGRA, 2014; Meier et al., 2020). Given the need to increase agriculture output for food security, agricultural emissions in Africa are projected to increase most rapidly.

Zimbabwe has an agricultural-based economy with the sector contributing about 15 per cent each year to the GDP. Agriculture provides about 60 per cent of the total employment and also supplies raw materials to the industry. Zimbabwe's agricultural sector is divided into four major sub-sectors namely; large-scale commercial farms, small-scale commercial farms, communal and resettlement areas. The agrarian structure has changed with the recent land reform in Zimbabwe with 99 per cent of the farmers now being smallholder farmers. Zimbabwe has not been spared by climate change. The country is experiencing hotter and fewer cold days and the annual mean surface temperature has warmed by about 0.4^0C from 1900 to 2000 (GOZ, 2015). The timing and amount of rainfall received are becoming increasingly uncertain and since 1990, there has been a reduction in total annual rainfall or heavy rainfall and drought occurring back to back in the same season. The frequency and length of dry spells during the rainy season have increased while the frequency of rain days has declined and this has negatively affected productivity.

There are various interventions particularly appropriate to the Zimbabwean context and SSA setting in general, which have great potential to increase agricultural productivity and resilience to climate change while simultaneously reducing agricultural greenhouse gas emissions. Smallholder agriculture is broadly perceived as the driving force for rural transformation and poverty alleviation in Zimbabwe hence, mainstreaming climate change into the country's agricultural and economic development agendas should be a key priority. Climate-smart agriculture (CSA) has been identified as a noble approach to addressing food security challenges under the new realities of climate change (AGRA, 2014). Research and development organisations have been promoting conservation agriculture and fodder production as the dimension of CSA which enhances synergies and trade-offs among food security, adaptation and mitigation as a basis for agricultural policy and practice reorientation in response to climate change. It is anticipated that by employing climate-smart technologies, climate change threats and risks to agriculture can be reduced by enhancing the adaptive capacity of smallholder farmers, improving resilience and resource use efficiency and increasing the mitigation potential of agricultural landscapes. This research study seeks to investigate the relevance of conservation agriculture and fodder production as climate-resilient strategies towards the attainment of food security among crop-livestock integrated farming systems. It will also determine the mix of crop and livestock that maximizes gross returns among farmers in Zimbabwe.

CSA promotes agricultural best practices such as integrated crop management, Conservation Agriculture, use of improved seeds and fertilizer management practices in addition to encouraging the use of all available and applicable climate change solutions in a pragmatic and impact-focused manner. The approach ensures the management of agro-ecosystems for improved and sustainable productivity, increased profits, and increased food security while at the same time preserving and enhancing the resource base and environmental protection (Singh, 2017). Table 1 shows a range of practices that are consistent with climate-smart agriculture in smallholder farming systems. Most of these apply to all regions and climates of the tropics and subtropics. These practices address food security and lead to higher productivity, but their ability to address adaptation and mitigation varies with the farmer and agro-ecological region.

2.4.3 CSA technologies in Zimbabwe

In the context of Zimbabwe, key climate-smart agriculture technologies that have been promoted include drought-tolerant maize hybrid varieties, fodder production and soil and water management practices such as conservation agriculture (Mujeyi, 2018). These CSA technologies were promoted by the government, international research organisations, universities and Non-Governmental Organisations (NGOs). Although CSA technologies address food security, their ability to address adaptation and mitigation to climate change varies (Lipper and Campbell, 2014).

2.4.3.1 Drought tolerant maize Hybrid Technology

Improved crop varieties are a key output of agricultural research and have contributed to significant increases in agricultural production and food security. Communities may adapt to climate change by adopting drought and heat tolerant crops better suited to a warmer and drier climate and have the potential to offset yield losses linked to climate change. These crop varieties are critical for managing current climatic variability and for adaptation to progressive climate change.

The Department of Research and Specialist Services of Zimbabwe (DRSS) in collaboration with the International Maize and Wheat Improvement Centre (CIMMYT) has been breeding drought-tolerant maize and working with seed companies to market any released varieties. Collaborations with other CGIAR centres like International Centre for Tropical Agriculture (CIAT) have also involved the breeding of legumes such as beans that are drought tolerant and suitable to smallholder farmers. The Seed Services Institute under DRSS has also bred high yielding small grains e.g. sorghum and pearl millet varieties. These varieties have been complemented by agronomic interventions such as soil fertility management technologies including conservation agriculture that is also a CSA technology**.**

In SSA, the Drought Tolerant Maize for Africa (DTMA) project was implemented from 2007 to 2015 by CIMMYT, International Institute for Tropical Agriculture (IITA), and national research and extension. The project developed certified drought-tolerant (DT) well-adapted maize hybrids and open-pollinated varieties (Tesfaye et al., 2017). A DT maize variety produces approximately 30% of its potential yield (1–3 t ha^{-1}) after suffering water stress for six weeks before and during flowering and grain-filling (Lunduka et al., 2019). The variety thus offers some insurance over mid-season droughts and dry spells. A study on impacts in two districts in south-eastern Zimbabwe showed that non-DT maize yield was lower at 436.5 kg/ha and higher at 680.5 kg/ha for households that grew DT maize varieties (Lunduka et al., 2019). The researchers found that a switch to DT maize seeds could give an extra income of US$240/ha or more than nine months of food at no additional cost. A study of 415 smallholder farmers in KwaZulu-Natal, South Africa analysed impacts using the propensity score matching method, the treatment effect model, and the Tobit selection model and found that improved maize varieties positively increased household food security (Sinyolo, 2020). Results showed that an additional one hectare of land under improved maize varieties increases annual food expenditure per capita levels by over R4,000. Similarly, another study in Uganda showed that the adoption of DT maize increased yield by 15% and reduced the likelihood of crop failure by 30% (Simtowe et al., 2019).

2.4.3.2 Conservation Agriculture

Conservation agriculture (CA) is based on three practices promoted as a means for sustainable agricultural intensification and these include minimum tillage, mulching with crop residue, and crop rotation (Brouder and Gomez-macpherson, 2014). Conservation agriculture improves yields through increased water infiltration, conserving moisture (when mulch is applied) and improving soil fertility. Farmers can also save labour and other costs from reduced tillage and precision in the application of inputs such as fertilisers. To maximize the benefits of CA, complementary practices are needed i.e. appropriate nutrient management to increase productivity and biomass; improved stress-tolerant varieties to overcome biotic and abiotic stresses; careful use of crop chemicals to control pest, diseases and weed pressure; improved groundcover with alternative organic resources or diversification with green manures and agroforestry; increased efficiency of planting and mechanization to reduce labour, facilitate timely planting and to provide farm power for seeding; and an enabling policy environment to promote the technology (Thierfelder et al., 2018). Despite these benefits, adoption rates have been low with high dis-adoption rates. Empirical evidence on the performance of CA including the climate-smart properties have mostly relied on data from agronomic on the station and on-farm trials, thereby missing potential effects of actual farmer behaviour. Few studies that do use observational data, often fail to account for selection bias or fully control for all potential sources of endogeneity (Andersson and Souza, 2014; Ngombe et al., 2017). CA was first implemented in Zimbabwe by Brian Oldrieve at Hinton Estates in the North-eastern parts of the country in the late 1980s. Widespread promotion throughout the country was then done in 2003 with donor provided input packages such as the Protracted Relief Programme (Jaleta et al., 2019). These efforts were supported by the government through the formation of a national CA task force that was established including the Ministry of Agriculture and NGOs. The task force was coordinated and supported by FAO and with players from international research institutes and NGOs. The adoption of CA has been limited with about 8.3% of arable area by the year 2014 being under CA in Zimbabwe (Mugandani and Mafongoya, 2019).

Table 1: CSA technologies among smallholder farmers

CSA Category	Examples	Benefits	Selected References
Crop Management	Intercropping with legumes, Drought resistant varieties, Improved storage and processing techniques, Bio-fortified crop varieties, Crop rotation, Crop diversification, Use of cover crops Sowing date adjustments	Increased food diversity, improved yields Increased incomes and Improved soil fertility	(Katengeza et al., 2019; Lunduka et al., 2019; Makate et al., 2016; Setimela et al., 2017)
sLivestock management	Improved feeding strategies, Fodder production and conservation Integrated manure management Rangeland management, reclamation and conservation, Improved livestock health, Animal husbandry improvements, Improved feeding strategies (e.g. cut and carry) Improved livestock health Animal husbandry improvement Animal breeding genetic improvement and conservation	Improved livestock health, improved market off-take rates	(Enahoro et al., 2019; Shikuku et al., 2016; Zougmoré et al., 2016)
Soil, Water and Nutrient Management	Cereal legume intercropping, Conservation agriculture (e.g. minimum tillage, no-till tied ridges, crop residue management.) Contour planting Terraces and bunds, vetiver grass Planting pits Water storage (e.g. water pans) Infield water harvesting technologies (e.g. potholing, tied ridges, tied contours, dead level contours, infiltration pits) Dams, pits, ridges Improved irrigation (e.g. drip irrigation, irrigation scheduling)	Increased infiltration, less soil erosion, improved soil fertility, increased yields and Improved water use efficiency	(Mupangwa et al., 2017; Steward et al., 2018; Thierfelder et al., 2017a) (Makate et al., 2019; Mango et al., 2020; Mupangwa et al., 2017; Steward et al., 2018; Thierfelder et al., 2017b)

CSA Category	Examples	Benefits	Selected References
	Mulching Catchment management		
Greenhouse Gas reducing technologies	Agroforestry (e.g. Nitrogen-fixing trees, Multipurpose trees, Integrated Pest Management, Fodder production Afforestation Climate-smart forestry Solar energy	Increased removal of CO emissions, organic fertiliser	(Bowditch et al., 2020; Heeb et al., 2019; Shikuku et al., 2016)
Integrated Food energy systems	Biogas, Growing wood fuel on-farm, Improved energy-efficient cooking stoves	Reduced environmental pollution through reduced greenhouse gas emissions	(Paolini et al., 2018; Rosenstock et al., 2019)
Knowledge Related	Extension advisory based on weather, Seasonal Climate forecasts, Farmer e-learning Digital credit to access CSA technologies Soil Management with remote sensing	Improved knowledge, enhanced financial inclusion, Improved planning (when to plant, what variety to plant, what technology to use, fertiliser application rates, when to weed etc.), reduced transaction costs, access to market prices, access to agronomic tips.	(Rosenstock et al., 2019)

2.4.3.3 Fodder Production and Agroforestry

Farmers in crop-livestock integrated farming systems benefit from livestock through their provision of milk, dung for manure which provides soil fertility nutrients, investment, meat, draught power for ploughing and income (meat, milk sales, hiring out ploughing animals). One of the biggest constraints to livestock productivity is the low quality and quantity of feed for smallholder farmers who rely on natural pastures. The grazing area has continued to dwindle as a result of climate change. Cattle are in poor condition particularly during the dry winter season when they subsist on poor quality roughages, i.e., crop residues and grass. This feeding shortage culminates in the increased incidence of diseases, low milk production from cows, low body condition score, and even poor performance for draught animals.

New CSA technologies like fodder production and agroforestry have emerged over the last decade and have been promoted among smallholder farmers to improve livestock in the face of climate change. Tree fodder banks have great potential to increase productivity through enriching livestock diets with protein supplements 2014). Fodder trees are grown most frequently in hedges along field boundaries or along the contours to limit soil erosion *Calliandra calothyrsus* is the most commonly planted species. The trees are fast-growing, tolerant to frequent pruning and droughts. These include trees such as *Leucaena diversifolia, Leucaena tri-chandra*, *Chamaecytisus palmensis Sesbania sesban*, *L. leucocephala*, *A. angustissima*, *L. diversifolia,* and *L. pallida* (Paul et al., 2020). The International Centre for Research in Agroforestry (ICRAF) in Zimbabwe has spearheaded the adoption of a variety of agroforestry technologies. The International Livestock Research Institute (ILRI) has also provided training on the processing of homemade mucuna and lablab-based diets for feeding both dairy and beef cattle. On-farm demonstrations to spearhead the adoption of fodder were run by ILRI under the ZimCLIFS (Zimbabwe Crop Livestock Integration for Food Security) from 2013 to 2015. Currently, the Zimbabwe Livelihoods and Food Security Programme (LFSP), the Zimbabwe Resilience Building Fund (ZRBF), Zimbabwe Agriculture Growth Program (ZAGP) are also promoting fodder production and value addition of crops such as velvet bean and lablab.

Researchers have evaluated fodder adoption from various agro-ecological zones using logit modelling to identify the drivers of adoption and even gross margin analysis to determine profitability. A study on small scale farmers who grew fodder to supplement their dairy cattle revealed that dairy herd size, landholding size, membership of the dairy association and agro-ecological zone are the key factors influencing farmers' adoption of fodder bank (Jera and Ajayi, 2008). Benefits from supplementing livestock with fodder include, increased milk yields after feeding cows and increased grain and stover yield when the technology is applied to crop enterprises. A study carried out in the Philippines found out that fodder trees were the most important feed source during the dry season and increased net incomes from livestock production from US$68 to US$503 per household (Franzel et al., 2014). Other benefits of fodder shrubs include the provision of products such as firewood, stakes, bee forage and seeds which are sometimes sold and services such as fencing, soil fertility improvement, soil erosion control, and improvement in animal health and reproduction. Fodder trees depending on their location can help to reduce runoff and soil erosion. The trees are deep-rooted, resistant to drought and they maintain high protein levels during the dry season when high-quality feed is scarce. They also improve livestock productivity, which helps reduce methane emissions per unit of output and helps reduce carbon emissions by substituting for commercially manufactured concentrates. Fodder crops such as Mucuna pruriens and Lablab purpureus are nitrogen-fixing, so they improve soil fertility. They also contribute to improved productivity when used in home formulated legume-based diets. No study, according to the author’s knowledge, has however been done to evaluate the effects of adopting these CSA livestock technologies on household food security in Zimbabwe.

2.4.3.4 Climate-smart pest management

Climate-Smart Pest Management (CSPM) refers to the interdisciplinary approaches and strategies that use integrated pest management (Heeb et al., 2019). It includes the provision of tools and information to farmers such that they can proactively put into action pest prevention practices (e.g. crop diversification, or practices that reduces susceptibility to pest attack). Examples of pest prevention approaches include pest control through chemical, biological, cultural, or mechanical methods, building the resilience of the farm through e.g. push-pull technologies and pest scouting to monitor existing and any new pests. Among the various constraints responsible for lower yields are those whose control has remained a challenge. The International Centre of Insect Physiology and Ecology (ICIPE) with partners developed a climate-smart ‘push-pull’, based on companion cropping that effectively controls pests in cereal crops (maize, sorghum, and millets) including the parasitic weed Striga and Stem borer. This, therefore, calls for efficient and early pest warning systems in the country. The government also needs to enforce the Plant, Pests and Diseases Act [Chapter 19:08] to control pests and diseases that affect crops. The act provides for the mandatory destruction of tobacco and cotton plants by a specified date and also prohibits the planting of tobacco or cotton or tobacco between specified dates as part of efforts to prevent the spread of plant pests and diseases in Zimbabwe

2.4.3.5 Climate-Smart Bio-fortified Crops

Recently there has been the expansion of high yielding drought tolerant but micronutrient-rich crop varieties through genetic bio-fortification with minerals and vitamins to achieve nutrition security even in the presence of climate change (Kumar et al., 2019; Signh et al., 2018). Harvest Plus, a global consortium co-led by the International Food Policy Research Institute (IFPRI) and CIAT has promoted and released seven, conventionally bred, bio-fortified crops in 13 countries (Lividini and Fiedler, 2015). In Zimbabwe, CIAT has spearheaded the promotion of Pro-Vitamin A maize, Quality Protein Maize (QPM), Orange Fleshed Sweet Potato (OFSP), and zinc and iron-enriched beans. CIAT has been working with DRSS with support from CIMMYT and the Pan Africa Bean Research Alliance (PABRA) through CIAT Malawi. The bean varieties that have been released to date in Zimbabwe include NUA 45, Cherry and Sweet Violet varieties. QPM maize released to date includes hybrid ZS261, the open-pollinated Obatanpa variety, SC527 and SC643 (Seed Co varieties) (Braizer, 2019).

All the discussed CSA technologies contribute to household incomes and food security and ultimately improved livelihoods in various ways. Researchers in Ethiopia found that the adoption of CSA increased dietary diversity and improved nutrition (protein and calorie intake). Benefits were even more pronounced for households that adopted combinations in comparison to those that adopted each technology in isolation (Teklewold et al., 2019).

2.4.4 Econometric theories and models

Adoption is a decision-making process in which individuals first learn about an innovation and have to decide to either adopt or reject it (Rogers, 2003). Farmer's adoption behaviour has been explained by researchers using three paradigms namely the innovation-diffusion model, economic constraint model, and the adopter's perception models.

2.4.4.1 Innovation diffusion model

The model shows that diffusion of technology consists of four components namely the innovation-decision process, the perceived attributes of the technology, the rate of adoption, and individual innovativeness (Rogers, 2003). The innovation-decision process is characterized by five stages i.e. knowledge, persuasion, decision, implementation and confirmation. In the first stage, the farmer is exposed to the CSA technology package. The farmer is taught how the technology works and the potential benefits that the technology offers to farmers**.** The model assumes that while technology is technically and culturally suitable, information asymmetry and high search costs may limit its adoption and as such, it is very important for farmers to get all necessary information on the technology. Research and development organisations have therefore used various approaches to ensure farmers get CSA information. Methods have ranged from the use of government extension, innovation platforms, lead farmers and the use of local non-governmental organisations extension staff. In analysing adoption, it is thus important to get to know the level of contact between extension personnel and farmers. Farmers also get information from mass media (television, radio and newspaper) and through interpersonal communication. Once the farmer is persuaded to use the new technology, farmers decide whether or not to use the technology. The stage is followed by confirmation during which the individual seeks reinforcement for the decision made. The farmers proceed to judge a technology using five attributes i.e. relative advantage, compatibility, complexity, friability and observability. Thus, farmers will consider the advantages and disadvantages of technology. Relative advantage is often expressed in terms of economic, social or other benefits, referring to the degree to which an innovation is perceived as better than the conventional practice it replaces. Compatibility refers to the degree to which an innovation is perceived by potential adopters to be consistent with their existing values or practices. Compatibility with what is already in place makes the new practice seem less uncertain, more familiar and easier to adopt. Complexity refers to the degree to which an innovation is considered difficult to understand and use. If potential adopters perceive innovation as complex, its adoption rate is low. Friability refers to the extent to which an innovation may be subjected to limited experimentation. Finally, observability refers to the degree to which the results of an innovation are visible to others. The technology will then spread gradually over time and among people resulting in various adopter categories depending on the rate of adoption. The adoption category depends on the availability of information on the technology.

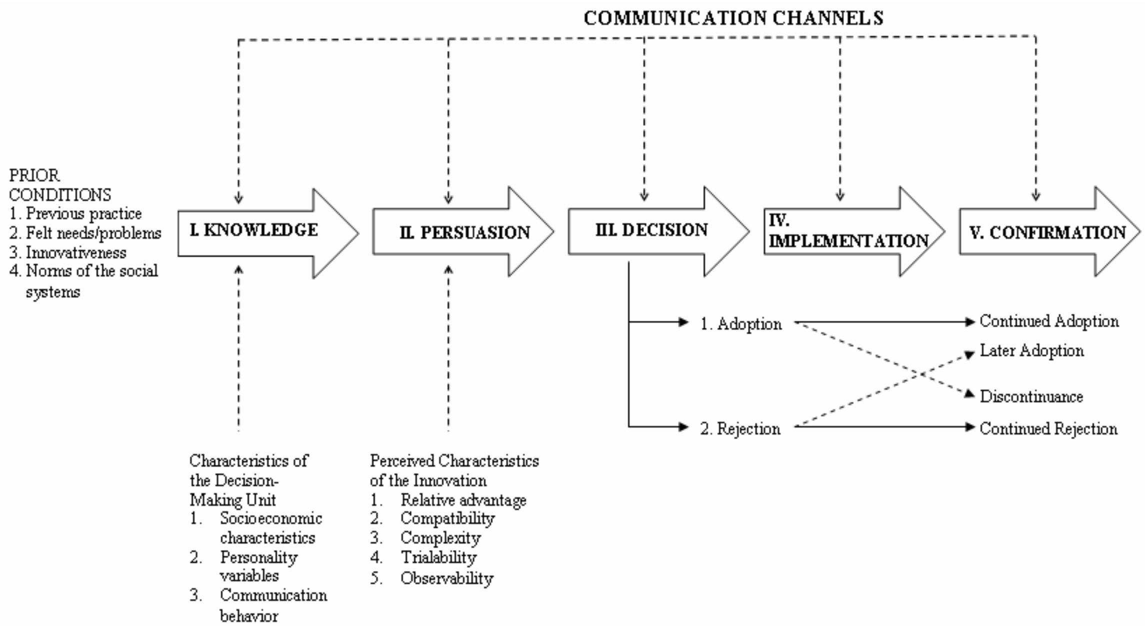

Figure 1: Technology diffusion. Source: Rogers (2003)

Rogers classified the adopters into five categories namely innovators, early adopters, early majority, late majority and laggards. Innovators are individuals who are venturesome, eager to try new ideas and willing to take risks. Early adopters are usually the local opinion leaders in the system who function as role models and are quick to see the value of innovations. The early majority is formed by the largest category and these make decisions after they are convinced of the benefits. The late majority are cautious and sceptical persons who do not adopt until the large majority has done so. They are usually relatively poor and are averse to risk. The last group of adopters is the laggards. They are suspicious of innovations and change agents. They are usually poor and seldom take risks. Information on patterns of adoption is important as it can act as good feedback to the technology developers and policymakers. For instance, some farmers adopt and dis-adopt over the years, while some will never adopt CSA technologies. The innovation diffusion model has several limitations. One of the major shortcomings of the model is that it generally assumes that the most important variable is information and the willingness of the individual to change. An individual is characterised according to his behaviour without considering factors that influence his behaviour. In reality, many other factors are known to influence the adoption of agricultural innovation. These include the farmer's objectives, the level of the resource endowments of the individuals, access to resources, availability of support systems and the characteristics of the innovation. For example, access to resources such as labour and land can limit the adoption of CSA technologies to a small number of individuals in farming communities. This could apply to female-headed households whose productive resources are limited in some communities compared to their male counterparts. In such cases, an innovative individual may be labelled as a laggard, while late or non-adoption is caused by a lack of land or labour resources that might be associated with the technology. Information and support services from the extension systems may also limit the spread of innovation by targeting innovators and early adopters while ignoring the others.

2.4.4.2 Economic constraint model

Economic constraint model highlights that farm households make choices on all operations during production e.g. which crops to grow, on what field size, whether or not to use purchased inputs, which crops to grow on which fields, etc. Decision making depends on their goals or objectives and the resource constraints of the individual farming household. The model assumes that the household acts as a unified unit of production and consumption that aims to maximise utility subject to its production function, income, and total time constraint. This is not, however, the case in real-life situations as household members do not have the same utility functions and thus the study asked households to specify decision-makers for operations as well as specifying who decides to adopt certain agriculture technologies. The model highlights that in the short run, input fixity such as access to credit, land and labour restricts production flexibility and therefore conditions technology adoption decision. It emphasizes the factors that affect profitability that asymmetrical distribution in resource endowments determine observed adoption behaviour.

2.4.4.3 Adopter perception model

The model suggests that the perceived attributes of the technologies conditions the adoption behaviour of farmers. Thus, even with full information, farmers may subjectively evaluate any given technology. Farmer's perceptions are subjective but have a direct influence on the decision to adopt CSA. A study in Uganda found that perception of future climate changes affected the decision to adopt drought-tolerant maize varieties. Similarly, the perception of Striga severity affected the adoption of climate-smart pull technology. It is therefore important to consider perceptions even in econometric modelling. It is also important because researchers have found that new technologies affect men and women differently as they experience social, economic, and environmental reality in different ways (Rao et al., 2019). Men and women play different roles in crop-livestock integrated farming systems and thus contribute differently to agriculture. Literature highlights that women contribute over 50% of agriculture labour besides reproductive roles. Effective dissemination and adoption of CSA technologies can be achieved where there is complete knowledge of how these technologies are perceived.

2.4.5 Econometric data for adoption and impact

Researchers have used time-series data, cross-sectional data and panel data in adoption studies. Time series data has been used in which the aggregate measure of adoption is measured e.g. the percentage of farmers using technology each time. Adoption is thus captured as a logistic shaped function (Atnafe et al., 2018). This approach is however limited as it does not give the intensity of the adoption and does not say much about the underlying dynamic process. Cross-sectional studies take a snapshot of farmer's technology use at some date. The cross-section has limitations in that the technology may be incompletely diffused through the population. Thus, the adoption process itself is less understood from this data unless recall data is included in the data collection instrument. Panel studies collect data at certain points for the same farmers. The data can allow for household effects changes to be investigated. Panel data combines inter-individual diversity and intra-individual dynamics which have advantages of more accurate inference of model parameters, make simpler computation and statistical inference as well as having a greater capacity of capturing human behaviour complexity over time (Hsiao, 2001).

2.4.5.1 Single and multiple equation models

In the econometrics literature, single and multiple equation models have been used to analyse adoption decisions. Three models have been frequently used to analyse technology adoption namely the linear probability, logistic function (logit) and the normal density function (Probit) models (Mazvimavi and Twomlow, 2009). These models use a binary choice variable as a dependent variable. The Logit Logistic regression is a mathematical-statistic method that is applied when the dependent variable is dichotomous (only takes two values). Logistic regression predicts the occurrence or non-occurrence of an event. However, the use of a binary choice variable as a dependent variable may not capture adoption intensity. To overcome this problem, a Tobit estimation method can be used to analyse adoption intensity where the dependent variable is continuous with a zero limit. The Tobit model is however statistically restrictive as it assumes that similar factors affect both the probability of non-zero adoption and level of intensity (Danso-Abbeam et al., 2019). Logit, Probit, and Tobit are all examples of single equations models. Despite the appropriateness of the single-equation models, they have limitations associated with them. The adoption of technologies is often incremental resulting in various levels of adoption. The adoption levels and rates also change over time with the learning of new knowledge and as such multi equation model becomes more appropriate. An example is a study in Madagascar that used a dynamic Probit model to analyse the trial of the technology, then the Tobit model to verify intensity and finally the Probit model to isolate factors associated with dis-adoption (Moser and Barrett, 2006). Examples of multiple equation models include the double hurdle model and the structural equation models (SEM). The SEM is a comprehensive and flexible multivariate statistical model that measures relationships between observable and latent variables. The model combines regression analysis, factor analysis, among others.

2.4.5.2 The Double hurdle model

The model assumes that farmers are faced with two hurdles in agricultural decision-making processes. Farmers decide to adopt firstly and then secondly decide on the level of production under the CSA technology chosen. Factors affecting these two stages are different. The double hurdle model is ideal because it allows distinctions between determinants of production participation using CSA technologies and the level of participation through two separate stages. The model involves running a Probit regression model to identify factors affecting the decision to adopt CSA technologies in the first stage. The second stage involves using a truncated regression model on the participating households to analyse the extent of adoption. The double hurdle model allows a subset of data to pile up at some value without causing bias in estimating the determinants of the continuous dependent variable in the second stage (Burke, 2009) and hence all data in the remaining sample for participants is obtained.

2.4.6 Factors affecting Adoption of CSA technologies

Reasons behind farmer adoption of climate-smart technologies are multifaceted and lessons can be drawn from earlier research on farmers' unwillingness to adopt agriculture technologies. Researchers have investigated several endogenous (human capital, attitude towards risk, access to financial capital, etc.) and exogenous (institutional, location, soil quality, rainfall patterns, farming system, market infrastructure, etc.) factors that influence technology adoption. These factors can be classified into four main categories including socio-demographic characteristics, institutional factors and farmer perceptions of the technology and socio-economic factors (Mozzato et al., 2018). Factors affecting risk may be observable and unobservable such as attitudes toward risk and ambiguity. Individuals' varied preferences for uncertainty may reflect the technology adoption pattern. Such preferences affect individuals' utility functions or their value functions, which in turn may result in otherwise sub-optimal investment and/or production decisions. It is thus important to investigate unobservable factors, along with observable ones when studying technology adoption.

2.4.6.1 Farmers Socio demography characteristics

Farmers' socio-demographic characteristics include household heads' age, gender, education and household size. Household head's age has been found to have both positive and negative effects on adoption by different researchers. Researchers in Vietnam found both negative and positive relationship between age and adoption of CSA technologies in rice production in different provinces. In one province named Ha, the older farmers were more likely to adopt CSA while in Bac Lieu and Thai Binh provinces, the younger farmers were more likely to adopt CSA (Tran et al. 2019). Older farmers have a likelihood of adopting CSA technologies because they have accumulated capital or have greater access to credit particularly for technologies that need some investment. Also, older farmers learn from experience on how they cope with climate change and variability shocks and thus can better evaluate any new technologies based on experience compared to younger farmers. In some areas, however, age can be a deterrent to technology adoption as an aged farmer has decreased physical ability (Abegunde et al., 2019). This infers that younger farmers are more risk-takers than older farmers. Risk-averse farmers will wait longer to adopt new technologies. The education of the household head has a positive influence on the adoption of new technology. The reason is that a more educated household head is expected to be more likely to understand and obtain new technologies in a shorter period than uneducated people. Also, the education level is assumed to increase the farmer's ability to obtain, process and use the information relevant to adoption.

Gender of the household head also plays a role in adoption and researchers have reported mixed evidence. Some empirical studies report a higher rate of technology adoption among male-headed households, compared to female-headed households because of discrimination i.e. women have less access to external inputs, services and information due to socio-cultural values (Amadu et al., 2020; Martey et al., 2020) Adoption is positively influenced because men in male-headed households in most societies are the ones who control productive resources such as land, labour and capital which are critical for the adoption of new technology. In comparison, female-headed households have limited adoption due to differential access to production resources (land, labour, capital) as well as access to training and extension services. Thus, higher access to resources and information gives such households the ability to adopt.

Household size is linked to labour availability and will affect adoption decisions depending on the labour required by the technology (e.g. basins in conservation agriculture (or labour-saving (e.g. ox based cultivation). Technology adoption usually requires more labour inputs and if this requirement is fulfilled by family members then adoption is positively influenced. There is however likely to be non-adoption or low adoption of labour-intensive technologies for families with scarce labour. Various researchers found a positive relationship between household size and the adoption of labour-intensive CSA technologies such as row marking and intercropping (Beyene et al., 2017; Martey et al., 2020).

2.4.6.2 Institutional factors

Institutional factors include services such as finance, insurance, information dissemination and belonging to a social group. Technology adoption usually goes along with the use of inputs like fertilizer and pesticides, among others. Credit access enables the farmer to purchase these various inputs thereby positively influencing technology adoption. Differential adoption of technologies happens where there is differential access to credit. Some researchers have found out that access to credit promotes the adoption of risky technologies through relaxation of the liquidity constraint and enhancing of household's risk-bearing ability. A household that accesses credit can drop inefficient income diversification strategies and take up riskier but efficient investments. Credit access can reduce the income constraints on farmers, making it possible for them to buy key inputs as well as hiring labour. This positive influence is realised when the credit is invested in agriculture activities rather than used for social purposes (Aryal et al., 2017). Low adoption rates have however been reported in countries where female-headed households are discriminated against by credit institutions, and as such, they are unable to finance yield-raising technologies.

Acquisition of information about new technology is another factor that determines the adoption of technology. It enables farmers to learn the existence as well as the effective use of technology, thereby facilitating its adoption. Access to extension services has a positive impact on technology adoption because of the extension agent's support in creating awareness about innovation and its potential. Extension services play an important role in the implementation and diffusion of innovation and bridge the gap between farmers and the new technology. Extension services link innovators (researchers) and technology users (farmers) through the dissemination of information to farmers on the effective use and benefit of new technology. Extension workers do this through the use of lead farmers, farmer meetings and visits to farmers. Extension worker information dissemination can counterbalance the negative effect of lack of formal education by farmers in the overall decision to adopt some technologies (Mwangi and Kariuki, 2015). Access to information through extension enables farmers to make informed decisions as it reduces the uncertainty about a technology's performance hence may change an individual's assessment. Information disseminated should be reliable, consistent and accurate, otherwise, it can act as a hindrance to adoption.

Membership to social groups enhances social capital allowing trust, ideas and information exchange about new technologies. Farmers who participate more in community-based organizations are likely to engage in social learning about the technology hence raising their likelihood to adopt the technologies. However social groups may also have a negative impact on technology adoption, especially where free-riding behaviour exists. Some researchers propose an inverted U-shaped individual adoption curve, implying that network effects are positive at low rates of adoption but negative at high rates of adoption (Bandiera and Rasul, 2006b). As more people engage in the experimentation of new technologies, others join in and free ride on experimentation of others.

2.4.6.3 Farmer's perception of the technology

Benefits received by an adopter and the associated costs of production play an important role in adoption consistent with the conventional neoclassical model view that that rational economic man maximizes his utility. Farmers are more interested in the short term than long term benefits. Farmer perceptions of technologies may provide a better understanding of technology adoption since farmers deal with the technologies and probably perceive technologies differently from researchers and extension agents. These perceptions of innovation mainly depend upon their knowledge and information about the innovation and socio-economic situation. The level of information depends on the farmer's level of education and training that they receive about the technology. A study in the Ethiopian highlands found that educational level and access to training had a positive and significant influence on farmer's perceptions to adopt soil and water conservation technologies (Moges and Taye, 2017). Researchers also found that the perceived benefits of CSA in terms of contribution towards productivity and income positively influenced adoption (Ntshangase et al., 2018; Ouédraogo et al., 2019). Farmers who also perceive the technology to be consistent with their needs and compatible with their environment are more likely to adopt it since they find it as a positive investment. Thus farmers' perception of the performance of CSA technologies can significantly influence the decision to adopt them. Adoption depends on users' judgments of the value of the technology and judgment factors like utility and efficiency of the technology. Preference for a certain technology is influenced by farmers' evaluation of yield and total benefit accrued within a year. Technologies that need few assets, have a lower risk premium and are less expensive, have a higher probability of being adopted. On the other hand, technologies that require new skills, are time-consuming and costly to learn, may face slow adoption. Thus the level of participation depends on the net economic benefits of the technology to other options.

2.4.6.4 Socio-economic factors

Socio-economic factors such as farm size, the income of the household head, ownership of assets and livestock have a positive and negative influence on adoption. Some studies, however, found a negative influence of farm size on adoption. Small farm size may provide an incentive to adopt input-intensive innovation such as labour-intensive or land-saving technology. Farmers with a small piece of land are likely to adopt land-saving technologies such as greenhouse technology and zero-grazing among others as an alternative to increased agricultural production (Mwangi and Kariuki, 2015). An inverse relationship between arable land size has been found for some technologies e.g. crop diversification where intensification will improve yields through improved moisture conversation and increased soil fertility (Teklewold et al., 2019). Landholding size can however have a positive relationship to technology adoption particularly for scale dependant technologies that need more land. Households with larger landholdings can opt to try new technologies compared to those with smaller land sizes. Asset ownership positively influences technology adoption. Researchers reported that farmers with more assets were likely to have money, equipment and materials needed for new technologies (Rosenstock and Nowak, 2019). Assets generate the income necessary for accessing inputs associated with new technologies. Non-agricultural income allows farmers to meet capital costs associated with new technology and reduces the risk of experimenting with new technologies. Instead of analysing factors affecting adoption only, it is ideal and most appropriate for studies to further look at factors affecting the intensity of use of these technologies. This is crucial for stakeholders in value chains as it helps them design better strategies for scaling up adoption in crop-livestock integrated smallholder communities to improve productivity and subsequent household food security. Table 2 gives a summary of some studies on adoption and impact. It gives the analytical model used and the results in terms of significant factors affecting adoption and the impact.

The differences in the discussed characteristics (farm and farmer characteristics, institutional factors etc.) reveal that out scaling of CSA technology cannot be a one-size-fits-all model. CSA technologies should be tailor-made to meet the diversity that exists in farming communities. A study (Makate et al., 2018) of Southern Africa using Principal Component and clustering found that typologies affected adoption. The inexperienced, poor and illiterate farmers were low adopters compared to the rich, well-resourced and experienced counterparts.

Table 2: A summary of some key adoption and impact studies

Details investigated	Sample size and Analytical Model	Significant factors/Results	Sources
Factors affecting adoption of no-till in KwaZulu Natal	185 farmers Logistic Regression	Number of extension visits, Age, education	(Ntshangase et al., 2018)
Adoption of multiple CSA and impact on nutrition in Ethiopia	917 farmers Multivariate Probit model Endogenous switching regression model	Plot accessibility, Social capital and networks, Tenure security	(Teklewold et al., 2019)
Impact of CA on productivity and food security	488 farmers The propensity score-matching approach	CA had a positive impact on maize grain yield (ATT = 473 kg ha-1	(Siziba et al., 2019)
Determinants of CSA Small-Scale Farming Households in South Africa	357 farmers interviewed Generalized Ordered Logit Regression model	Educational status, farm income, farming experience, size of farmland, contact with agricultural extension, exposure to media, agricultural production activity, membership of an agricultural association or group and perception of the impact of climate change	(Abegunde et al., 2019)
The potential impact of the adoption of soil and water conservation technologies on household food security in the Chinyanja Triangle	312 households Propensity Score Matching	CA has a significant impact on cereal consumption.	(Mango et al., 2020)
Impact of CSA on household income and asset accumulation among smallholder farmers in Kenya	433 households Propensity Score Matching (PSM)	Adoption significantly enhances household income which, in turn, improves household asset accumulation	(Ogada et al., 2020a)
Determinants of Adoption and Impacts of Sustainable Land	1760 households The multinomial endogenous switching regression model	Age of household head, family size, Literacy of household head, Parcel characteristics (i.e. soil quality, the distance of parcel, the slope of the parcel)	(Beyene et al., 2017)

Details investigated	Sample size and Analytical Model	Significant factors/Results	Sources
Management and Climate-smart Agricultural Practices in Ethiopia		Climate variables (rainfall and temperature), The occurrence of shocks, extension visits. Adoption yielded both positive and negative returns	

2.4.7 Principal Component Analysis used with Cluster Analysis

The presence of heterogeneity among farmers caused by differences in location, resource endowments, constraints faced and farming objectives leads to differences in the choice and level of use of CSA technologies adopted by farmers. Researchers have classified farms into groups that have common characteristics (household typologies) (Gebrekidan et al., 2020; Kuivanen et al., 2016; Lopez-ridaura et al., 2018; Makate et al., 2018)(Kuivanen et al., 2016; Lopez-ridaura et al., 2018; Makate et al., 2018) and also classified farmers on multiple technology adoption (Lambert 2015, Mabe 2019) using two multivariate statistical techniques (PCA and Cluster analysis) which are employed sequentially.

Principal Component Analysis (PCA) is a statistical dimension reduction estimation procedure that uses an orthogonal transformation to convert a set of correlated observations into a set of linearly uncorrelated variables called principal components (Jolliffe, 2002; Mabe et al., 2019). PCA identifies a reduced set of features that represent the original data in a lower-dimensional subspace with minimal loss of information. PCA and related methods provide a means to summarize the data and extract information about individual differences. It reduces the dimensionality of the data and identifies primary patterns.

PCA have several assumptions that include the presence of multiple variables, linearity between variables, sample size adequacy which should be 50 or more, (tested by Kaiser-Meyer- Olkin (KMO) test of sample adequacy), factorability implying that adequate correlations among variables for data reduction should exist (tested using Bartlett's sphericity) and that the number of outliers should not be significantly high to reduce the heterogeneous influence on the results (Mabe et al., 2019). The KMO test compares the correlations and the partial correlations between the variables with a small KMO suggestive of highly correlated data. Barlett's test of sphericity checks the null hypothesis that the inter-correlation matrix came from a population in which the variables to be used in the PCA are all non-collinear.

The PCA output (retained PC's) are then subjected to cluster analysis to get the technology bundles/clusters. Cluster analysis split a set of observations into groups or clusters such that observations that are placed in the same group are more similar to each other than observations placed into two different clusters (Jolliffe, 2002).

2.4.8 Conceptual framework

Based on the review of literature on adoption and impact of technologies discussed in detail in this chapter, this study is therefore conceptualised in the manner shown in Figure 2. The Schematic and simplified representation shows climate change effects and the dynamics surrounding the introduction of CSA technologies, drivers of adoption and the potential impacts. Farmers involved in integrated crop and livestock farming systems face low productivity which has been worsened by climate change. Various organisations have thus introduced CSA technologies as a solution. Farmers will adopt different combinations of the CSA technologies to maximise utility (welfare e.g. household income, food security). The main drivers of technology adoption are hypothesized to comprise farm and farmer characteristics, access to markets, institutions and technical advice. The adoption is further hypothesized to have varying impacts on welfare indicators such as household income security and household income in addition to effects on resources i.e. labour, fertiliser and some environmental benefits.

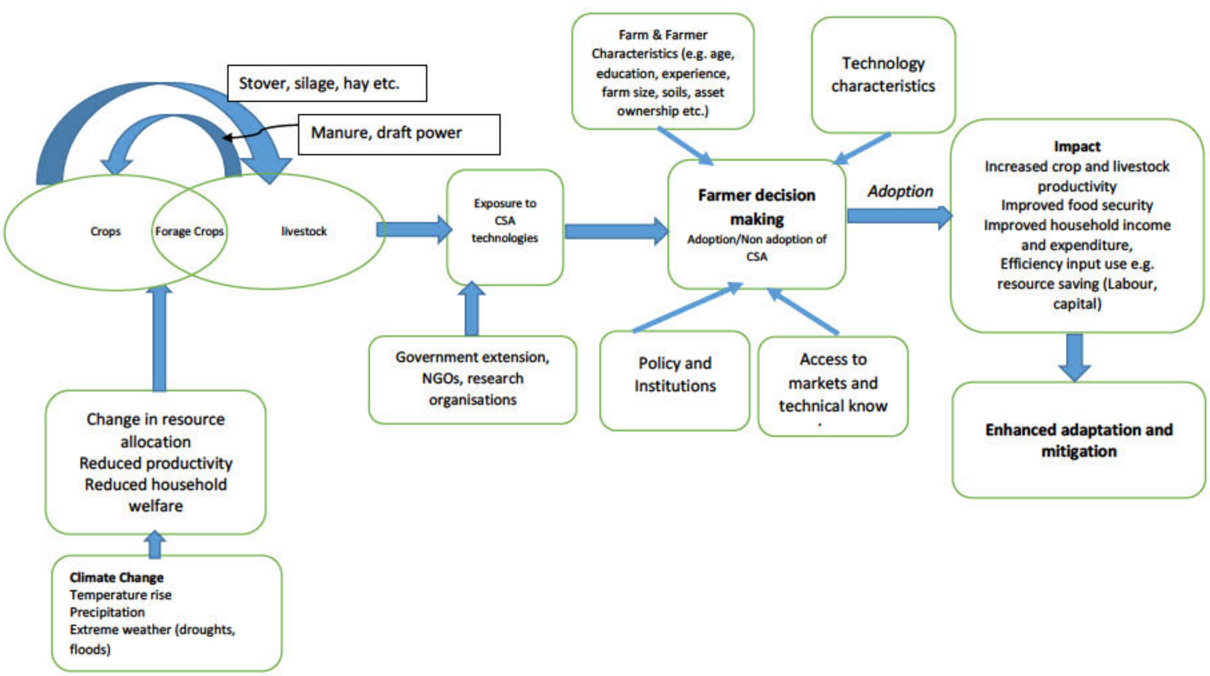

Figure 2: Conceptual framework

2.5 Conclusion and Recommendations

The review shows that climate change will affect smallholder rain-fed agriculture through a reduced amount of rainfall and increased temperatures. These will ultimately lead to reduced productivity from heat stress as well as the increased incidence of pests and diseases. The promotion of various CSA technologies offers solutions to these negative effects. Conservation Agriculture has emerged as the most popular form of Climate-smart agriculture promoted in Zimbabwe in addition to drought-tolerant maize varieties. Fodder production to supplement livestock during the dry season is still very low. Adoption and intensity of adoption are affected by many factors ranging from farm and farmer characteristics, access to information, perceptions among others. To date, it can be seen that CSA technologies are adopted differently among smallholder farming communities depending on actual and perceived benefits, thus it is important for development workers scaling out CSA to take that into consideration and tailor-make technologies depending on the needs of the various types of farmers. CSA have differing potential multiple benefits from increased yields, improved incomes and food security to environmental benefits and improved resilience of communities. Researchers and extension workers should share the evidence of these impacts with government policymakers to promote buy-in and supporting policies for CSA technologies. To achieve a widespread impact, there is a need for all actors along the key farmer value chains to be involved. It should however be noted that while Zimbabwe stands to benefit from CSA, a few research has explored technology combinations adopted by farmers as well as modelling optimal combinations for the smallholder farming communities. The few existing studies on CSA in Zimbabwe focused on the adoption of individual CSA technologies and studies on impact are largely dependent on-farm demonstrations rather than actual adoption by farmers without support from NGOs. Further, no study according to the author’s knowledge attempts to model maximizing combinations of CSA in these crop-livestock integrated farming systems.

References

Abegunde, V. O., Sibanda, M., and Obi, A., 2019. Determinants of the Adoption of Climate-Smart Agricultural Practices by Small-Scale Farming Households in King Cetshwayo District Municipality, South Africa. *Sustainability*, *12*(195), 1–27.

AGRA, 2014. *Africa Agriculture Status Report: Climate change and smallholder agriculture in sub-Saharan Africa. Nairobi, Kenya.*

Amadu, F. O., McNamara, P. E., and Miller, D. C., 2020. Understanding the adoption of climate-smart agriculture: A farm-level typology with empirical evidence from southern Malawi. *World Development*, *125*(104692), 1–27. https://doi.org/10.1016/j.worlddev.2019.104692

Andersson, J. A., and Souza, S. D., 2014. Agriculture, Ecosystems and Environment From adoption claims to understanding farmers and contexts : A literature review of Conservation Agriculture (CA) adoption among smallholder farmers in southern Africa. *"Agriculture, Ecosystems and Environment," 187*, 116–132. https://doi.org/10.1016/j.agee.2013.08.008

Aryal, J. P., Jat, M. , Sapkota, T. B., Kassie, M., Rahut, B. D., and Maharjan, S., 2017. Adoption of multiple climate-smart agricultural practices in the Gangetic plains of Bihar, India. *International Journal of Climate Change Strategies and Management*, *10*(3), 407–427. https://doi.org/10.1108/IJCCSM-02-2017-0025

Aryal, J. P., Rahut, D. B., Maharjan, S., and Erenstein, O., 2018. Factors affecting the adoption of multiple climate-smart agricultural practices in the Indo-Gangetic Plains of India. *Natural Resources Forum, 42*, 141–158. https://doi.org/10.1111/1477-8947.12152

Atnafe, Y., Mugera, A., El-shater, T., Aw-hassan, A., Piggin, C., Haddad, A., Loss, S., 2018. Technological Forecasting and Social Change Enhancing adoption of agricultural technologies requiring high initial investment among smallholders. *Technological Forecasting and Social Change*, *134*(April), 199–206. https://doi.org/10.1016/j.techfore.2018.06.006

Bandiera, O., and Rasul, I., 2006. Social Networks and Technology Adoption in the Zambezia province of Northern Mozambique. *The Economic Journal*, *116*(1957), 869–902.

Baumgard, L. H., Rhoads, R. P., Rhoads, M. L., Gabler, N. K., Ross, J. W., Keating, A. F., … Sejian, V., 2012. *Impact of Climate Change on Livestock Production*. https://doi.org/10.1007/978-3-642-29205-7

Beyene, A. D., Mekonnen, A., Kassie, M., Di Falco, S., and Bezabih, M., 2017. Determinants of Adoption and Impacts of Sustainable Land Management and Climate Smart Agricultural Practices (SLM-CSA). *Environment for Development*, pp. 1–30.

Beyene, A. D., Mekonnen, A., Kassie, M., Falco, S. Di, and Bezabih, M., 2017. Determinants of Adoption and Impacts of Sustainable Land Management and Climate Smart Agricultural Practices (SLM-CSA): Panel Data Evidence from the Ethiopian Highlands. In *Environment for Development*. www.efdinitiative.orgorcontactinfo@efdinitiative.org.

Bowditch, E., Santopuoli, G., Binder, F., La, N., Kluvankova, T., Lesinski, J., Campobasso, I., 2020. What is Climate-Smart Forestry ? A definition from a multinational collaborative process focused on mountain regions of Europe. *Ecosystem Services*, *43*(May 101113), 1–13. https://doi.org/10.1016/j.ecoser.2020.101113

Braizer, A., 2019. *Livelihoods and Food Security Programme Agriculture Productivity and Nutrition.The Status of Biofortification in Zimbabwe. Paper prepared for FAO and edited by Jannie Armstrong*.

Brouder, S. M., and Gomez-macpherson, H., 2014. Agriculture, Ecosystems and Environment The impact of conservation agriculture on smallholder agricultural yields : A scoping review of the evidence. *"Agriculture, Ecosystems and Environment," 187*, 11–32. https://doi.org/10.1016/j.agee.2013.08.010

Burke, W. J., 2009. Fitting and interpreting Cragg's Tobit alternative using Stata. *The Stata Journal*, *9*(4), 584–592.

Dahlin, A. S., and Rusinamhodzi, L., 2019. Yield and labour relations of sustainable intensification

options for smallholder farmers in sub - Saharan Africa. A meta-analysis. *Agronomy for Sustainable Development*, *39*(32), 1–18. https://doi.org/10.1007/s13593-019-0575-1
Danso-Abbeam, G., Dagunga, G., and Ehiakpor, D. S., 2019. Adoption of Zai technology for soil fertility management: evidence from Upper East Region, Ghana. *Journal of Economic Structures*, *8*(32), 1–14.
Enahoro, D., Croz, D. M., Mul, M., Rich, K. M., Robinson, T. P., Thornton, P., and Staal, S. S., 2019. Supporting sustainable expansion of livestock production in South Asia and Sub-Saharan Africa : Scenario analysis of investment options. *Global Food Security*, *20*(May 2018), 114–121. https://doi.org/10.1016/j.gfs.2019.01.001
FAO., 2018. Climate-Smart Agriculture: Building Resilience to Climate Change. In *Natural Resource Management and Policy* (Vol. 52). https://doi.org/10.1007/978-3-319-61194-5
Fentie, A., and Beyene, A. D., 2019. Climate-smart agricultural practices and welfare of rural smallholders in Ethiopia: Does planting method matter? *Land Use Policy*, *85*(May 2018), 387–396. https://doi.org/10.1016/j.landusepol.2019.04.020
Franzel, S., Carsan, S., Lukuyu, B., Sinja, J., and Wambugu, C., 2014. Fodder trees for improving livestock productivity and smallholder livelihoods in Africa. *Environmental Sustainability*, *6*, 98–103.
Gotosa, J., Kodzwa, J., Nyamangara, J., and Gwenzi, W., 2019. Effect of Nitrogen Fertiliser Application on Maize Yield Across Agro-Ecological Regions and Soil Types in Zimbabwe : A Meta-analysis Approach. *International Journal of Plant Production*, (0123456789). https://doi.org/10.1007/s42106-019-00045-9
GOZ., 2012. *Comprehensive agricultural policy framework (2012-2032). Government of Zimbabwe*.
GOZ., 2015. *Zimbabwe's National Climate Change Response Strategy. Government of Zimbabwe. Ministry of Environment, Water and Climate*.
Hadush, M., 2018. Welfare and food security response of animal feed and water resource scarcity in Northern Ethiopia. *Agricultural and Food Economics*, *6*(22), 1–24.
Harvey, Celia ARodríguez, M. S., Rodríguez, M. R. M., Viguera, B., Guadarrama, A. C., Vignola, R., and Alpizar, F., 2018. Climate change impacts and adaptation among smallholder farmers in Central America. *Agriculture and Food Security*, *7*(57), 1–20.
Heeb, L., Jenner, E., and Cock, M. J. W., 2019. Climate-smart pest management : building resilience of farms and landscapes to changing pest threats. *Journal of Pest Science*, *92*(2019), 951–969.
Hsiao, C., 2001. *Analysis of Panel Data* (Third Edition): Cambridge University Press (Econometric Society monograph.
IPCC., 2018. *Global Warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change*, In Press.
Issahaku, G., and Abdulai, A., 2020. Household welfare implications of sustainable land management practices among smallholder farmers in Ghana. *Land Use Policy*, *94*(December 2019), 1–14. https://doi.org/10.1016/j.landusepol.2020.104502
Jaleta, M., Baudron, F., Krivokapic-skoko, B., and Erenstein, O., 2019. Agricultural mechanization and reduced tillage : antagonism or synergy ? *International Journal of Agricultural Sustainability*, *17*(3), 219–230. https://doi.org/10.1080/14735903.2019.1613742
Jera, R., and Ajayi, O. C., 2008. Agrekon : Agricultural Economics Research, Policy and Practice in Southern Africa Logistic modelling of smallholder livestock farmers ' adoption of tree-based fodder technology in Zimbabwe Logistic modelling of smallholder livestock farmers ' adoption of. *Agrekon*, *47*(3), 379–392. https://doi.org/10.1080/03031853.2008.9523806
Kanyenji, M. G., Oluoch-kosura, W., Onyango, M. C., and Ng'anga, K. S., 2020. Heliyon Prospects and constraints in smallholder farmers ' adoption of multiple soil carbon enhancing practices in Western Kenya. *Heliyon*, *6*(November 2019). https://doi.org/10.1016/j.heliyon.2020.e03226

Kassie, M., Jaleta, M., Shiferaw, B., Mmbando, F., and Muricho, G., 201). Plot and Household-Level Determinants of Sustainable Agricultural Practices in Rural Tanzania. In *Environment for Development*.

Katengeza, S. P., Holden, S. T., and Lunduka, R. W., 2019. Adoption of Drought Tolerant Maize Varieties under Rainfall Stress in Malawi. *Journal of Agricultural Economics*, *70*(1), 198–214. https://doi.org/10.1111/1477-9552.12283

Khatri-Chhetri, A., Aggarwal, P. K., Joshi, P. K., and Vyas, S., 2017. Farmers' prioritization of climate-smart agriculture (CSA) technologies. *Agricultural Systems*, *151*, 184–191. https://doi.org/10.1016/j.agsy.2016.10.005

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) 706-706. https://doi.org/10.1016/j.worlddev.2014.09.008

Kumar, S., Palve, A., Joshi, C., and Srivastava, R. K., 2019. Heliyon Crop biofortification for iron (Fe), zinc (Zn) and vitamin A with transgenic approaches. *Heliyon*, *5* (February e01914), 1–6. https://doi.org/10.1016/j.heliyon.2019.e01914

Lawal, S., Lennard, C., and Hewitson, B., 2019. Response of southern African vegetation to climate change at 1 . 5 and 2. 0 ° global warming above the pre-industrial level. *Climate Services*, *16* (November), 100134. https://doi.org/10.1016/j.cliser.2019.100134

Lipper, L., and Campbell, B., 2014. Climate-Smart Agriculture for Food Security. *Nature Climate Change,* 4 (12), 1068–1072. https://doi.org/10.1038/nclimate2437

Lividini, K., and Fiedler, J. L., 2015. Assessing the promise of biofortification : A case study of high provitamin A maize in Zambia. *Food Policy*, *54*, 65–77. https://doi.org/10.1016/j.foodpol.2015.04.007

Lunduka, R. W., Mateva, K. I., and Magorokosho, C., 2019. Impact of adoption of drought-tolerant maize varieties on total maize production in south Eastern Zimbabwe. *Climate and Development ISSN: 11*(1), 35–46. https://doi.org/10.1080/17565529.2017.1372269

Makate, C., Makate, M., Mango, N., and Makate, M., 2018. Farm household typology and adoption of climate-smart agriculture practices in smallholder farming systems of southern Africa. *African Journal of Science, Technology, Innovation and Development*, *0*(0), 1–19. https://doi.org/10.1080/20421338.2018.1471027

Makate, C., Makate, M., Mango, N., and Siziba, S., 2019. Increasing resilience of smallholder farmers to climate change through multiple adoption of proven climate-smart agriculture innovations. Lessons from Southern Africa. *Journal of Environmental Management*, *231*(October 2018), 858–868. https://doi.org/10.1016/j.jenvman.2018.10.069

Makate, C., Wang, R., Makate, M., and Mango, N., 2016. Crop diversification and livelihoods of smallholder farmers in Zimbabwe : adaptive management for environmental change. *SpringerPlus*, *5*(1135), 1–18. https://doi.org/10.1186/s40064-016-2802-4

Mango, N., Makate, C., Tamene, L., Mponela, P., and Ndengu, G., 2020. Impact of the adoption of conservation practices on cereal consumption in a maize-based farming system in the Chinyanja Triangle, Southern Africa. *Sustainable Futures*, *2*(December 2019), 100014, 1-9. https://doi.org/10.1016/j.sftr.2020.100014

Mango, N., Siziba, S., and Makate, C., 2017. The impact of the adoption of conservation agriculture on smallholder farmers ' food security in semi-arid zones of southern Africa. *Agriculture and Food Security*, 4–11. https://doi.org/10.1186/s40066-017-0109-5

Mango, N., Zamasiya, B., Makate, C., Nyikahadzoi, K., and Siziba, S., 2014. Factors influencing household food security among smallholder farmers in the Mudzi district of Zimbabwe. *Development Southern Africa*, *31* (January 20154), 37–41. https://doi.org/10.1080/0376835X.2014.911694

Martey, E., Maxwell, P., Abdoulaye, T., and Tl, P. O. B., 2020. Land Use Policy Welfare impacts of climate-smart agriculture in Ghana : Does row planting and drought-tolerant maize varieties matter ? *Land Use Policy*, *95*((2020) 104622), 1–10. https://doi.org/10.1016/j.landusepol.2020.104622

Mazvimavi, K., and Twomlow, S., 2009. Socioeconomic and institutional factors influencing

adoption of conservation farming by vulnerable households in Zimbabwe. *Agricultural Systems*, *101*(1–2), 20–29. https://doi.org/10.1016/j.agsy.2009.02.002
Meier, E. A., Thorburn, P. J., Bell, L. W., Harrison, M. T., Biggs, J. S., and Meier, E. A., 2020. Greenhouse Gas Emissions From Cropping and Grazed Pastures Are Similar : A Simulation Analysis in Australia. *Frontiers in Sustainable Food Systems*, *3*(January), 1–18. https://doi.org/10.3389/fsufs.2019.00121
Misra, A. K., 2014. Climate change and challenges of water and food security Anil. *International Journal of Sustainable Built Environment*, *3*, 153–165. https://doi.org/10.1016/j.ijsbe.2014.04.006
Moges, D. M., and Taye, A. A., 2017. Determinants of farmers' perception to invest in soil and water conservation technologies in the North-Western Highlands of Ethiopia. *International Soil and Water Conservation Research, 5*(1), 56–61. https://doi.org/10.1016/j.iswcr.2017.02.003
Moser, C. M., and Barrett, C. B., 2006. The complex dynamics of smallholder technology adoption : the case of SRI in Madagascar. *Agricultural Economics, 35 (2006)*, 373–388.
Mozzato, D., Gatto, P., Defrancesco, E., Bortolini, L., Pirotti, F., Pisani, E., and Sartori, L., 2018. The Role of Factors Affecting the Adoption of Environmentally Friendly Farming Practices : Can Geographical Context and Time Explain the Differences Emerging from Literature ? *Sustainability*, *10,* 1–23. https://doi.org/10.3390/su10093101
Mugandani, R., and Mafongoya, P., 2019. Behaviour of smallholder farmers towards adoption of conservation agriculture in Zimbabwe. *Soil Use and Management*, 2019 (00), 1-15. https://doi.org/10.1111/sum.12528
Mujeyi, A., 2018. Policy and Institutional Dimensions in Climate-Smart Agriculture Adoption : Case of Rural Communities in Zimbabwe. In W. Leal Filho (ed.) (Ed.), *Handbook of Climate Change Resilience*. 1-15. https://doi.org/10.1007/978-3-319-71025-9_66-1
Mujeyi, A., Mudhara, M., and Mutenje, M. J. (2019). Adoption determinants of multiple climate-smart agricultural technologies in Zimbabwe : Considerations for scaling-up and out. *African Journal of Science, Technology, Innovation and Development*, *0*(0), 1–13. https://doi.org/10.1080/20421338.2019.1694780
Munjenjema, S., 2019. January Disease kills 50 000 cattle .The Sunday Mail.
Mupangwa, W., Mutenje, M., Thierfelder, C., Mwila, M., Malumo, H., Mujeyi, A., and Setimela, P., 2017. Productivity and profitability of manual and mechanized conservation agriculture (CA) systems in Eastern Zambia. *Renewable Agriculture and Food Systems*, 1–15. https://doi.org/10.1017/S1742170517000606
Mupangwa, W., and Thierfelder, C., 2014. Intensification of conservation agriculture systems for increased livestock feed and maize production in Zimbabwe. *International Journal of Agricultural Sustainability*, *12*(4), 425–439. https://doi.org/10.1080/14735903.2013.859836
Murage, A. W., Midega, C. A. O., Pittchar, J. O., Pickett, J. A., and Khan, Z. R., 2015. Determinants of adoption of climate-smart push-pull technology for enhanced food security through integrated pest management in eastern Africa. *Food Security*, 1–16. https://doi.org/10.1007/s12571-015-0454-9
Mwangi, M., and Kariuki, S., 2015. Factors Determining Adoption of New Agricultural Technology by Smallholder Farmers in Developing Countries. *Journal of Economics and Sustainable Development*, *6*(5), 2222–1700. www.iiste.org
Nezomba, H., Mtambanengwe, F., Rurinda, J., and Mapfumo, P., 2018. Field Crops Research Integrated soil fertility management sequences for reducing climate risk in smallholder crop production systems in southern Africa. *Field Crops Research*, *224*(May), 102–114. https://doi.org/10.1016/j.fcr.2018.05.003
Ngombe, J. N., Kalinda, T. H., and Tembo, G., 2017. Agricultural Economics Research, Policy and Practice in Southern Africa Does adoption of conservation farming practices result in increased crop revenue ? Evidence from Zambia Does the adoption of conservation farming practices results in. *Agrekon*, *0*(0), 1–17. https://doi.org/10.1080/03031853.2017.1312467
Ntshangase, N. L., Muroyiwa, B., and Sibanda, M., 2018. Farmers' perceptions and factors

influencing the adoption of no-till conservation agriculture by small-scale farmers in Zashuke, KwaZulu-Natal province. *Sustainability (Switzerland)*, *10*(2), 1–16. https://doi.org/10.3390/su10020555

Ogada, M. J., Rao, E. J. O., Radeny, M., Recha, J. W., and Solomon, D., 2020. Climate-smart agriculture, household income and asset accumulation among smallholder farmers in the Nyando basin of Kenya. *World Development Perspectives*, 1–11. https://doi.org/10.1016/j.wdp.2020.100203

Ouédraogo, M., Houessionon, P., Zougmoré, R. B., and Partey, S. T. (2019). Uptake of climate-smart agricultural technologies and practices: Actual and potential adoption rates in the climate-smart village site of Mali. *Sustainability (Switzerland)*, *11*(4710), 1-19. https://doi.org/10.3390/su11174710

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

Pandey, P., Irulappan, V., Bagavathiannan, M. V, and Sanchez, L. E., 2017. Impact of Combined Abiotic and Biotic Stresses on Plant Growth and Avenues for Crop Improvement by Exploiting Physio-morphological Traits. *Frontiers in Plant Science*, *8*(April), 1–15. https://doi.org/10.3389/fpls.2017.00537

Paolini, V., Petracchini, F., Segreto, M., Tomassetti, L., Naja, N., Cecinato, A., Tomassetti, L., 2018. Toxic / Hazardous Substances and Environmental Engineering Environmental impact of biogas : A short review of current knowledge. *Journal of Environmental Science and Health, Part A*, *53*(10), 899–906. https://doi.org/10.1080/10934529.2018.1459076

Paul, B. K., Koge, J., Maass, B. L., Notenbaert, A., Peters, M., and Groot, J. C. J., 2020. Tropical forage technologies can deliver multiple benefits in Sub-Saharan Africa. A meta-analysis. *Agronomy for Sustainable Development*, *40*(22), 1–17.

Rao, N., Lawson, E. T., Raditloaneng, W. N., Solomon, D., Angula, M. N., Rao, N., Solomon, D., 2019. Gendered vulnerabilities to climate change : insights from the semi-arid regions of Africa and Asia. *Climate and Development*, *11*(1), 14–26. https://doi.org/10.1080/17565529.2017.1372266

Raza, A., Razzaq, A., Mehmood, S. S., Zou, X., Zhang, X., and Lv, Y., 2019. Impact of Climate Change on Crops Adaptation and Strategies to Tackle Its Outcome : A Review. *Plants*, *8*(34), 1-29. https://doi.org/10.3390/plants8020034

Rogers, E. M., 2003. *Diffusion of Innovations* (3rd ed.). New York: Free Press, https://doi.org/82-70998

Rosenstock, T. S., Nowak, A., and Girvetz, E., 2019. The Climate-Smart Agriculture Papers: Investigating the Business of a Productive, Resilient and Low Emission Future. Springer, Cham. 1-314. https://doi.org/10.1007/978-3-319-92798-5

Sain, G., Loboguerrero, A. M., Corner-Dolloff, C., Lizarazo, M., Nowak, A., Martínez-Barón, D., and Andrieu, N., 2017. Costs and benefits of climate-smart agriculture: The case of the Dry Corridor in Guatemala. *Agricultural Systems, 151,* 163–173. https://doi.org/10.1016/j.agsy.2016.05.004

Sebata, A., 2018. An Insight into Current and Future Production of Forage Crops in Zimbabwe,. In *New Perspectives in Forage Crops, Ricardo Loiola Edvan and Leilson Rocha Bezerra, IntechOpen*. 89-104 https://doi.org/10.5772/intechopen.71997

Serdeczny, O., Adams, S., Coumou, D., Hare, W., and Perrette, M., 2016. Climate change impacts in Sub-Saharan Africa: from physical changes to their social repercussions. Special Issue on Models for Adaptive Forest Management. *Regional Environmental Change*, *15*(8), 1–19. https://doi.org/10.1007/s10113-015-0910-2

Setimela, P., Allah, Z., and Ndoro, O. F., 2017. Performance of elite drought-tolerant maize varieties across eastern and southern Africa, season. 2017-18. *International Maize and Wheat Improvement Centre (CIMMYT) Report*. 1–12.

Shikuku, K. M., Valdivia, R. O., Paul, B. K., Mwongera, C., Winowiecki, L., Läderach, P., Silvestri, S., 2016. Prioritizing climate-smart livestock technologies in rural Tanzania : A minimum data approach. *Agricultural Systems*, 1–13. https://doi.org/10.1016/j.agsy.2016.06.004

Signh, K. A., Singh, R. ., Velmurugan, A., Kumar, R. R., and Biswas, U., 2018. Harnessing Genetic Resources in Field Crops for Developing Resilience to Climate Change in Biodiversity and Climate Change in Bio-diversity and Climate Change Adaptation in Tropical Islands. In *Biodiversity and Climate Change Adaptation in Tropical Islands*. https://doi.org/10.1016/B978-0-12-813064-3/00022-3

Simtowe, F., Amondo, E., Marenya, P., Rahut, D., Sonder, K., Erenstein, O., 2019. Land Use Policy Impacts of drought-tolerant maize varieties on productivity, risk, and resource use : Evidence from Uganda. *Land Use Policy*, *88*((2019) 104091), 1–10. https://doi.org/10.1016/j.landusepol.2019.104091

Singh, R. S. G. S., 2017. Traditional agriculture : a climate-smart approach for sustainable food production. *Energy, Ecology and Environment*, *2*(5), 296–316. https://doi.org/10.1007/s40974-017-0074-7

Sinyolo, S., 2020. Technology in Society Technology adoption and household food security among rural households in South Africa : The role of improved maize varieties. *Technology in Society*, *60*((2020) 101214), 1–10. https://doi.org/10.1016/j.techsoc.2019.101214

Siziba, S., Nyikahadzoi, K., Makate, C., and Mango, N., 2019. Impact of conservation agriculture on maize yield and food security : Evidence from smallholder farmers in Zimbabwe. *African Journal of Agricultural and Resource Economics Volume*, *14*(2), 89–105.

Sova, C., Grosjean, G., Baedeker, T., Ninh Nguyen, T., Wallner, M., Jarvis, A., Girvetz, E., 2018. Bringing the Concept of Climate-Smart Agriculture to Life Insights from CSA Country Profiles across Africa, Asia, and Latin America.*" World Bank, and the International Centre for Tropical Agriculture*, Washington, DC.

Steenwerth, K. L., Hodson, A. K., Bloom, A. J., Carter, M. R., Cattaneo, A., Chartres, C. J., Jackson, L. E. (2014). Climate-smart agriculture global research agenda : scientific basis for action. *Agriculture and Food Security*, *3*(11), 1–39. http://www.agricultureandfoodsecurity.com/content/3/1/11

Steward, P. R., Dougill, A. J., Thierfelder, C., Pittelkow, C. M., Stringer, L. C., Kudzala, M., and Shackelford, G. E., 2018. The adaptive capacity of maize-based conservation agriculture systems to climate stress in tropical and subtropical environments: A meta-regression of yields. *Agriculture, Ecosystems and Environment*, *251*(September 2017), 194–202. https://doi.org/10.1016/j.agee.2017.09.019

Teklewold, H., Gebrehiwot, T., and Bezabih, M., 2019. Climate-smart agricultural practices and gender-differentiated nutrition outcome : An empirical evidence from Ethiopia. *World Development*, *122*, 38–53. https://doi.org/10.1016/j.worlddev.2019.05.010

Tesfaye, K., Kassie, M., Cairns, J. E., Michael, M., Stirling, C., Abate, T., Gerard, B., 2017. Potential for Scaling up Climate Smart Agricultural Practices : Examples from Sub-Saharan Africa. *Climate Change Management*, 185–203. https://doi.org/10.1007/978-3-319-49520-0

Tesfaye, K., Kruseman, G., Cairns, J. E., Zaman-allah, M., Wegary, D., Zaidi, P. H., Erenstein, O., 2018. Climate Risk Management Potential benefits of drought and heat tolerance for adapting maize to climate change in tropical environments. *Climate Risk Management*, *19*(April 2017), 106–119. https://doi.org/10.1016/j.crm.2017.10.001

Thierfelder, C., Baudron, F., Setimela, P., Nyagumbo, I., Mupangwa, W., Mhlanga, B., Gérard, B., 2018. Complementary practices supporting conservation agriculture in southern Africa. A review. *Agronomy for Sustainable Development*, *38*(16), 1–22. https://doi.org/10.1007/s13593-018-0492-8

Thierfelder, C., Chivenge, P., Mupangwa, W., Rosenstock, T. S., Lamanna, C., and Eyre, J. X., 2017b. How climate-smart is conservation agriculture (CA)? – its potential to deliver on adaptation, mitigation and productivity on smallholder farms in southern Africa. *Food Security*, *9*(3), 537–560. https://doi.org/10.1007/s12571-017-0665-3

Thierfelder, C., Matemba-Mutasa, R., Bunderson, W. T., Mutenje, M., Nyagumbo, I., and Mupangwa, W., 2016. Evaluating manual conservation agriculture systems in southern

Africa. *Agriculture, Ecosystems and Environment*, *222*(February), 112–124. https://doi.org/10.1016/j.agee.2016.02.009
Thierfelder, C., Rusinamhodzi, L., Ngwira, A. R., Mupangwa, W., Nyagumbo, I., Kassie, G. T., and Cairns, J. E., 2014. Conservation agriculture in Southern Africa : Advances in knowledge. *Renewable Agriculture and Food Systems*, 1–21. https://doi.org/10.1017/S1742170513000550
Thornton, P. K., Steeg, J. Van De, Notenbaert, A., and Herrero, M., 2009. The impacts of climate change on livestock and livestock systems in developing countries : A review of what we know and what we need to know. *Agricultural Systems*, *101*, 113–127. https://doi.org/10.1016/j.agsy.2009.05.002
Tran, N. L. D., Rañola, R. F., Ole Sander, B., Reiner, W., Nguyen, D. T., and Nong, N. K. N., 2019. Determinants of adoption of climate-smart agriculture technologies in rice production in Vietnam. *International Journal of Climate Change Strategies and Management*, *12*(2), 238–256. https://doi.org/10.1108/IJCCSM-01-2019-0003
Vanlauwe, B., Descheemaeker, K., Giller, K. E., Huising, J., Merckx, R., Nziguheba, G., Zingore, S., 2015. Integrated soil fertility management in sub-Saharan Africa: Unravelling local adaptation. *Soil*, *1*(1), 491–508. https://doi.org/10.5194/soil-1-491-2015
Yigezu, Y. A., Mugera, A., El-shater, T., Aw-hassan, A., Piggin, C., Haddad, A., Loss, S., 2018. Technological Forecasting and Social Change Enhancing adoption of agricultural technologies requiring high initial investment among smallholders. *Technological Forecasting and Social Change*, *134*(November 2017), 199–206. https://doi.org/10.1016/j.techfore.2018.06.006
ZIMSTAT, 2012. The Zimbabwe 2012 Population Census National Report. *Zimbabwe National Statistics Agency*. Harare, Zimbabwe.
ZIMSTAT, 2019. Zimbabwe Smallholder Agricultural Productivity Survey 2017 Report. *Zimbabwe National Statistics Agency*. 1–100. Harare, Zimbabwe.
Zougmoré, R., Partey, S., Ouédraogo, M., Omitoyin, B., Thomas, T., Ayantunde, A., Jalloh, A., 2016. Toward climate-smart agriculture in West Africa : a review of climate change impacts, adaptation strategies and policy developments for the livestock, fishery and crop production sectors. *Agriculture and Food Security*, *5*(26), 1–16. https://doi.org/10.1186/s40066-016-0075-3

CHAPTER 3 ADOPTION PATTERNS OF CLIMATE-SMART AGRICULTURE IN INTEGRATED CROP LIVESTOCK SMALLHOLDER FARMING SYSTEMS

3.1 Abstract

This chapter maps adoption patterns of Climate-smart Agriculture (CSA) technologies among diverse smallholder farmers. A multivariate analysis approach that combined PCA and cluster analysis using survey data from 386 households was employed to generate household typologies and technology bundles. Findings showed that patterns of CSA varied across the household typologies. Resource endowed and experienced farmers have a high use of technologies such as crop rotation and minimum tillage that require more resources while resource-constrained clusters avoided resource-intensive CSA technologies. The Cragg double hurdle model results showed that the adoption of CSA is significantly affected by distance to the tarred road, access to weather information, livestock income share and ownership of transport assets. Adoption intensity is significantly affected by factors such as sex of household head, labour size, frequency of extension contact, access to credit, access to weather forecasts, off-farm income, distance to input and output markets, number of traders and asset ownership. The study, therefore, recommends policies that ensure access to weather forecasts information, coupled with frequent access to extension officers by farmers and ensuring access to credit. Furthermore, government efforts should be directed towards input markets decentralization, the establishment of rural all-season tarred roads to ensure increased adoption intensity of CSA.

Keywords: *adoption patterns, intensity, household typology, Cragg double-hurdle model, Zimbabwe*

3.2 Introduction

Climate-smart Agriculture (CSA), refers to agriculture that “sustainably increases productivity and resilience (adaptation), reduces or removes Greenhouse Gases (GHGs) (mitigation), and enhances achievement of national food security and sustainable development goals” (FAO, 2018). CSA is very crucial for smallholder farmers who rely on rain-fed production and are constrained by poor farming methods, high levels of soil degradation, drought and prolonged dry spells (FAO, 2018). At a local level, CSA can be conceived as a suite of practices ideally ones assessed for local suitability that can improve a farmer’s capacity to adapt to changes in climate and/or increase the mitigation potential of production through carbon sequestration or reduced emissions, while still meeting or exceeding food security goals. Smallholder farmers in southern Africa have been a target of CSA technologies since 2010 when the term was first coined by the Food and Agriculture Organisation (FAO), mainly because they are experiencing declining agricultural productivity and are vulnerable to climate change.

CSA offers numerous benefits in addressing current constraints. Minimum tillage technologies prevent the washing away of nutrients by erosion and better retention of soil moisture. An increasing number of Zimbabwean farmers have a challenge of declining soil fertility and animal manure is widely used to improve soil fertility. In crop-livestock integrated farming systems there is a complementary adoption strategy where farmers rely on livestock to produce manure while the crops supply the livestock with fodder. Researchers found that manure and fertilizer inputs are complementarities due to the beneficial interactive effects of manure on fertilizer efficiency (Marenya et al., 2017). Farmers also intercrop maize with legumes such as beans and cowpeas. A maize-legumes intercrop has benefits that include an increase in yield per area of land, reduction in farm inputs, diversification of diet, increased labour utilization efficiency, and can hedge against the risk of crop failure as different crops have different patterns of growth and are affected by different pests and diseases. Researchers in Tanzania found that intermediate intercropping maize and common bean enhanced productivity in comparison to sole crop (Nassary et al., 2020). The systems of maize–legume intercrop can improve soil fertility through nitrogen fixation by legumes. Other researchers also found greater land equivalent ratios (LERs) in intercrop patterns versus sole cropping (Kermah et al., 2017). Households adopt different combinations of agricultural innovations because of their combined effect to improve soil fertility and crop productivity.

Despite the potential of CSA technologies proven through on-station and on-farm trials showing that these technologies increase farm productivity, adoption has been generally low (Corbeels et al., 2013; Mango et al., 2017). Adoption in Zimbabwe has been on smaller pieces of land i.e. 0.2 to 0.4 ha of land for fodder (Ngongoni et al., 2007), and approximately 5% of the area allocated to maize by a household is under conservation agriculture (Marongwe et al., 2011). This is a pointer to issues involving diffusion, dissemination and implementation. Farmers adopt these technologies in varying combinations. Farmers' decision making processes in terms of which technology to adopt are more complex and depend on factors such as asset base, access to information through various institutions, underlying agro-ecology, and motivational factors in areas such as yield, labour, soil quality and weeding time benefits (FAO, 2018; Lalani et al., Dorward et al., 2016). The success of new CSA innovations therefore implicitly calls for an understanding of the adoption patterns across diverse household types. This will help agricultural policy programs and technological interventions in agriculture to be compatible with farmer priorities and expectations. Such policies and technologies would have a greater chance of being accepted and practised sustainably than programs based on donor calls or some incentives.

Few studies in Zimbabwe have analysed the adoption of CSA across household types using the double hurdle. Studies done so far have used a single equation approach (i.e. Probit or Tobit, Logit) and these do not separate factors affecting adoption and intensity. The double hurdle model is more representative because it distinguishes the adoption decision from the intensity of adoption. The main objective of this chapter is therefore to map adoption patterns across heterogeneous households and to assess the intensity of adoption of CSA technologies among smallholder farmers in crop-livestock integrated farming systems. This information is important for precise and effective technology targeting and up-scaling activities by government and development organisations.

3.3 Methodology

This section outlines the data collected which applies to all the empirical chapters. The study used a cross-sectional survey approach using both qualitative and quantitative data. Primary data were generated from a household survey and key informant interviews held with eight ward-based extension officers (one from each ward) and four District Agriculture extension officers.

Secondary data were collected from a review of published journal articles mainly within the last 20 years from the time the CSA was coined.

3.3.1 Study Area

The study was conducted in four districts (Goromonzi, Murehwa, Mutoko, and Uzumba-Maramba-Pfungwe) of the Mashonaland East province in Zimbabwe (Figure 1). The districts were selected based on the variations in the agro-ecological conditions and on the fact that they had been exposed to CSA technologies by the government, in collaboration with non-governmental and research organisations. The agro-ecology of the sites varies in terms of their mean annual rainfall and dominant soil types. Goromonzi and Murehwa are located in agro-ecological regions IIa and IIb, which receive a reliable high rainfall of 750 to 1,000 mm per year, respectively.

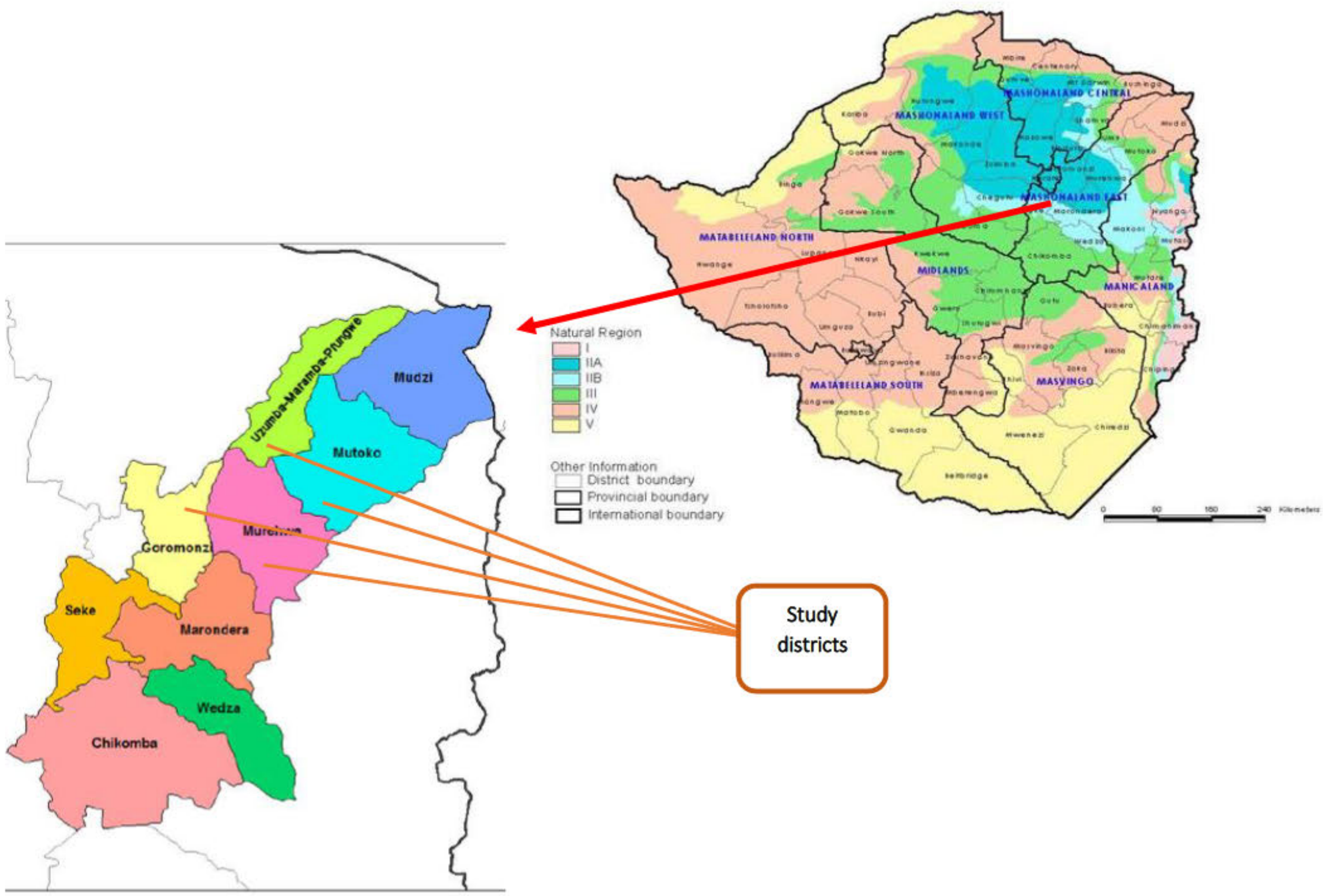

Figure 3: Study sites

Mutoko and Uzumba-Maramba-Pfungwe lie in agro-ecological regions III and IV, which receive an erratic low annual rainfall of 500 to 800 mm, respectively, and are characterized by seasonal mid-season dry spells. Crop-livestock integration is the common farming system in all the sites.

3.3.2 Sampling Design

The selection of smallholder households for sampling began with the identification of the four districts in which CSA technologies have been promoted by the government and NGOs (see Appendix 4). The desired target sample size of 400 was obtained using the survey monkey and raosoft sample size calculator for a population of 15511 households from the 8 wards in the four districts (ZIMSTAT, 2012a), (5% margin of error, 95% confidence level = 376 households + 24 to allow for any non-responses). One village was then randomly selected from each ward from a list provided by the extension officers of villages where CSA technologies have been promoted over the lasts 20 years. The multi-stage random sampling technique was used to select the representative sample of farming households. In the first stage, two wards were randomly selected from each district, giving a total of eight wards. Secondly, one village from each ward was selected. Households were then randomly selected from the sampling frame, namely, the village head's list of all the farming households. Sample households were distributed within the wards according to the ward sizes (i.e., proportionate sampling). The households were randomly selected from the lists provided by the village heads. A cross-sectional household survey was carried out using structured questionnaires designed to capture information on a range of potential indicators related to household livelihoods. The interviews were conducted in March 2018 by trained enumerators at the farmer's homestead and directly supervised by the researcher. The enumerators informed the participants of the research objectives and highlighted that the information would be treated confidentially. Consent was then sought to proceed with the interview and a consent form was signed if the participant agreed (see Appendix 2). The survey managed to get responses from 386 households.

3.3.3 The Questionnaire

A structured household survey questionnaire was administered by the trained enumerator under the supervision of the researcher to the smallholder farmers in their homes, and key informant interviews were administered to government extension officers in their wards. The structured questionnaire had seven sections (complete details included in Appendix 1). Section 1 collected general information (date, district, wards and characteristics of respondent) while Section 2 collected household characterisation information (household head sex, age, education level, farming experience, etc.). Section 3 gathered information on access to services such as extension, markets, social capital, and asset ownership while Section 4 covered access to credit and determined the household savings, incomes and expenditure. Section 5 gathered information on land ownership and crop production (inputs used, their costs, harvested amounts), and Section 6 detailed the access and use of various crop and livestock CSA technologies. Section 7 dealt with food security situations. The questionnaire was subjected to validity and reliability tests through pre-testing in a village outside the sample areas. This was done to assess the ability of the trained enumerators to correctly administer the questionnaire and to customize it to the target farmers.

3.4 Data Analysis

This sub-section outlines the analytical approaches and techniques used to generate results that have been used in presenting and discussing the findings of the study. The analysis, which encompassed both descriptive and inferential statistics, sought to generate an understanding of adoption patterns, determinants of adoption and household typologies in the adoption of different CSA technology bundles.

3.4.1 Adoption Patterns

Both descriptive, as well as econometric analysis, was employed in the analysis. Frequencies means and percentages were computed for different variables. Household farm typologies and technology bundles (combinations) were created using sequential multivariate statistical PCA and successive cluster analysis. Farmers were then clustered into roughly homogenous groups using some variables that have been used by other researchers in the literature (education, crop diversification, household income, asset ownership, Biophysical (e.g. climate, slope soil fertility, etc.) and socio-economic (e.g. production objectives, prices, preferences, etc.), farm resources (e.g. cash and labour), infrastructure (e.g. markets, road network), management practices (Goswami et al., and 2014). Analysis of the number and type of technologies adopted by each cluster was done. The derived clusters were interpreted as typologies. The significance of the difference between clusters (‘farm types’) was tested using the chi-square test.

3.4.2 Determinants of Adoption Patterns

Researchers in literature have used models such as Tobit, Heckman and the Cragg Double Hurdle models to explain the intensity of adoption. The Tobit model assumes that the factors explaining the decision to adopt and the number of technologies adopted have the same effect on these two decisions. The Tobit model cannot handle the situation in which participation and the number of technologies adopted may be a separate decision, possibly influenced by different variables. The double-hurdle model, originally formulated by Cragg in 1971, assumes that households make two decisions concerning adoption and the extent, each of which is determined by a different set of explanatory variables (Newton et al., 2014). Each decision process is modelled differently i.e. with a Probit model to determine participation and a Tobit model to determine the level of adoption. The Heckman model assumes that in the second stage, there will be no zero observations once the first stage is passed, whereas the double hurdle still considers that there might be a possibility of a zero observation which may arise from the individual's choice (farmer's deliberate choice) or random circumstances. Decision-making on new technologies has a probability of being made at these two-levels and thus this research adopted Cragg's Double Hurdle Models. The double-hurdle is a combined Probit and Tobit estimator (Newton et al., 2014). This chapter decomposes adoption into two separate components i.e. decision to adopt or not and then the intensity of adoption (number of CSA adopted). A household must cross these two hurdles for it to be categorized as an adopter. A positive number of CSA used by a household implies that it has crossed the second hurdle. Factors affecting these two hurdles may be different. The Double Hurdle Model has two components namely the Participation model and the Quantity Decision model i.e. level of use model. Table 3 highlights the variables used in the model.

The double Hurdle Model has the dependent variable as a dummy variable (i.e. takes two values) in the first stage and a continuous dependent variable in the second stage. The decision equation is a binary decision that is modelled using a Probit model as follows:

Participation Decision model: $D_i = w_i\alpha + \varepsilon_i$

Di is a dichotomous variable that takes the value of 1 if the respondent is a participant in and 0 otherwise, w is a vector of explanatory variables, α denotes a vector of parameters, and εi is the error term.

The empirical model for farmers' decision to adopt CSA is specified for this study as follows:

CSA Adoption (D_i)= α_0+ $\alpha_1$sexhead + $\alpha_2$agehead +$\alpha_3$eduhead +$\alpha_4$farmexperience +α_5m2 laboursize +$\alpha_6$mtarred+$\alpha_7$kminputmkt +$\alpha_8$kmoutputmkt +α_9m$_3$CropShare +α_{10}membershipgrps +α_{11}AssetImplement+α_{12}contactsextension+α_{13}weatherforecasts +α_{14}LivestockShare+α_{15}landsize + $_{16}$draft +α_{17}soiltypedummy +α_{18}credit + α_{19}Savings+α_{20}NonAgriShare+α_{21}assetComms + α_{22}tlu +α_{23}AssetTransport + ε_i

Table 3: Explanatory variables used in the Cragg Double Hurdle model

Category and meaning	Variable name	Nature of variable
Dependent variable		
Adoption (hurdle 1)	Adoption	dummy 1=yes 0=no
Adoption intensity(hurdle2)	Adoption intensity	Continuous
Explanatory Variables		
Household Characteristics		
Sex of household head	SexHH	Dummy (1=male 0=female)
Age of household head in years	AgeHH	Continuous
Education of household head in years	EduHH	Continuous
Farming experience in years	ExperienceHH	Continuous
Labour size (number)	Laboursize	Continuous
Household size	Household size	Continuous
Market access		
Distance to the tarred road in Kilometres	KMtarred	Continuous
Distance to input market in Kilometres	KMinputmkt	Continuous
Distance to output market in Kilometres	KMoutputmkt	Continuous
Number of buyers in the village	Traders	Continuous
Social capital and information access		
Membership to farm groups	Grpmembership	Dummy (1=yes 0=no)
Frequency extension contacts	EXTNcontact	Continuous
Access to weather forecasts	Infoweather	Dummy (1=yes 0=no)
Farm characteristics		
Land Size (Land) in hectares	Landsize	Continuous
Land quality (Soil)	Soiltype	Dummy 1=good 0=poor
Institutional Access and Resource endowments		
Amount of credit accessed	Credit	Continuous
TLU (Total Livestock Units)	TLU	Continuous
Share of Income from crops	CropShare	Continuous
Share of Income from livestock	LivestockShare	Continuous
Off-farm income	OffFarm	Dummy (1=yes 0=no)
Owns communication assets	assetcomms	Dummy (1=yes 0=no)
Owns transport assets	assettransport	Dummy (1=yes 0=no)
Owns tillage implement assets	assettillageimplement	Dummy (1=yes 0=no)

The second equation (Quantity equation) in the double-hurdle is estimated using a regression truncated at zero with the following formulation:

Quantity/Level of use model (Number of technologies adopted)

$$Y_{i^*} = X_i \beta + \varepsilon_i$$

$Y_i = Y_i{*}\ if\ D_i = 1\ and\ Y_i{*} > 0\ u_i \approx N\ 0{,}1;\ \varepsilon_i \approx N(0, \sigma 2) \bullet corr(u_i, \varepsilon_i) = \rho$ unobserved elements affecting participation may affect the number of technologies adopted.

where $Yi\ *$ represents the observed number of technologies adopted and β denotes a vector of explanatory variables, Xi represents a vector of parameters to be estimated, and εi is a random error term.

Empirically, the truncated regression model is specified for this study as follows:

$Y_i{*} = \beta_0 + \beta_1$ SexHead + β_2 m2agehead + β_3m2eduhead + β_4m2farmexperience + $\beta_5$laboursize + β_6m3membershipgrps + β_7m3cropsShare + β_8m3contactsextension + β_9m3weatherforecasts + β_{10}m5landsize + β_{11}soiltypedummy + β_{12}m4credit + β_{13}savings + β_{14}tlu + β_{15} AssetComms + β_{16}m3livestockShare + β_{17}m3NonAgricShareShare + β_{18} AssetTransport + β_{19} AssetImplement + εi……………………………………(…)

where $Y_i{*}$ is the number of CSA technologies adopted by the ith farmer, β are coefficients of the explanatory variables, and εi is the random error term.

3.5 Results and discussion

3.5.1 Household socio-economic characteristics

The descriptive statistics of the selected farm households are presented in Table 1. Farm households are comparable in family size across the four districts with a mean of five household members per household. There are significant differences across districts in characteristics of household heads in terms of age, education and farming experience (Table 4). Despite significant investment in formal education, overall the results showed an average of primary education level (i.e., 7.14 years and thus pointing towards a low completion rate of formal education. Generally, most households are headed by middle-aged household heads but household heads in UMP are older than those in the other three districts. Older farmers seem to have more farming experience than their younger counterparts. There was also a significant difference in land ownership across the districts. Farmers in UMP own bigger tracts of land averaging 4.36 acres whereas land sizes in the other three districts are less than 3 acres per household.

Table 4: Descriptive Statistics for continuous variables of the surveyed households

Variable	Goromonzi	Murehwa	Mutoko	U.M.P	All districts n=386	Test statistics	
			Mean			F value	P value
Age of household head in years	50.52	47.91	46.24	53	49.42	2.37*	0.07
Education of household head in years	8.49	8.13	10.06	7	8.42	7.14***	0.00
Farming experience (years)	18.56	16.42	11.88	26	18.22	14.507***	0.00
Household size	4.88	4.59	4.86	5	4.83	1.91	0.13
Total arable land (acres)	2.56	2.65	2.86	4.36	3.11	16.24***	0.00
Total Livestock units	1.85	2.46	2.28	2.59	2.29	1	0.39
Current Asset Value (US$)	319.63	511.08	496.88	339.53	416.78	1.1	0.35
Household annual Income (US$)	785.37	875.74	874.24	874.26	852.4	0.1	0.96
Household annual expenditure (US$)	438.32	583.71	622.4	542.5	546.73	1.99	0.12

*Source: Field Survey results in 2018. *, **, *** indicates statistical significance at 10% level, 5% level and 1% level respectively*

Table 5 presents summary statistics of characteristics of the households for categorical variables overall and across the four districts. More households are male-headed (59.6%). Overall, the majority are married (over70%) and have farming as the major principal economic activity (more than 90%). Over 80% are full-time farmers.

Table 5: Descriptive statistics for categorical variables of the surveyed households

		% Frequencies					Test Statistic	
Variable	Values	Goromonzi	Murehwa	Mutoko	U.M.P	Overall Sample	Chi-square	P value
Household head type	Male headed	59.6	69.1	70	74.2	68.23	6.18	0.10
	Female headed	40.4	30.9	30	25.8	31.78		
Household head marital status	Married	66.4	66	74	74.2	70.15	11.79	0.23

Variable	Values	% Frequencies					Test Statistic	
		Goromonzi	Murehwa	Mutoko	U.M.P	Overall Sample	Chi-square	P value
	Widowed	24.7	22.7	18	22.6	22		
	Divorced	6.2	6.2		2.2	4.87		
	Single	2.7	5.2	8	1.1	4.25		
Principal Economic Activity	farming	81.94	90.32	100	91.4	90.92	16.49*	0.06
	trading	7.64	3.23	0	4.3	3.79		
	formal employment	6.94	2.15	0	2.15	2.81		
	other	3.47	4.3	0	2.15	2.48		
Type of a farmer	fulltime	81.51	78.35	96	96.77	88.16	20.59***	0.00

*Source: Field Survey results in 2018. *, **, *** indicates statistical significance at 10% level, 5% level and 1% level respectively*

3.5.2 Household Typologies and adoption of various technology bundles

Understanding household typologies in smallholder farming communities is very important in informing out-scaling work with regards to CSA technology adoption. Using Principal components and cluster analysis the surveyed households were categorized into three typologies. Table 6 summarises the characteristics of the three household typologies.

Table 6: Descriptive statistics of the variables across household typologies

Variable	Variable definition	Household Typology/cluster		
		1.00	2.00	3.00
AgeHH	Age of Household head	50.82	66.37	40.29
EduHH	Education of household head (years)	7.65	5.26	10.10
ExperienceHH	Experience of household head (years	21.97	31.47	11.25
EXTN contact	Frequency of extension contact	11.32	5.46	6.13
Asset index	Asset index	13.53	7.72	7.13
Crop Income	Income from crops (US$)	810.12	63.66	69.89

Variable	Variable definition	Household Typology/cluster		
		1.00	**2.00**	**3.00**
Livestock Income	Income from livestock (US$)	1457.18	142.96	241.58
Off-farm income	Off farm income (US$)	21.21	62.50	46.50
Land size	Land size (hectares)	2.33	1.35	1.00
Labour size	Labour size	4.74	3.59	3.29
Tlu	Total livestock units	9.50	1.90	1.33
Area Cash crops	Area under cash crops (hectares)	0.10	0.01	0.00
Area Groundnut	Area under Groundnut (hectares)	1.03	0.28	0.15
Area maize	Area under maize (hectares)	2.15	0.68	0.52
Area horticulture	Area under horticulture (hectares)	0.19	0.05	0.08

Household typology 1 consists of medium-aged (50 years) with minimum primary level education (7 years), experiences in farming (21 years) well resourced (most cattle, biggest land size (2.33 ha) with commercially oriented (cash crops and horticulture). Typology 2 are the aged (>60years), less educated (primary level education i.e <7 years), but very experienced (31 years) with average resources and are subsistence-oriented. Household typology 3 is the young (40 years) well educated (secondary level > 7 years) with average farming experienced (> 11 years) but resource-constrained. They are subsistence-oriented as well and have a considerable off income source ($46). CSA technologies were also grouped into popular technology bundles. Higher use of three crop CSA technologies (rotation, minimum tillage, and use of animal manure) which can be said to be labour saving and soil fertility enhancing CSA practices characterize technology bundle 1. The highest use of CSA practices (intercropping, rotation, minimum tillage, mulching, drought-tolerant maize, improved legumes, and use of animal manure) can be said to be yield increasing and soil fertility enhancing characterize cluster 2. Very limited use of CSA practices with only crop rotation dominating characterize technology bundle 3.

Table 7: Technology bundles use across identified household types

District	Technology bundle	Household Typology 1	2	3	Test Statistic Chi square
	1	25	41.18	63.22	11.31**
Goromonzi	2	62.5	52.94	35.63	
	3	12.5	5.88	1.15	
	1	40	60.61	47.46	3.23
Murehwa	2	40	36.36	42.37	
	3	20	3.03	10.17	
Mutoko	3	100	100	100	
	1	50	38.46	22.5	
	2	14.29	17.95	22.5	
UMP	3	35.71	43.59	55	4.32

*, **, *** *indicates statistical significance at 10% level, 5% level and 1% level respectively* *, **, *** *indicates statistical significance at 10% level, 5% level and 1% level respectively*

The chi-square test of association (Table 7) showed that there were significant differences in technology combinations across household types in Goromonzi districts. The differences across the other three districts were not significant. Most (62.5%) of the Household typology 1 farmer in Goromonzi uses technology bundle 2 while in Murehwa the same typology predominantly uses technology bundle 1 and 2 (40%). This is different for UMP where household typology 1 predominantly uses technology bundle 1 (50%), typologies 2 and 3 mostly using bundle 3. The analysis of CSA adoption shows that different technologies have been adopted by different types of farmers at different scales. To achieve maximum returns to CSA technologies investment such as improved yield, soil, and water conservation, farmers are recommended to adopt a number of the technologies particularly those that complement each other. Some researchers have noted that Crop management innovations are adopted in various combinations to deal with several production constraints (Jaleta et al., 2016; M. Kassie et al., 2012). Results from the household survey on the 4 districts indicated that more than half (50%) of the surveyed respondents are aware of crop CSA technologies such as crop rotation, intercropping, manure, and minimum tillage except for orange maize, agriculture insurance (for Goromonzi and Murehwa) and drought-tolerant maize (Goromonzi, Murehwa, and UMP) where awareness was less than 50%.

Rotation and minimum tillage are popular for all household typologies including resource-constrained (cluster 3). This is because these technologies are resource-saving and help in fertility improvement of the soil. The average, less educated but most experienced farmers (cluster 2) are using the least number of technologies with rotation and minimum tillage dominating. The young resource-constrained farmers (cluster 3) frequently adopted bundle 1 (resource-saving bundle) in Goromonzi and Murehwa whereas, in UMP and Mutoko, the resource-constrained adopted little or no CSA technologies. Mutoko has all household typologies adopting little or no CSA. Adoption levels are still very low in the Mutoko district. Minimum tillage is suitable for land and draught power-constrained farmers. Land is a major agricultural productive asset and land size is strongly associated with climate change adaptation technology options (Ali and Erenstein, 2017). Farmers with large landholdings can try out and invest in new technology compared to farmers with smaller land sizes. This finding is consistent with findings from other researchers (Kassie et al. 2012) who found that households who owned more land were more likely to adopt conservation tillage practices.

These results on the adoption of technology bundles across households by farmers support the results of previous studies (Kassie et al., 2009; Teklewold et al., 2013; Aryal et al., 2017). Findings indicate that there are associations among the multiple CSA practices. Farmers make several technology adoption choices and, therefore, it is important to further analyse determinants of adoption patterns among these rural farmers. Table 8 shows the results of the Cragg double hurdle and table 9 gives the marginal effects after the double hurdle model.

The first stage double hurdle model revealed that coefficients of four regressors had a significant impact on the likelihood of adopting CSA technologies in the study area. The double regression coefficients of the first equation (first hurdle) give signs of the partial effect of the regressors on the probability of adoption.

Table 8: Results of the double hurdle model

Variable	First Hurdle (Adoption)		Second Hurdle(Adoption intensity)	
	Coefficients	**Std. Error**	**Coefficients**	**Std. Error**
SexHH	0.06	0.28	-0.49*	0.26
AgeHH	-0.45	1.09	0.25	1.07
EduHH	-0.47	0.48	0.13	0.43
ExperienceHH	0.49	0.39	-0.18	0.37
Laboursize	-0.17	0.6	1.89***	0.56
HouseholdSize	0.29	0.62	-0.37	0.6
KMtarred	1.01**	0.42	-0.51	0.38
KMinputmkt	-0.31	0.31	-0.49*	0.27
KMoutputmkt	-0.14	0.27	1.13***	0.21
Traders	0.07	0.34	-1.39***	0.32
Grpmembership	-0.2	0.28	0.13	0.25
EXTNcontact	0.05	0.4	0.91***	0.32
Infoweather	0.49*	0.28	1.86***	0.29
Landsize	0.8	0.54	0.21	0.48
Soiltype	0.73	0.49	-0.42	0.34
Credit	-0.19	0.17	0.3*	0.16
TLU	0.09	0.19	0.01	0.17
CropShare	0.15	0.18	-0.12	0.17
LivestockShare	0.35*	0.2	0.09	0.17
OffFarm	0.23	0.41	-0.86**	0.36
Assetcomms	0.58	0.41	-0.38	0.44
Assettransport	-0.68**	0.3	-0.72**	0.26
Assettillageimplement	0.05	0.32	-0.05	0.28
Awarenesscsa	0.11	0.26		
_cons	0.42	1.91	2.19	1.95
lnsigma				
_cons	0.58***	0.05		

Variable	First Hurdle (Adoption)		Second Hurdle(Adoption intensity)	
	Coefficients	Std. Error	Coefficients	Std. Error
/sigma	1.78	0.09		
Number of observations=386				
LR chi2(23)= 236.95				
Prob > chi2=0.00				
Pseudo R2=0.142				
Log likelihood = -715.72625				

*, **, *** *indicates statistical significance at 10% level, 5% level and 1% level respectively*

The second hurdle (adoption intensity) was significantly affected by ten regressors, i.e., sex of household head, household labour size, distance to inputs and output markets, number of traders locally, frequency of extension contacts, access to the weather forecast, credit, off-farm income access and ownership of transport assets.

Distance to the nearest tarred Road: This had a positive and significant relationship with the probability of adoption. This model result indicates that an increase in distance to the tarred road will increase adoption probability. This is against findings from other researchers who found that increased distances to tarred roads lowered the likelihood of adoption. This relationship is however negative for adoption intensity implying that the longer the distance, the lower the probability of increased intensity of CSA by farmers. This might mean the majority of the farmers adopt the technologies to guarantee a harvest that will meet food security at the household level thus adoption is on smaller pieces of land. The households are thus not worried about producing excess crops for the market hence the reduced intensity. The government should thus work towards the improvement of infrastructure such as tarred roads if ever farmers are to move from subsistence levels of production to commercial levels where income generation is increased for households. Most rural feeder roads are gravel in nature and often deteriorate in the wet summer season and this disrupts transport services and make access to markets more difficult and expensive. Transaction costs will thus increase if roads are not well maintained and public transport operators end up charging higher fees (Iskandar and Gatzweiler, 2016). Evidence from Bangladesh showed that rural road investments reduced poverty significantly through higher agricultural production, lower input and transportation costs, and higher agricultural output prices at local village markets and more gains were significant for the poor and in some cases disproportionately higher than for the non-poor (Khandker et al., 2009).

Access to weather Forecasts: The estimated coefficient of this dummy regressor was positive for both adoption and intensity. This finding corroborates that of previous researchers who found out that farmers in Tanzania minimized risks by adjusting planting dates and planting areas (hillside versus. valley bottom have differential soil moisture content) in reaction to seasonal forecasts (Nyasimi et al., 2017). Researchers in Ethiopia also found a positive impact of exposure to early warning systems (Amare and Simane, 2017). Farmers make use of forecast from the meteorological department (scientific weather forecast) as well as indigenous knowledge systems. Indigenous knowledge systems cited during community discussion included interpreting bird sounds, observing tree flowering and fruiting patterns as well as observing animal movement patterns. The government can come up with a scheme where ward-based extension workers gets timely weather forecasts for their areas and disseminate it quickly via mobile-based social media groups in their localities and even displays the information at strategic areas like local shops, clinics or schools.

Credit: The credit coefficient had a significant and positive impact on the intensity of adoption. A household that accesses credit has funds to invest in adaptive strategies. Access to credit in rural areas could be achieved in two ways i.e through government-owned banks with wide geographical coverage like People's Own Savings Bank (POSB) and Agricultural Bank of Zimbabwe (Agribank), engaging the private sector to provide credit schemes for cash crops at reasonable interest rates and local income savings and lending schemes (ISALS). Tax incentives could also be availed for commercial banks that offer loans at reduced lending rates costs to smallholder farming communities adopting CSA technologies. Financial literacy and lending in groups will however need to be considered to reduce repayment defaulting (Gaurav and Singh, 2012; Ruben et al., 2019; Twine et al., 2019).

Livestock Income: Increase in the contribution of livestock to household income increases the intensity of adoption. The probable reason for this might be that livestock sales have the potential to generate capital that might be needed for investments that go along with CSA technologies. This finding calls for the strengthening of the capacity of smallholder farmers to produce for both subsistence (home consumption) and the market as this has the potential to generate income that can be used to buy livestock assets. An alternative way would be to avail a credit scheme for livestock purchases. Repayments could be done when there is reproduction. An additional way is availing livestock breeds with improved fertility traits and ensuring good animal husbandry practices that support good calving interval.

Ownership of Transport Asset: The dummy denoting farmer's ownership of transport assets had a negative and significant impact on the intensity of CSA technologies by farming households. This was unexpected as generally, studies have found positive significant relationships between adoption intensity and asset ownership e.g. (Ali and Erenstein, 2017). During community meetings, some farmers indicated that wealthy people perceived that CSA technologies were meant for poor households. The negative may be an indication of low ownership of transport assets which include scotch carts, tractors, bicycles, and cars.

Sex of household head: Adoption intensity of CSA is significantly affected by Sex of household head. The result of the model shows that male-headed households are less likely to use more CSA. The marginal results indicate that being male-headed reduce intensity by 0.33. The negative and significant effect of Sex on household heads conforms with findings of some researchers (Amare and Simane, 2017; Hassan and Nhemachena, 2008). These researchers revealed that female-headed households were more likely to take up climate change adaptation methods.

Distance to input markets: As expected, distance to the inputs market had a negative significant relationship with the probability of intensity of use of CSA. An increase in distance by one kilometre would lower the intensity of use by 0.44. Increased distance to markets means farmers will have increased transaction costs to procure production inputs.

Distance to output markets: This explanatory variable was positive and significant. This was not expected but goes along with other researchers who also found similar results (Amare and Simane, 2017). Smallholder farmers located far away from tarred roads who have farming as the principal economic activity have limited income-generating activities and as such are likely to adopt any yield-enhancing and input savings CSA.

Availability of local traders: The coefficient of availability of traders locally was negative and significant on adoption intensity in the study area. This implies that an increase in the number of local traders reduced the intensity of adoption.

Extension Contacts: The coefficient of frequency of contact between farmers and extension workers was positive and significant. The probable reason being that frequency of extension implies that farmers can access information from government, NGOs or private sector extension on climate-smart agriculture technologies as well as weather forecasts. This helps farmers make comparative decisions among alternative CSA practices and hence choose the ones that enable them to address their constraints. This is in line with the findings of other researchers. (Akinola et al., 2010) found out that an additional contact through a visit to or from the extension officer, increased hectares under improved maize seeds by 0.06. Researchers in Nigeria also found that access to agricultural extension service enhances the number of CSA practices used in India and Nigeria respectively (Aryal et al., 2017; Awotide et al., 2016a). Another study in Tanzania also found a positive effect of extension on the adoption of CSA technologies in Tanzania (Mwungu et al., 2018).

Table 9: Marginal Effects after Regression

Variable	dy/dx	Std.	p-value
GenderHH	-0.33	0.20	0.10
AgeHH	0.05	0.83	0.95
EduHH	-0.04	0.34	0.90
ExperienceHH	0.02	0.29	0.95
Laboursize	1.30***	0.44	0.00
Householdsize	-0.18	0.46	0.70
KMtarred	-0.07	0.30	0.82
KMinputmkt	-0.44**	0.21	0.04
KMoutputmkt	0.76***	0.17	0.00
Traders	-0.97***	0.24	0.00
Grpmembership	0.03	0.20	0.88
EXTNcontact	0.67**	0.26	0.01
Infoweather	1.47	0.21	0.00
Landsize	0.39	0.37	0.30
Soiltype	-0.09	0.28	0.75

Variable	dy/dx	Std.	p-value
Credit	0.16	0.12	0.19
TLU	0.03	0.13	0.81
CropShare	-0.04	0.13	0.74
LivestockShare	0.17	0.13	0.21
OffFarm	-0.55	0.28	0.06
assetcomms	-0.10	0.34	0.77
assettransport	-0.72	0.20	0.00
assettillageimplement	-0.02	0.22	0.94
Awareness	0.03	0.08	0.68

*, **, *** *indicates statistical significance at 10% level, 5% level and 1% level respectively*

The marginal effects calculations showed that laboursize, distance to output market, availability of traders locally and extension contact were significant. For every added Km to the input market, a farmer adopts CSA 0.97 less and for every trader added locally, a farmer adopts CSA 0.44 less. For every extension contact, a farmer adopts CSA 0.67 more and this pattern is similar i.e positive and significant for distance to output markets. An increase in distance to output markets by 1 Km, increases the intensity of adoption by 0.76. This might be because these distance markets pay higher returns in comparison to selling at the farm gate.

3.6 Conclusion and Recommendations

The chapter assesses CSA practices that have been adopted by different household typologies across four districts in Mashonaland East province (Goromonzi, Murehwa, Mutoko and UMP) in 2018. Data variables obtained from 386 smallholder households are evaluated by a multivariate statistical method that combines principal component analysis with cluster analysis. Three household typologies are identified for the four districts. Resource endowed and experienced farmers have a high use of technologies such as crop rotation and minimum tillage that require more land and resources in terms of labour and initial capital investment. Minimum tillage that has been promoted in Zimbabwe require an initial investment of herbicides or even machinery when it is mechanized. Resource-constrained clusters avoided adopting more CSA practices. Livestock CSA technologies still have very low adoption rates across all household typologies in the 4 agro-ecological regions. The drier UMP region has however witnessed some adoption of the livestock CSA technologies.

In addition, the study uses the double-hurdle model to determine the determinants of adoption patterns of CSA in smallholder farming systems. The Cragg double model estimation results reveal that adoption is mainly affected by four factors i.e. access to the weather forecast, distance from the tarred road, livestock income source and ownership of transport asset. The intensity of CSA technology use is mainly determined by household head characteristic (Sex), household characteristics variables (labour size), economic variables (credit, off-farm income), market variables (distance to input and output markets, number of traders locally) and access to information (frequency of extension contact and access to weather forecasts). Weather forecast is very significant as they affect both adoption and intensity of use. This implies that ensuring that weather forecasts are timely given to farmers is very critical in spearheading adoption. All-season roads such as tarred roads are a necessity if farmers are to intensify adoption of CSA technologies and reap more benefits compared to adopting on small pieces of land. The government can commit resources to develop a fixed length of tarred road in each district every year using fees that are collected from tollgates and vehicle licensing.

Therefore, our results suggest that policies that ensure access to weather forecasts information coupled with frequent access to extension officers by farmers, input markets decentralization, access to credit will go a long way in increasing the intensity of adoption of CSA by smallholder farmers. The government can consider setting up smallholder low interest and easily accessible credit schemes or offer incentives for financial institutions that give loans to farmers adopting CSA as a way of accelerating farm technology adoption. Lastly, the government should also ensure the mobility of extension officers so that they can meet farmers frequently.

References

Akinola, A. A., Alene, A. D., Adeyemo, R., Sanogo, D., Olanrewaju, A. S., Nwoke, C., and Nziguheba, G., 2010. Determinants of adoption and intensity of use of balanced nutrient management systems technologies in the northern Guinea savanna of Nigeria. *Quarterly Journal of International Agriculture*, *49*(1), 25–45.

Ali, A., and Erenstein, O., 2017. Assessing farmer use of climate change adaptation practices and impacts on food security and poverty in Pakistan. *Climate Risk Management*, *16*, 183–194. https://doi.org/10.1016/j.crm.2016.12.001

Amare, A., and Simane, B. (2017). Determinants of smallholder farmers ' decision to adopt adaptation options to climate change and variability in the Muger Sub basin of the Upper Blue Nile basin of Ethiopia. *Agriculture and Food Security*, 1–20. https://doi.org/10.1186/s40066-017-0144-2

Aryal, J. P., Jat, M ., Sapkota, T. B., Kassie, M., Rahut, B. D., and Maharjan, S., 2017. Adoption of multiple climate-smart agricultural practices in the Gangetic plains of Bihar, India. *International Journal of Climate Change Strategies and Management*, *10*(3), 407–427. https://doi.org/10.1108/IJCCSM-02-2017-0025

Awotide, B. A., Karimov, A. A., and Diagne, A., 2016. Agricultural technology adoption, commercialization and smallholder rice farmers' welfare in rural Nigeria. *Agricultural and Food Economics*, *4*(1), 1–24. https://doi.org/10.1186/s40100-016-0047-8

Corbeels, M., Graaff, J. De, Hycenth, T., Penot, E., Baudron, F., Naudin, K., Solomon, I., 2013. Understanding the impact and adoption of conservation agriculture in Africa: A multi-scale analysis. *"Agriculture, Ecosystems and Environment."* https://doi.org/10.1016/j.agee.2013.10.011

FAO. (2018). Climate-Smart Agriculture: Building Resilience to Climate Change. In *Natural Resource Management and Policy* (Vol. 52). https://doi.org/10.1007/978-3-319-61194-5

Goswami, R., Chatterjee, S., and Prasad, B. (2014). Farm types and their economic characterization in complex agro-ecosystems for informed extension intervention: a study from coastal West Bengal, India. *Agricultural and Food Economics*, *2*(5), 1–24. https://doi.org/10.1186/s40100-014-0005-2

Hassan, R., and Nhemachena, C. (2008). Determinants of African farmers' strategies for adapting to climate change: Multinomial choice analysis. *African Journal of Agricultural Resource Economics*, *2*(1), 83–104.

Jaleta, M., Kassie, M., Tesfaye, K., Teklewold, T., and Ranjan, P., 2016. Resource-saving and productivity-enhancing impacts of crop management innovation packages in Ethiopia. *Agricultural Economics*, *47*, 513–522. https://doi.org/10.1111/agec.12251

Kassie, M., Jaleta, M., Shiferaw, B., Mmbando, F., and Muricho, G. (2012). Plot and Household-Level Determinants of Sustainable Agricultural Practices in Rural Tanzania. *Environment for Development*.

Kassie, M., Zikhali, P., Manjur, K., and Edwards, S., 2009. Adoption of Organic Farming Technologies: evidence from the semi-arid region of Ethiopia. *Environment for Development*, (9–01).

Kermah, M., Franke, A. C., Adjei-Nsiah, S., Ahiabor, B. D. K., Abaidoo, R. C., and Giller, K. E., 2017. Maize-grain legume intercropping for enhanced resource use efficiency and crop productivity in the Guinea savanna of northern Ghana. *Field Crops Research*, *213*(July), 38–50. https://doi.org/10.1016/j.fcr.2017.07.008

Lalani, B., Dorward, P., Holloway, G., and Wauters, E., 2016. Smallholder farmers' motivations for using Conservation Agriculture and the roles of yield, labour and soil fertility in decision making. *Agricultural Systems*, *146*, 80–90. https://doi.org/10.1016/j.agsy.2016.04.002

Mango, N., Siziba, S., and Makate, C., 2017. The impact of the adoption of conservation agriculture on smallholder farmers ' food security in semi-arid zones of southern Africa. *Agriculture and Food Security*, 4–11. https://doi.org/10.1186/s40066-017-0109-5

Marenya, P. P., Kassie, M., Jaleta, M., Rahut, D. B., and Erenstein, O., 2017. Predicting minimum tillage adoption among smallholder farmers using micro-level and policy variables. *Agricultural and Food Economics*, *5*(12), 1–22. https://doi.org/10.1186/s40100-017-0081-1

Marongwe, L. S., Kwazira, K., Jenrich, M., Thierfelder, C., Kassam, A., and Friedrich, T., 2011. *An African success : the case of conservation agriculture in Zimbabwe*. *9*(1), 1–9. https://doi.org/10.3763/ijas.2010.9121

Mwungu, C. M., Mwongera, C., Shikuku, K. M., Acosta, M., and Läderach, P., 2018. Determinants of Adoption of Climate-Smart Agriculture Technologies at Farm Plot Level : An Assessment from Southern Tanzania. In W. L. Filho (Ed.), *Handbook of Climate Change Resilience*. Springer International Publishing.

Nassary, K. E., Baijukya, F., and Ndakidemi, A. P., 2020. Productivity of intercropping with maize and common bean over five cropping seasons on smallholder farms of Tanzania. *European Journal of Agronomy*, *113*((2020) 125964), 1–10. https://doi.org/10.1016/j.eja.2019.125964

Newton, H. J., Cox, N. J., Nichols, A., Dc, W., and Gilmore, L., 2014. The Stata Journal. *The Stata Journal*, *4*, 778–797.

Ngongoni, N. T., Mwale, M., Mapiye, C., Moyo, M. T., and Hamudikuwanda, H., 2007. *Evaluation of cereal-legume intercropped forages for smallholder dairy production in Zimbabwe*. *19*(9).

Nyasimi, M., Kimeli, P., Sayula, G., Radeny, M., Kinyangi, J., and Mungai, C., 2017. Adoption and Dissemination Pathways for Climate-Smart Agriculture Technologies and Practices for Climate-Resilient Livelihoods in Lushoto, Northeast Tanzania. *Climate*, *5*, 1–22. https://doi.org/10.3390/cli5030063

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 labour. *Ecological Economics*, *93*, 85–93. https://doi.org/10.1016/j.ecolecon.2013.05.002

CHAPTER 4 ADOPTION DETERMINANTS OF MULTIPLE CLIMATE-SMART AGRICULTURAL TECHNOLOGIES IN ZIMBABWE: CONSIDERATIONS FOR SCALING-UP AND OUT

4.1 Abstract

Using a multistage sampling technique, data were collected from 386 households in four districts of Zimbabwe to investigate current Climate-smart agriculture (CSA) technology combinations being adopted by smallholder farmers practising integrated crop-livestock farming as well as the determinants. The study used two econometric techniques to address the objectives. Firstly, Principal Component Analysis was employed to identify the CSA technology combinations smallholder farmers adopted. Secondly, the multinomial logistic regression model was then used to analyse the adoption of the constructed CSA technology bundles. The study identified three prominent technology bundles/combinations. The multinomial logistic selection model results reveal that observable household and market access characteristics influence the likelihood of a farming household adopting any CSA technology bundle. The results highlight that gender of household head, farm characteristics (soil type and labour size) and institutional factors (market access, information access and access to credit) are the main factors that determine the adoption of various CSA technology combinations. Thus, the study recommends that the government should design policies aimed at improving farmers' knowledge with regards to CSA, including early warning systems and programs that enhance access to information, markets and credit.

Keywords: *crop-livestock integrated farming; CSA technology bundle; multinomial logit model; Principal Component Analysis*

4.2 **Introduction**

Agriculture is key to the rural Zimbabwean economy as more than 70% of the population relies on it for livelihoods (Government of Zimbabwe, 2012). However, it is prone to climatic and natural risks that impact negatively on crop yields, and market risks that may lead to agricultural price fluctuations (Ahmed and Serra, 2015). Climate variability poses a threat to agriculture production and the livelihoods of smallholder farmers who rely on rain-fed farming (Wood et al., 2014). Consequently, development and research practitioners have promoted climate-smart agriculture (CSA) practices for crop and livestock enterprises, which enable farmers to mitigate production losses and maintain or improve household welfare. CSA incorporates a wide range of agricultural best practices such as integrated crop management, agroforestry, improved animal supplementary feeding, conservation agriculture, use of improved seed varieties (high yielding and drought tolerant), composting and fertilizer management practices, in addition to encouraging the use of all available and applicable climate change solutions in a pragmatic and impact-focused manner (Notenbaert et al., 2017). The approach ensures the management of agro-ecosystems for improved and sustainable productivity, increased profits and food security while at the same time preserving and enhancing the resource base and environmental protection (FAO, 2018).

The range of potential CSA techniques available to farmers is large and as such the number of technologies adopted is likely to be highly dependent on the farmer characteristics, farm conditions and other macro-economic factors such as market and information access. Farmers can adopt several technologies simultaneously in cases where technologies are complementary. For example, water conservation can be achieved through various techniques, including those that reduce soil erosion (minimum tillage and mulching), while a farmer undertaking livestock rearing may use the manure from that enterprise for soil fertility improvement in the crop fields.

Smallholder farmers who practice integrated crop-livestock farming system rely predominantly on rain-fed agriculture, a situation that leaves them vulnerable to the vagaries of climate change. As a result of the increasing vulnerability to climate change, they have increasingly been adopting various CSA practices as a coping strategy. Despite a large body of research on CSA technologies that have been promoted, relatively little information is available regarding the combinations of technologies adopted and their determinants. Development literature has focused mainly on the adoption of single technologies and analysis of factors that affect the adoption. Few researchers have taken note of the fact that farmers can adopt combinations of technologies that may be supplementary or complementary to deal with their overlapping constraints such as pest infestations, low soil fertility and moisture (Ndiritu et al., 2014; Teklewold et al., 2013). Information on complementary or substitutes technologies is important because some researchers have found significant increases in net income and reduction in production risk for joint adoption of some technologies compared to the individual adoption (Jaleta et al. 2016; Teklewold et al. 2013). In India, for instance, Jeetendra et al. (2018) used multivariate and ordered probit models to analyse CSA adoption and found out that farmers adopt CSA practices as complements and substitutes. Characteristics found to affect the adoption of multiple technologies included education, gender, social and economic capital, access to market, access to extension services and farmland characteristics. The adoption of multiple CSA technologies in Zimbabwe is still weakly documented and understood. In order to develop sound technology scaling out strategies for development practitioners, it is important to understand the available technology bundles smallholder farmers adopt and determinants of their adoption. The chapter seeks to add to a small but growing literature that has examined multiple CSA technology adoption decisions in smallholder crop-livestock integrated farming systems. Thus, in a nutshell, the research aims to understand the technology combinations, their determinants and to answer the following research questions:

a. What are the popular technology combinations in smallholder farming systems?

b. What characteristics motivate farmers to adopt certain technology bundles?

4.3 Data Analysis

This sub-section outlines the analytical approaches and techniques that have been used in other studies in assessing technology adoption. This will lay the foundation for the approach used in this study, as presented in section 4.3.2. The analysis, which encompassed both descriptive and inferential statistics, sought to generate an understanding of determinants of various CSA technology bundles.

4.3.1 Determinants of multiple technology adoption

Reasons behind farmer adoption of climate-smart technologies are multifaceted and lessons can be drawn from earlier research on farmers' unwillingness to adopt agriculture technologies. Researchers have investigated many endogenous factors (human capital, attitude towards risk, access to financial capital, etc.) and exogenous factors (institutional, location, soil quality, rainfall patterns, farming system, market infrastructure, etc.) that influence technology adoption. The innovation-diffusion model has explained the determinants of technology adoption (Rogers 2003), which highlights information access as key to enabling farmers to get knowledge of an innovation which can influence their attitudes and ultimately a decision to either adopt or reject. The perception of farmers with regards to the impact of climate change as well as regarding the benefits from CSA has an impact on the adoption of CSA (Abegunde et al., 2019; Issahaku and Abdulai, 2020). A study in South Africa found that farmers who perceived climate change to have an adverse effect on agricultural production adopted CSA (Abegunde et al., 2019). Furthermore, ownership or access to natural and physical capital (e.g. land, livestock, finance, off-farm income) can offer farmers the capacity to adopt recommended CSA (Abegunde et al., 2019; Kurgat et al., 2020). Therefore, factors can be classified into four main categories, i.e., socio-demographic characteristics, institutional factors, household socio-economic characteristics and farmer perceptions of the technology (Kallas et al. 2010). Individuals' varied preferences for uncertainty may reflect the technology adoption pattern. Such preferences affect individuals' utility functions or their value functions, which in turn may result in otherwise sub-optimal investment and/or production decisions. It is thus important to investigate unobservable factors, along with observable ones, when studying technology adoption.

Farmers' socio-demographic characteristics refer to the personal background of the primary decision-maker within the household. The skills and abilities of the main decision-maker influence the decision to adopt CSA practices. Different researchers have found household head's age to have both positive and negative effects on adoption. Some researchers have found that age positively influences adoption highlighting that older farmers tend to adopt the technology because they have accumulated capital or have greater access to credit, due to their age. Other researchers have, however, cited age as a deterrent to technology adoption by emphasizing that it erodes the farmer's confidence in the adoption of new technology, or old-aged farmers are more risk-averse to new technologies than younger ones (Langyintuo and Mulugetta, 2008; Kassie et al., 2009;

Maguza-Tembo et al., 2017). This infers that younger farmers are more risk-takers than older farmers. Risk-averse farmers will, therefore, wait longer to adopt new technologies.

Education of the household head is hypothesized to have a positive influence on the adoption of new technology. The reason behind this is that highly educated household heads are expected to be more likely to readily understand and access information about new technologies in a shorter period than less educated people. Education level is assumed to increase farmer's ability to obtain, process and use the information relevant to adoption. Some researchers have found that increasing levels of education among farmers leads to an increased likelihood of adopting climate adaptation strategies. A study in Pakistan found that younger and highly educated farmers are more likely to use climate change adaptation technologies than their counterparts (Ali and Erenstein, 2017).

Gender of the household head also plays a role in adoption and researchers have reported mixed evidence. Few studies report a higher rate of technology adoption among male-headed households, compared to female-headed households because of discrimination, i.e., women have less access to external inputs, services and information due to socio-cultural values. A study of 613 households in Kenya using a multivariate probit model found that female plot managers were less likely to adopt sustainable intensification practices such as minimum tillage and use of manure (Ndiritu et al., 2014b). Adoption is positively influenced because in most societies men control productive resources such as land, labour and capital, which are critical for the adoption of new technologies (Obisesan, 2014; Abunga et al., 2012). In comparison, female household headships have a negative influence on technology adoption due to poor access to productive resources as well as discrimination in accessing extension services (Langyintuo and Mulugetta, 2008). Thus, improved access to resources and information increases households' propensity to adopt. Women identify certain technologies depending on labour benefits associated with it or other aspects like taste since they are involved in preparing household meals. A study of smallholder farmers in South Africa found out that women farmers value the labour-saving benefit of herbicide-tolerant maize which requires less weeding, an activity that female farmers traditionally undertake (Gouse et al., 2016). Theriault et al., (2017) applied a multivariate probit model to a nationwide panel of 4,130 households in Burkina Faso and found that adoption of sustainable intensification practices differed across gender. Variables expressing the availability of household labour strongly influenced the adoption of soil-restoring strategies by female plot managers while resources such as livestock ownership, the value of non-farm income, and area planted to cotton affected the adoption choices of male plot managers (Theriault et al. 2017).

Few studies found no significant association between gender and the probability of adoption. For instance, a study in Ghana found no effect of gender on the adoption of improved maize varieties (Doss and Morris, 2001). The study concluded that technology adoption decisions depend primarily on access to resources, rather than on gender and that adoption of improved maize depends on access to land, labour, or other resources. Since men or women have differences in access to these resources, then technologies will not benefit men and women in the same way.

Household size is linked to labour availability and will affect adoption decisions depending on whether the technology is labour-intensive (e.g., basins in conservation agriculture) or labour-saving (e.g., ox-based cultivation). Technology adoption usually requires more labour inputs and if family members fulfilled this requirement then adoption is positively influenced. A study in the semi-arid zone of Nigeria found that increasing household size significantly increased the possibility of adopting more labour intensive technologies such as soil conservation, planting trees and mixed cropping (Ndiritu and Berresaw, 2014). There is however likely to be non-adoption or low adoption of labour-intensive technologies for families with limited labour.

Institutional factors that affect technology adoption include services such as finance, insurance, information dissemination and belonging to a social group which can influence the behaviour of a farmer. Technology adoption usually goes along with the use of inputs like fertilizer and pesticides, among others. Credit access enables the farmer to purchase these various inputs thereby positively influencing technology adoption. Differential adoption of technologies can, therefore, happen where there is a disparity in access to credit. Some researchers have found out that access to credit promotes the adoption of risky technologies through relaxation of the liquidity constraint and enhancing of households' risk-bearing ability and adoption of technologies that require additional resources (Awotide et al., 2016). Ali and Erenstein (2017) found a positive relationship between credit and extension services, and technology adoption. A household that has access to credit can, therefore, drop inefficient technologies and take up riskier but efficient investments. Access to credit relaxes income constraints of farmers and enables them to have access to key inputs for the new technology, e.g., fertilisers, labour and herbicides (Awotide et al., 2016). Low adoption rates have, however, been reported in countries where credit institutions discriminated against female-headed households, and as such, they are unable to finance yield-enhancing technologies.

Acquisition of information about a new technology enables farmers to learn the existence as well as the effective use of technology and this facilitates its adoption. Access to extension services has a positive impact on technology adoption because extension agent's support in creating awareness about the innovation and its potential plays an important role in the diffusion of innovation and bridges the gap between farmers and the new technology. Extension services link researchers and farmers through the dissemination of information to the latter on effective use and benefits of new technology. Extension services are a vital source of information on agronomic and animal husbandry practices in integrated crop-livestock farming systems. Extension workers do this through various ways, e.g., the use of lead farmers, farmer meetings and visits to farmers. Extension worker information dissemination can counterbalance the negative effect of farmer's lack of formal education in the overall decision to adopt some technologies. Access to information through extension enables farmers to make informed decisions as it reduces the uncertainty about a technology's performance. Information disseminated should be reliable, consistent and accurate, otherwise, it can hinder adoption.

Membership to social groups enhances social capital, allowing trust, ideas and information exchange about new technologies. A study of 600 farmers in Nigeria on improved rice technology using the Tobit model found that farmers who were members of farmer organisations were likely to adopt the technologies (Awotide et al., 2016). Membership in such groups enables farmers to learn about the technology, hence raising their likelihood to adopt the technologies. However, social groups may also have a negative impact on technology adoption, especially where free-riding behaviour exists. Some researchers propose an inverted U-shaped individual adoption curve, implying that network effects are positive at low rates of adoption but negative at high rates of adoption (Bandiera and Rasul, 2006). As more people engage in the experimentation of new technologies, others join in and free ride on experimentation of others.

Perceived benefits an adopter received and the associated costs of production play an important role in adoption consistent with the conventional neoclassical model view that a rational economic actor seeks to maximize utility. Farmers are more interested in short, rather than long-term benefits. Farmer perceptions of technologies may provide a better understanding of technology adoption since farmers deal with the technologies and probably perceive technologies differently from researchers and extension agents. Farmers' perception of innovation mainly depends upon their knowledge and information about the innovation and socio-economic situation. The level of education and training that farmers receive about technology affect their perceptions. A study in Ethiopian highlands found that perception of erosion problem as well as education level and access to training had a positive and significant influence on farmer's perceptions to adopt soil and water conservation technologies (Teshome et al., 2016; Moges and Taye, 2017). A study in Western Kenya, which investigated the determinants of adopting Imazapyr-Resistant maize (IRM) technology (Mignouna et al., 2011), argued that farmers who perceive the technology as being consistent with their needs and compatible with their environment were likely to adopt since they found it as a positive investment. Thus, farmers' perception about the performance of CSA technologies can significantly influence the decision to adopt them. Adoption depends on users' judgments of the value of the technology to them and judgment factors like utility and efficiency of the technology. Farmers' evaluation of yield and total benefit accrued influenced their preference for a certain technology. Technologies that need few assets, have a lower risk premium, and are less expensive, have a higher probability of being adopted. On the other hand, technologies that require new skills, are time-consuming and costly to acquire the knowledge on them, may face slow adoption. Thus level of participation also depends on net economic benefits of the technology in relation to other options.

Socio-economic factors such as farm size, the income of the household head, ownership of assets and livestock have positive and negative influences on adoption. Literature has reported both positive and negative effects of farm size on technology adoption. A study on climate change adaptation in Pakistan found a positive and significant relationship between land ownership and adoption (Ali and Erenstein, 2017). A study of 461 respondents conducted in East Africa (Kenya, Uganda, Tanzania, and Ethiopia) on the climate-smart push and pull technology using the Tobit model showed that being well endowed with resources such as land increased the extent of adoption (Murage et al., 2015). This is particularly popular in scale dependant technologies that need more land. Households with larger landholdings can opt to try new technologies compared to those with smaller land sizes. Some studies, however, found a negative influence of farm size on adoption. Small farm size may provide an incentive to adopt input-intensive innovation such as labour-intensive or land-saving technology. A study of 613 households using the probit regression model in Tanzania found that the adoption of improved high yielding pigeon pea varieties was more pronounced among farmers with smaller landholdings who opted for intensification in the face of land pressure (Simtowe et al., 2011). Another study in Nigeria found that farmers with smaller farm sizes were more likely to invest in soil conservation technologies (Gumel et al., 2015). Farmers with smaller landholdings are likely to adopt land-saving technologies such as greenhouse technology and zero-grazing, among others, as an alternative to increased agricultural production (Mwangi and Kariuki, 2015). Asset ownership positively influences technology adoption. This is because assets generate the income necessary for accessing inputs associated with new technologies (Amaza et al., 2007). Non-agricultural income allows farmers to meet capital costs associated with new technology and reduces the risk of experimenting with new technologies. This study will carry out an analysis of factors affecting the adoption of combinations of CSA practices. This is crucial for stakeholders in value chains as it helps them design better strategies for scaling up adoption in crop-livestock integrated smallholder farming systems to enhance productivity and hence improve household welfare, including food security.

4.3.2 Analytical approach

Two analytical techniques were used, namely, PCA and multinomial logistic regression model, to study the factors affecting technology combinations farmers adopted. Firstly, PCA was employed to identify the number of, and the technologies which constitute technology ‘sets/combinations’. PCA is a statistical exploratory approach to data analysis used to compress a large set of variables into a smaller set of representative variables or latent factors. In this analysis, the original data are binary dummies that record CSA techniques currently adopted. The researcher employed the K-means clustering method to group farmers into three technology combinations according to nine dummy variables for CSA technology adoption, i.e., use of intercropping, crop rotation, mulching, drought-tolerant maize, improved legumes, minimum tillage, fodder crops, fodder trees and use of purchased livestock feed.

Secondly, the multinomial logistic regression model was then used to explain the adoption of the constructed technology bundles. Given that there are various CSA practice combinations, the appropriate econometric model is either a Multinomial Probit (MNP) or Multinomial Logit (MNL) regression model. The MNL model has been used to estimate the effect of explanatory variables on a dependent variable involving multiple combinations with unordered response categories. The advantage of the MNL is that it permits the analysis of decisions across more than two categories, (Wooldridge, 2002). The theoretical foundation of the MNL model is centred on the random utility theory which highlights that consumer preference is modelled primarily using a discrete choice utility framework. Thus farmer characteristics, access to information, and access to markets, among other factors, influenced farmer utility.

The MNL computes a different continuous latent variable for each choice, and these variables are like evaluation scores of each individual for each choice. For each CSA practice, combination j for farmer i or combination k:

$U_{ij} = \beta_j X_i + \varepsilon_j$ and $U_{ik} = \beta_k X_i + \varepsilon_k$……………………………………..(1)

Where: U_j and U_k are perceived utilities of technology bundles *j* and *k*, respectively

X_i is the vector of explanatory variables

B_j and B_k are parameters to be estimated,

ε_j and ε_k are error terms (assumed to independently and identically distributed)

The probability that household *i* with characteristics X chooses CSA practice adaptation option *j* over *k* happens when utility from bundle *j* is greater than utility from bundle *k* is specified as follows:

$U_{ij} (\beta_j X_i + \varepsilon_j) > U_{ik} (\beta_k X_i + \varepsilon_k), k \neq j$,…………………………………..(2)

Following Greene (2003), the probability of a farmer adopting a combination of CSA practices is assumed to be a function of some attributes. In this study, it is hypothesized to be a function of socio-demographic characteristics, farmer perceptions, and socio-economic and institutional factors, X, (equation 2). Therefore, the probability of a household using bundle *j* among the set of combinations available is:

$$P(Y=1/X) = P(U_{ij}>U_{ik}|X)$$
$$= P(\beta_j X_i + \varepsilon_j - \beta_k X_i - \varepsilon_k > 0|X)$$
$$= P(\beta_j - \beta_k)X_i + \varepsilon_j - \varepsilon_k > 0|X) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots(3)$$

where: *P* is a probability function,

$\varepsilon^* = \varepsilon_j - \varepsilon_k$ is a random disturbance term,

$\beta^* = \beta_j - \beta_k$ is a vector of unknown parameters (net influence of the vector of independent variables influencing adoption),

F ($\beta^* X_i$) is a cumulative distribution function of ε^* evaluated at B^*X_i. The multinomial logistic regression is thus used to estimate how marginal changes independent variables will affect the probabilities of fitting into any one technology combination relative to another. The Multinomial logit model is equivalent to simultaneously estimating a set of binary logits (BLM) for all pairs of outcome categories (Freese and Long, 2000).

Various hypothesized signs of the coefficients of the explanatory variables are shown in Table 10. Male-headed households are expected to have a better opportunity to adopt CSA practices because of their access and control over land and other productive assets, whose ownership is normally skewed towards men. As the age of the farmer increases, the household's probability of adopting new CSA practices is expected to decrease as most of the practices are labour-intensive. Thus, younger farmers are expected to adopt than older farmers. The coefficient for age is therefore hypothesized to be negative. The expected sign for education is positive as educated farmers are believed to acquire, analyse and evaluate information on CSA practices. Labour can have a positive or negative sign. High household labour size means farmers have an opportunity to embrace innovations but on the other hand, a household with a high labour force may be compelled to divert part of the family labour to off-farm activities to get extra income to ease the consumption pressure. More farming experience is hypothesized to positively influence the adoption of productivity-enhancing CSA practices.

Table 10: Hypothesized explanatory variables

Category and meaning	Variable name	Nature of variable	Expected sign	Empirical Evidence
Household Characteristics				
Gender of the household head	GenderHH	Dummy 1=male 0=female	+ve	(Wagura et al., 2014; Doss and Morris 2001; Theriault et al., 2017; Gouse et al. 2016)
Age of household head in years	AgeHH	Continuous	-ve	(Kassie et al. 2009; Maguza-tembo et al., 2017; Danso-abbeam et al. 2018; Langyintuo and Mulugetta, 2008)
Education of household head in years	EduHH	Continuous	+ve	(Mase et al., 2017; Ali and Erenstein, 2017; Danso-abbeam et al. 2018)
Farming experience in years	ExperienceHH	Continuous	+ve	(Mwangi and Kariuki 2015)
Labour size (number)	Laboursize	Continuous	+ve/-ve	(Wagura et al., 2014; Zeleke and Aberra, 2014)
Market access				
Distance to the tarred road in Kilometres	KMtarred	Continuous	-ve	(Doss and Morris, 2001)
Distance to input market in Kilometres	KMinputmkt	Continuous	-ve	(Asfaw et al. 2011; Awotide, 2016)
Distance to output market in Kilometres	KMoutputmkt	Continuous	-ve/+ve	(Zhang et al., 2012)
Number of buyers in the village	NUMtraders	Continuous	+ve	(Kassie et al., 2012)
social capital and information access				
Membership to farm groups	Grpmembership	Dummy 1=yes 0=no	+ve	(Danso-abbeam et al., 2018; Shikuku et al. 2017)
Social capital= number of relatives or friends who give support to household	SocialCapital	Continuous	+ve	(Ramirez, 2013; Wollni and Andersson, 2014; Awotide et al., 2016b; Teshome and Kassie, 2016; Yigezu et al., 2018)
Frequency extension contacts	EXTNcontact	Continuous	+ve	(Mwangi and Kariuki, 2015; Simtowe et al 2016; Zhang et al., 2012)
Access to weather forecasts	INFOweather	Dummy 1=yes 0=no	+ve	(Nyasimi et al., 2017)
Knowledge of CSA practices	KnowledgeCSA	Dummy 1=knowledgeable 0=otherwise	+ve	(Meijer et al., 2015; Mango et al., 2017; Muddassir et al., 2019)
Farm characteristics				
Land Size (Land) in hectares	Landsize	Continuous	+ve	(Ali and Erenstein, 2017; Teshome and Kassie, 2016)
Number of draft cattle owned	Draftcattle	Continuous	+ve/-ve	(Grabowski et al., 2016)

Category and meaning	Variable name	Nature of variable	Expected sign	Empirical Evidence
Land quality (Soil)	Soiltype	Dummy 1=good 0=poor	-ve	(Jeetendra et al., 2018)
Resource endowments				
Access to credit,	Credit	Dummy 1=yes 0=no	+ve	(Ali and Erenstein, 2017; Awotide et al., 2016b)
Asset value in dollars	Assetvalue	Continuous	+ve	(Awotide, 2012; Awotide et al., 2012; Ali and Erenstein, 2017)
Total Livestock Unit	TLU	Continuous	+ve	(Grabowski 2016)
Off-farm income access	Offfarmincome	Dummy 1=yes 0=no	+ve	(Henley and Dowell, 2017; Issahaku and Abdul-rahaman, 2019)

Some studies have found positive and significant relationships between wealth index and the adoption of agricultural innovations (Awotide et al., 2012). Facilitating access to information about technologies is expected to have a positive relationship with the intensity of adoption. Membership to farmer groups is expected to have a positive influence on adoption. Groups give easier access to credit necessary for inputs associated with new technologies, help in information sharing on technology benefits and can assist in the collective action of activities such as marketing. Social capital has a positive effect on adoption as farmers can get information from fellow relatives in the area. Farmers with access to weather forecasts can make informed decisions on what CSA to use for a particular season. Credit has a positive effect on adoption as it allows farmers to purchase inputs, e.g., fertilizer, improved crop varieties and irrigation that may be associated with new technology. Those with large land sizes could adopt CSA practices while those with smaller land size could not be in a position to test new technologies. Some studies have shown a negative influence of farm size on the adoption of new agricultural technology, particularly in the case of an input-intensive innovation such as a labour-intensive, or of a land-saving technology (Ntshangase et al., 2018). Those households with poor soils in their fields could adopt conservation agriculture and or fodder production since they also address low fertility in the soils. Farmers with more off-farm income are less risk-averse and can adopt technology better than farmers who rely mainly on on-farm income. The study hypothesizes that an increase in distance to output and input markets decreases the adoption of CSA practices. Markets can also act as a platform for the exchange of information on technologies with other farmers and with sellers.

4.4 Results and Discussion

The results of the study are presented in two parts. The first part presents the frequency and intensity of adoption of crop and livestock CSA technologies and the second part deals with the multinomial logistic regression model.

4.4.1 Adoption of CSA technologies and construction of technology combinations

Table 11 presents the descriptive and summary statistics of available CSA technologies that smallholder farming households in four study districts adopted.

Table 11: Adoption of CSA technologies in the study areas

	% of farmers using CSA technology					
CSA technology	**Goromonzi**	**Murehwa**	**Mutoko**	**U.M.P**	**All**	**Chi-square**
Intercropping	29.50	33.00	98.00	49.50	44.00	77.6***
Crop rotation	47.90	64.90	100.00	86.00	68.10	64.95***
Minimum tillage	61.60	42.30	100.00	65.60	62.70	47.46***
Drought-tolerant maize	21.20	13.40	98.00	67.70	40.40	149.39***
Improved legumes	2.10	0.00	98.00	46.20	24.60	240.28***
Manure use	31.50	38.10	100.00	47.30	45.90	73.55***
Orange maize	0.70	0.00	0.00	0.00	0.30	1.65
Fodder trees	1.40	0.00	0.00	0.00	0.50	3.31
Artificial insemination	0.00	0.00	0.00	1.10	0.30	3.16
Mulching	10.30	15.50	58.00	18.30	19.70	55.81***
Use of bought livestock feed	0.70	7.20	0.00	1.10	2.30	13.74***
Use of agriculture insurance	0.00	0.00	0.00	0.00	0.00	
Fodder crops (Mucuna, Lablab)	6.80	3.10	0.00	6.50	4.90	
	Mean number of technologies					
Adoption intensity (number of technologies adopted)	2.12(1.33)	2.16(1.58)	6.52(0.54)	3.84(2.19)	3.11(2.17)	

Numbers in parenthesis are standard deviation. *, **, *** *indicates statistical significance at 10% level, 5% level and 1% level respectively*

The results in Table 12 indicate that there is a significantly wide variation in CSA technologies being adopted by farmers across the four districts. Overall, there is high adoption of minimum tillage and crop rotation, i.e., 62% and 68%, respectively, across all the districts. Mutoko has the highest adoption of CSA technologies with at least 98% of the interviewed households using intercropping, crop rotation, and minimum tillage, drought-tolerant maize and improved legume technologies. However, various other forms of CSA technologies are not so widely adopted, particularly livestock-based CSA practices that have rates below 5% across all districts. This may be a reflection of the perceived effectiveness of these technologies or the costs associated with their use as well as the fact that these livestock CSA practices and crop CSA practices such as orange maize have just recently been promoted in smallholder farming communities of Zimbabwe. In terms of intensity of use, the average number of CSA technologies that survey respondents adopted is 3.11.

To construct the technology combinations, factor extraction considered factors that had an eigenvalue greater than one. Components above the elbow on the scree plot were retained as well as components with more responses of greater or equal to 0.3 in the component matrix as informed by literature (Jolliffe, 2002). The results identified five factors that resulted in three technology bundles of CSA technologies from k-means cluster analysis. A summary of the final set of technologies that have been employed in the subsequent MNL analysis is shown in Table 12.

Final cluster centres obtained through k-means cluster analysis interpret what is typical for a particular technology combination. Higher use of three crop CSA technologies (rotation, minimum tillage and use of animal manure) which can be said to be labour saving and soil fertility enhancing CSA practices characterize technology bundle 1.

Table 12: Cluster analysis results of CSA technology combinations

Technology Bundle	Technologies dominant in the bundle	% Frequency					Chi-Square
		Goromonzi	Murehwa	Mutoko	UMP	ALL Sample	
1 ***(Labour saving and soil fertility enhancing CSA practices)***	Crop Rotation Minimum Tillage Manure	59.59	52.58	0	33.33	**43.78**	**210.27*****
2 *(Yield and soil fertility enhancing CSA practices)*	Improved legume seeds Drought-tolerant maize Intercropping Crop Rotation Minimum Tillage Mulching Manure	3.42	8.25	100	47.31	**27.72**	
3*(Dominantly traditional way of farming)*	Crop Rotation	36.99	39.18	0	19.35	**28.50**	

, **, * Indicates statistical significance at 10% level, 5% level and 1% level respectively*

The highest use of CSA practices (intercropping, rotation, minimum tillage, mulching, drought-tolerant maize, improved legumes and use of animal manure) which can be said to be yield increasing and soil fertility enhancing characterize cluster 2. Very limited use of CSA practices with only crop rotation dominating characterize technology bundle 3.

4.4.2 Multinomial model variable description

The description of variables used in the MNL analysis is shown in Table 13. The mean or frequencies and standard deviation of the variables are discussed. The marginal probabilities measure the expected change in the likelihood of a particular choice being selected to a unit change in an independent variable. An increase in a particular characteristic variable increases the adoption rate for some technology bundle and the adoption rate then decreases for other bundles. Most of the households (68%) are male-headed with an average household labour size of four people. The mean age of the household head was 50 years and the mean level of education in terms of the number of years spent in school was eight years. This shows that most of the household heads are fairly educated, having attained some level of secondary education. On average, the farming household has about 19 years of experience in farming, which is quite high. In terms of ownership of productive land, the average size of arable landholding is about 3.06 ha. Very few farmers (14.2%) can qualify the dominant soil type in their fields as being of good quality; for the rest, they regarded the soil quality in their fields as poor. Approximately 48.4% of the households have at least a member belonging to farmer groups and a household had an average of three people within the community whom they rely upon for support, an indication of social capital among the farmers. Few farmers (18.7%) have access to credit and 87.3% have at least one off-farm income source. The mean current value of productive farm assets was US$395.50 per household. As shown in Table 13, the average TLU was 2.24, which is quite significant for smallholder farmers. The farmers access extension services about six times annually through various platforms such as field days, training workshops, agricultural shows and demonstrations.

Table 13:Description of variables used in the multinomial logit model

Variable name	Mean/ Frequency	Standard Deviation
Household Characteristics		
GenderHH (%)	66.80	
AgeHH (Years)	49.86	16.44
EduHH (Years)	8.28	3.75
ExperienceHH (Years)	18.9	13.8
Laboursize (number)	3.51	2.14
Market access		
KMtarred (KM)	7.52	9.56
KMinputmkt (Km)	14.02	23.01
KMoutputmkt (Km)	43.23	61.22
NUMtraders (Number)	4.17	6.64
Social capital and information access		
Grpmembership (%)	48.40	
SocialCapital (Number)	2.73	2.72
EXTNcontact (Number of times annually)	6.36	5.92
INFOweather (%)	64.50	
KnowledgeCSA (%)	63.50	
Farm characteristics		
Landsize in Hectares (Ha)	3.06	2.21
Draftcattle (Number)	0.44	0.97
Soiltype (%)	14.20%	
Resource endowments		
Credit Access (%)	18.70%	
Assetvalue (US$)	395.5	942.96
TLU	2.24	3.55
Offfarmincome (%)	87.30%	

4.4.3 Determinants of specific CSA technology combinations

Estimated results from the multinomial logistic regression are presented in Table 14. The base category is the technology bundle 3 (Very low adoption of CSA practices) against which the results are compared. Household characteristics (labour), market access (distance to input and output markets and tarred road), access to information (social capital, extension contact, access to weather forecasts, knowledge of CSA practices), resource endowments (credit access, TLU) and farm characteristics (land size owned, soil type of farm, draft cattle owned) significantly affected preference to technology bundles 1 and 2, in comparison to the base category.

Table 14: Multinomial logistic regression estimates of determinants of CSA adoption

Technology bundles	Multinomial logistic regression				Marginal Effects			
	1		2		1		2	
Household Characteristics	**Coef.**	**Std.err**	**Coef.**	**Std.**	**dy/dx**	**Std. err**	**dy/dx**	**Std. err**
GenderHH	-0.050	0.300	-0.780	0.470	0.058	0.067	-0.104	0.059
AgeHH	0.000	0.010	0.002	0.012	-0.001	0.003	0.001	0.002
EduHH	-0.010	0.040	-0.007	0.060	-0.004	0.009	0.003	0.008
ExperienceHH	0.000	0.010	0.002	0.014	0.001	0.003	0.001	0.003
Laboursize	0.080	0.070	0.24**	0.100	-0.002	0.015	0.028**	0.013
Market access								
KMtarred	-0.04*	0.020	-0.05**	0.030	-0.006	0.006	-0.004	0.004
KMinputmkt	-0.023	0.011	-0.001	0.006	-0.003	0.001	-0.003**	0.001
KMoutputmkt	0.026	0.005	0.001***	0.004	-0.004	0.001	0.004***	0.001
NUMtraders	-0.020	0.020	-0.21***	0.060	0.013**	0.006	-0.027***	0.008
social capital and information access								
Grpmembership	-0.090	0.300	-0.710	0.440	0.042	0.066	-0.089	0.055
SocialCapital	0.060	0.060	0.060	0.100	0.010**	0.013	0.003	0.013
EXTNcontact	0.083	0.030	0.08*	0.040	-0.008***	0.007	0.010**	0.005
INFOweather	1.08***	0.320	2.62***	0.510	0.065**	0.071	0.228***	0.050
KnowledgeCSA	0.76**	0.280	1.28***	0.440	0.060*	0.054	0.076*	0.043
Farm characteristics								
Landsize	0.110	0.080	0.060	0.110	0.022**	0.016	-0.001	0.012
Draftcattle	-0.380	0.250	-0.680	0.35*	-0.030	0.051	-0.063	0.040
Soiltype	0.83*	0.420	0.180	0.620	0.177**	0.077	-0.053	0.060
Resource endowments								
Credit	0.040	0.400	1.32**	0.500	-0.144*	0.080	0.227***	0.085
Assetvalue	-0.0003	0.000	0.0001*	0.0002	0.000	0.000	0.000	0.000
TLU	0.110	0.080	0.19*	0.100	0.011	0.015	0.015	0.011
Offfarmincome	-0.600	0.570	-0.770	0.700	-0.068	0.113	-0.049	0.093
_cons	-0.320	1.040	-3.18**	1.550				

*The reference category is technology bundle 3 which is low adoption *, **, *** indicates statistical significance at 10% level, 5% level and 1% level respectively*

4.4.3.1 Household characteristics

Labour size is statistically significant and positively affects the probability of a farmer's decision to adopt technology bundle 2. This conforms to the *a priori* expectation that households with more labour can allocate it for extra agriculture activities. CSA practices such as minimum tillage are labour intensive during the early years. Researchers should, therefore, invest more time in working towards availing more labour-saving CSA technologies to encourage adoption by all farmers regardless of labour size. Labour-saving CSA technologies can increase household income in two ways i.e. through a reduction in the cost of labour and creating more time to do other non-agriculture work that will generate more household economic benefits.

4.4.3.2 Resource endowments

Access to credit significantly increased the likelihood of adopting technology bundle 2 in comparison to the base category. As reported in Table 14, a unit increase in credit is associated with the adoption of technology bundles 1 and 2, respectively, being 9% and15 % more likely. This is in line with findings of other researchers that credit offers capital for farmers to purchase inputs associated with new technologies (Awotide et al., 2016; Ali and Erenstein, 2017; Danso-abbeam et al., 2018).

4.4.3.3 Information access

The analysis results revealed that frequent contact with extension services increases the likelihood of technology bundle 2 adoption. This is in line with findings from other studies highlighting extension practitioners from government, NGOs as main sources of information regarding new farmer technologies (Zhang et al. 2012). This is explained by the fact that most farmers got the opportunity to know about CSA through training workshops, field days, exchange visits organised through international research organisations such as CIAT and CIMMYT in partnership with local NGOs such as Cluster Agricultural Development Services (CADS), and Community Technology Development Organisation (CTDO) (Mujeyi, 2018). There has been recent thrust on livestock CSA through ILRI, which introduced improved fodder technologies. The positive and significant effect of awareness is consistent with the assertion that knowledgeable farmers can easily assimilate information. This is in line with findings from other researchers who found out that information access had positive effects on the adoption of technologies (Jaleta et al., 2016; Awotide et al., 2016). Yigezu et al., (2018) found that increasing exposure and awareness of zero tillage technology through field days and demonstration trials, accompanied by ensuring free access to expensive zero-tillage seeders for first-time users, increased the propensity, speed, and intensity of adoption.

Similarly, farmers with access to weather forecasts and awareness of CSA practices are 5% more likely to adopt both technology bundles 1 and 2. Farmers who have access to early warning systems like weather forecasts are more likely to be aware of changing climate and thus can adapt to changes through adopting CSA. These results are consistent with Nyasimi et al., (2017), who found that most farmers in Tanzania planned better for farming activities after having had access to weather forecast information from a community-managed weather station.

These findings call for the need to strengthen the dissemination of weather forecasts in farming communities through various approaches including radio, newspapers, cell phones, extension services, etc. Teklewold et al., (2013) and Hunecke et al., (2017) also found a positive and significant effect of social capital in the adoption of agriculture technologies i.e. multiple sustainable agricultural practices and irrigation technologies respectively.

4.4.3.4 Access to markets

An increase in distance to the nearest tarred road is associated with less likelihood of adopting technology bundle 2. This is because tarred roads facilitate access to cheaper transport for agriculture inputs thus reducing transaction costs. The results further indicated that increased distance to inputs markets makes adoption of technology bundle 2 less likely. This finding resonates with some researchers who found that excessive distance to inputs markets negatively affected the adoption of technologies such as improved seeds (Awotide et al., 2016). The farmers with distance constraining them will thus end up using low yielding unimproved and retained seed. An increase in distance to output market makes adoption of technology bundle 2 more likely. This means if access to markets is convenient, farmers tend to relax and seem to have no incentive to adopt CSA practices but if markets are a distance away, then they tend to adopt the yield-enhancing CSA practices so that their yield can cover high transaction costs to markets.

The presence of more traders (middlemen) locally make adoption of technology bundle 2 less likely. This might be because local farm-gate markets do not attract farmers because of the lower prices that they usually offer. Therefore, farmers adopt technologies with products that can be marketed further away from their villages, where they can fetch better prices and obtain opportunities for higher-income earnings.

4.5 Conclusion and Recommendations

Declining agricultural productivity in the face of climate change has been a major policy concern in Zimbabwe and the world over. This has led to increased investments in the development and dissemination of yield and soil fertility-enhancing climate-smart agriculture technologies. This chapter analysed the factors influencing multiple technology adoption at the smallholder household level. Adoption of technology bundles significantly varied across districts. Key factors such as labour, resource endowments, access to markets and access to information significantly affected the adoption of identified technology combinations. Therefore, the findings point to the importance of enhancing access to information on new technologies, inputs and output markets and productive capital.

The following recommendations are proffered to policymakers focusing on these factors. Firstly, enhanced access to information on CSA is key. The government should make concerted efforts to ensure the availability of properly packaged messages on available CSA technologies that are appropriate and adaptable to smallholder farmer conditions. The extension messages should include information about their potential impacts on household welfare outcomes. The Government can put in place financial resources to support regular dissemination of early warning agro-meteorological information from such bodies as the Meteorological Services Department. This kind of information is particularly more important towards and during the cropping season. The significant effect of awareness on adoption implies that a multi-sectoral private-public partnership initiative is a crucial initiative to disseminate CSA technology information.

Secondly, access to distant lucrative markets should be improved. Governments can provide incentives such as tax reductions to key input suppliers and agro-dealers who bring agricultural inputs closer to the farmers, particularly during the start of the agriculture season. The same should also be done for commodity off-takers to incentivize them to bring output markets in proximity to the smallholder farmers. Investment in infrastructure such as well functioning tarred roads should be prioritised by the government since it has positive multiplier effects on the agricultural sector. Improved roads result in lower transport costs and thus reduced prices for agriculture inputs. This can also enable farmers to access lucrative markets which help in contributing to increased incomes for households which enable them to purchase external inputs such as fertiliser, herbicides or even pesticides.

Thirdly, credit schemes could be set up specifically to support farmers who adopt the CSA as an incentive. The Government should encourage banks and micro-finance institutions to empower smallholder farmers through the provision of credit facilities. One consideration would be to lower tax thresholds for players that provide rural finance to support investments in productivity-enhancing and input-saving CSA technologies. Support could also be given to microfinance institutions and banks that provide loans to rural agro-dealers during the farming seasons to enable them to stock enough agriculture inputs. Similarly, the significant role information access plays suggest the need to strengthen and capacitate the existing government extension delivery system and encourage other actors like the private sector and NGOs to also support the dissemination of CSA information. There is a need to fund the timely sourcing and dissemination of early warning information, particularly weather forecasts to farmers to enable them to properly plan for the farming season.

Thus, the findings of this study have shown that the adoption of CSA is highly contingent on access to knowledge of these technologies. It is therefore important that the government, in collaboration with the private sector and NGOs, support and capacitate the extension system to be well resourced in the discharge of its duties. The support should be rendered in the form of enhanced mobility in terms of transport to reach out to farmers and also ensuring that frontline extension workers have access to modern Information and Communication Technologies (ICTs). These would aid them in their delivery of extension and advisory services. The support could be increased and intensified during the peak of the agricultural season when the information is needed particularly to inform production and marketing decisions by the farmers.

References

Abegunde, V. O., Sibanda, M., and Obi, A., 2019. Determinants of the Adoption of Climate-Smart Agricultural Practices by Small-Scale Farming Households in King Cetshwayo District Municipality, South Africa. *Sustainability*, *12*(195), 1–27.

Ahmed, O., and Serra, T., 2015. Economic analysis of the introduction of agricultural revenue insurance contracts in Spain using statistical copulas. *Agricultural Economics*, *46*, 69–79. https://doi.org/10.1111/agec.12141

Ali, A., and Erenstein, O., 2017. Assessing farmer use of climate change adaptation practices and impacts on food security and poverty in Pakistan. *Climate Risk Management*, *16*, 183–194. https://doi.org/10.1016/j.crm.2016.12.001

Aryal, J. P., Jat, M. ., Sapkota, T. B., Kassie, M., Rahut, B. D., and Maharjan, S., 2017. Adoption of multiple climate-smart agricultural practices in the Gangetic plains of Bihar , India. *International Journal of Climate Change Strategies and Management*, *10*(3), 407–427. https://doi.org/10.1108/IJCCSM-02-2017-0025

Atnafe, Y., Mugera, A., El-shater, T., Aw-hassan, A., Piggin, C., Haddad, A., Loss, S., 2018. Technological Forecasting and Social Change Enhancing adoption of agricultural technologies requiring high initial investment among smallholders. *Technological Forecasting and Social Change*, *134*(April), 199–206. https://doi.org/10.1016/j.techfore.2018.06.006

Awotide, B. A., Diagne, A., Omonona, B. T., and November, O., 2012. Impact of Improved Agricultural Technology Adoption on Sustainable Rice Productivity and Rural Farmers ' Welfare in Nigeria : A Local Average Treatment Effect (LATE) Technique. Paper Presentation at the African Economic Conference October 30- November 2, 2012 Kigali, Rwanda.

Awotide, B. A., Karimov, A. A., and Diagne, A., 2016. Agricultural technology adoption, commercialization and smallholder rice farmers' welfare in rural Nigeria. *Agricultural and Food Economics*, *4*(1), 1–24. https://doi.org/10.1186/s40100-016-0047-8

Bandiera, O., and Rasul, I. (2006). Social Networks and Technology Adoption in Northern Mozambique. *Economic Journal*, *116*(1957), 869–902.

Danso-abbeam, G., Bosiako, J. A., Ehiakpor, D. S., and Mabe, F. N. (2018). Adoption of improved maize variety among farm households in the northern region of Ghana. *Cogent Economics and Finance*, *109*(1), 1–14. https://doi.org/10.1080/23322039.2017.1416896

FAO, 2018. Climate-Smart Agriculture: Building Resilience to Climate Change. In *Natural Resource Management and Policy* (Vol. 52). https://doi.org/10.1007/978-3-319-61194-5

Freese, J., and Long, S. J., 2000. *Tests for the Multinomial Logit Model*. University of Wisconsin-Madison and Indiana University.

Gouse, M., Sengupta, D., Zambrano, P., and Zepeda, J. F., 2016. Genetically Modified Maize: Less Drudgery for Her, More Maize for Him? Evidence from Smallholder Maize Farmers in South Africa. *World Development*, *83*, 27–38. https://doi.org/10.1016/j.worlddev.2016.03.008

GOZ, 2012. Comprehensive agricultural policy framework (2012-2032). *Government of Zimbabwe*.

Gumel, Mohammed, B., Makmom, A., and Harun., 2015. Determinant of farmers ' adaptation to climate change : evidence from the semi-arid zone of north-eastern Nigeria. *Procedia Environmental Sciences*, 1–8. Elsevier B.V.

Hunecke, C., Engler, A., Jara-rojas, R., and Poortvliet, M., 2017. Understanding the role of social capital in adoption decisions : An application to irrigation technology. *Agricultural Systems*, *153*(March), 221–231. https://doi.org/10.1016/j.agsy.2017.02.002

Issahaku, G., and Abdulai, A., 2020. Household welfare implications of sustainable land management practices among smallholder farmers in Ghana. *Land Use Policy*, *94* (December 2019), 1–14. https://doi.org/10.1016/j.landusepol.2020.104502

Jaleta, M., Kassie, M., Tesfaye, K., Teklewold, T., and Ranjan, P., (2016). Resource-saving and productivity-enhancing impacts of crop management innovation packages in Ethiopia. *Agricultural Economics*, *47*, 513–522. https://doi.org/10.1111/agec.12251

Kallas, Z., Serra, T., and Gil, J. M., 2010. Farmers' objectives as determinants of organic farming adoption: The case of Catalonian vineyard production. *Agricultural Economics*, *41*(5), 409–423. https://doi.org/10.1111/j.1574-0862.2010.00454.x

Kassie, M., Zikhali, P., Manjur, K., and Edwards, S., 2009. Adoption of Organic Farming Technologies: evidence from the semi-arid region of Ethiopia. *Environment for Development*, (9–01).

Kurgat, B. K., Lamanna, C., Kimaro, A., Namoi, N., Manda, L., and Rosenstock, T. S., 2020. Adoption of Climate-Smart Agriculture Technologies in Tanzania. *Frontiers in Sustainable Food Systems*, *4*(May). https://doi.org/10.3389/fsufs.2020.00055

Langyintuo, a., and Mulugetta, M., 2008. Assessing the influence of neighbourhood effects on the adoption of improved agricultural technologies in developing agriculture. *African Journal of Agriculture and Resource Economics*, *2*(2), 151–169. http://ageconsearch.umn.edu/bitstream/56960/2/0202 Langyintuo

Maguza-tembo, F., Mangison, J., Edris, A. K., and Kenamu, E., 2017. Determinants of adoption of multiple climate change adaptation strategies in Southern Malawi : An ordered probit analysis. *Journal of Development and Agricultural Economics*, *9*(1), 1–7. https://doi.org/10.5897/JDAE2016-0753

Mignouna, D. B., Manyong, V. M., Mutabazi, K. D. S., and Senkondo, E. M., 2011. Determinants of adopting imazapyr-resistant maize for Striga control in Western Kenya : A double-hurdle approach. *Journal of Development and Agricultural Economics*, *3*(11), 572–580.

Moges, D. M., and Taye, A. A., 2017. Determinants of farmers' perception to invest in soil and water conservation technologies in the North-Western Highlands of Ethiopia. *International Soil and Water Conservation Research*, *5*(1), 56–61. https://doi.org/10.1016/j.iswcr.2017.02.003

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(2001), 27-39*

Mujeyi, A. (2018). Policy and Institutional Dimensions in Climate-Smart Agriculture Adoption : Case of Rural Communities in Zimbabwe. In W. Leal Filho (ed.) (Ed.), *Handbook of Climate Change Resilience*. https://doi.org/10.1007/978-3-319-71025-9_66-1

Murage, A. W., Pittchar, J. O., Midega, C. A. O., Onyango, C. O., and Khan, Z. R., 2015. Gender-specific perceptions and adoption of the climate-smart push-pull technology in eastern Africa. *Journal of Crop Protection*, *76*, 83–91. https://doi.org/10.1016/j.cropro.2015.06.014

Mwangi, M., and Kariuki, S., 2015. Factors Determining Adoption of New Agricultural Technology by Smallholder Farmers in Developing Countries. *Journal of Economics and Sustainable Development*, *6*(5), 2222–1700. www.iiste.org

Ndiritu, S. Wagura, Kassie, M., and Shiferaw, B., 2014b. Are there systematic gender differences in the adoption of sustainable agricultural intensification practices? Evidence from Kenya. *Food Policy*, *49*(P1), 117–127. https://doi.org/10.1016/j.foodpol.2014.06.010

Ndiritu, S Wagura, Kassie, M., and Shiferaw, B., 2014a. Are there systematic gender differences in the adoption of sustainable agricultural intensification practices ? Evidence from Kenya. *Food Policy*, *49*, 117–127. https://doi.org/10.1016/j.foodpol.2014.06.010

Ndiritu, Simon Wagura, and Berresaw, M. K., 2014. Are there systematic gender differences in the adoption of sustainable agricultural intensification practices ? Evidence from Kenya. *Food Policy*, *49*, 117–127. https://doi.org/10.1016/j.foodpol.2014.06.010

Notenbaert, A., Pfeifer, C., Silvestri, S., and Herrero, M., 2017. Targeting, out-scaling and prioritising climate-smart interventions in agricultural systems : Lessons from applying a generic framework to the livestock sector in sub-Saharan Africa. *AGSY*, *151*, 153–162. https://doi.org/10.1016/j.agsy.2016.05.017

Ntshangase, N. L., Muroyiwa, B., and Sibanda, M., 2018. Farmers' perceptions and factors influencing the adoption of no-till conservation agriculture by small-scale farmers in Zashuke, KwaZulu-Natal province. *Sustainability (Switzerland)*, *10*(2), 1–16. https://doi.org/10.3390/su10020555

Nyasimi, M., Kimeli, P., Sayula, G., Radeny, M., Kinyangi, J., and Mungai, C., 2017. Adoption and Dissemination Pathways for Climate-Smart Agriculture Technologies and Practices for Climate-Resilient Livelihoods in Lushoto, Northeast Tanzania. *Climate*, *5*, 1–22. https://doi.org/10.3390/cli5030063

Rogers, E. M., 2003. *Diffusion of Innovations* (3rd ed.). https://doi.org/82-70998

Simtowe, F., Kassie, M., Diagne, A., Asfaw, S., Shiferaw, B., Silim, S., and Muange, E., 2011. Determinants of Agricultural Technology Adoption : The Case of Improved Pigeonpea Varieties in Tanzania. *Journal of International Agriculture*, *50*(4), 325–345.

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 labour. *Ecological Economics*, *93*, 85–93. https://doi.org/10.1016/j.ecolecon.2013.05.002

Teshome, A., de Graaff, J., and Kassie, M., 2016. Household-Level Determinants of Soil and Water Conservation Adoption Phases: Evidence from North-Western Ethiopian Highlands. *Environmental Management*, *57*(3), 620–636. https://doi.org/10.1007/s00267-015-0635-5

Theriault, V., Smale, M., and Haider, H., 2017. How Does Gender Affect Sustainable Intensification of Cereal Production in the West African Sahel? Evidence from Burkina Faso. *World Development*, *92*, 177–191. https://doi.org/10.1016/j.worlddev.2016.12.003

Wood, S. A., Jina, A. S., Jain, M., Kristjanson, P., and DeFries, R. S., 2014. Smallholder farmer cropping decisions related to climate variability across multiple regions. *Global Environmental Change*, *25*(1), 163–172. https://doi.org/10.1016/j.gloenvcha.2013.12.011

Wooldridge, J. M. (2002). Econometric Analysis of Cross Section and Panel Data. *Michigan State University*, Department of Economics.

Zhang, W. S., Li, F. M., Xiong, Y. C., and Xia, Q., 2012. Econometric analysis of the determinants of adoption of raising sheep in folds by farmers in the semiarid Loess Plateau of China. *Ecological Economics*, *74*(February 2012), 145–152. https://doi.org/10.1016/j.ecolecon.2011.12.007

CHAPTER 5 THE IMPACT OF CLIMATE-SMART AGRICULTURE ON HOUSEHOLD WELFARE IN SMALLHOLDER INTEGRATED CROP–LIVESTOCK FARMING SYSTEMS: EVIDENCE FROM ZIMBABWE

5.1Abstract

Agriculture contributes significantly to the welfare of smallholder farmers, but it has become highly susceptible to climate change due to its reliance on the increasingly erratic rainfall patterns. Climate-smart agriculture (CSA) offers important opportunities for enhancing food security and incomes through increased agriculture productivity. Technology evaluation through impact studies provides information on the effect of CSA on farmer welfare, thereby highlighting its potential in optimizing agriculture productivity. This chapter analyses the impact of CSA adoption on food security and income of households. The analysis was done using the endogenous switching regression model which controls for selection bias and unobserved heterogeneity, a commonly used method in adoption impact analysis. The econometric results show that the status of soil fertility in fields, distance to input and output markets, ownership of communication assets and TLU have a significant impact on the decision to adopt CSA by farmers. The Average Treatment Effects on the Treated (ATT) and Average Treatment Effects on the Untreated (ATU) were found to be positive and significant for adopters and non-adopters, indicating that CSA adoption has had a significantly positive impact on the welfare of the farmers. An analysis of the outcomes revealed that the characteristics of farmers and farms, as well as market factors, significantly affect the welfare of households. The household income, with reference to the adoption of CSA, was significantly affected by factors such as the education of the household head, labour size, TLU and asset index. Food security was influenced by factors such as the education of household head, TLU, access to sanitation and arable land size. The study concludes by giving policy recommendations centred on access to inputs, sanitation and encouraging investing in assets and TLU. The findings indicate that the adoption of CSA has a positive impact on the welfare of farmers. To exploit the full potential of these technologies, the study suggests that access to timely weather forecasts must be ensured, that sanitation must be promoted and that incentives must be provided for agricultural input agro-dealers to decentralize to rural areas.

Keywords: household income; food security; endogenous switching regression; Zimbabwe

5.2 Introduction

The agricultural sector plays an important role in the economic growth and development of Zimbabwe, as evidenced by its 15-18% share of the Gross Domestic Product (GDP), its national export earnings (40%), its raw material provision to the agro-industry (60%) and its employment generation (50%) (GOZ, 2018; ZIMSTAT, 2012b). The country has key agricultural resources in the form of rich fertile land, which is ideal for producing high-value crops such as horticulture, field cash crops such as tobacco and cotton, as well as field food crops such as maize, groundnuts and cowpeas, among others. Important to note is that the country was previously dubbed as the 'breadbasket' of Africa. However, this status changed following the land reform of 2000, which was followed by a subsequent decrease in investments, along with other destabilizing macro-economic factors, such as hyperinflation and the unreliable supply of electricity and fuel. The country is now a net importer of food commodities annually (Bonga, 2018). Zimbabwe's smallholder farmers, who constitute about 70% of the population, own approximately 55% of the total cultivated land and rely on rain-fed agriculture for their livelihoods (Bonga, 2018). Agricultural productivity has remained low, averaging less than one tonne/ha over the past ten years for the staple crop maize (*Zea Mays*) and low livestock off-take rates of less than 10% (Enahoro et al., 2019; Ngema et al., 2018). Livestock productivity is constrained by the low quality and unreliable availability of forage during the dry season, while crop productivity is constrained by infertile sandy soils and the low use of technologies (i.e. improved varieties, fertilizers, etc.). In addition, farmers face under-developed markets that limit their financial returns because they are characterized by high input costs and low output prices, coupled with droughts as a result of climate change (Ndiritu et al., 2014; Mupangwa and Thierfelder, 2014; Muoni et al. 2019). Climate change has led to a shorter growing season, higher temperatures, frequent and severe droughts, as well as pest outbreaks e.g. the Army Worm and *Tuta* (Makate et al., 2016), which have resulted in reduced crop yields. Studies have found that crop yields have been reduced as a result of warming and the results of modelling studies further showed that the trend will continue and will be compounded by rising atmospheric CO_2 concentrations, leading to a decline in food and forage quality. Livelihoods and food security will be at risk from volatile price and yields caused by extreme weather conditions (Steenwerth et al., 2014; Wekesa et al., 2018). Models predict that warming in Sub-Saharan Africa will be greater than the global average leading to extreme events such as droughts and floods, thereby negatively affecting smallholder farmers who heavily depend on rain-fed agriculture for livelihoods (Belay et al, 2017). High incidence of pests and diseases have also been reported which negatively affected livestock and crop productivity (Belay et al., 2017). The progressive decline of yields over consecutive agriculture seasons will negatively affect food security for households who usually rely on their own production for staple crops (Ouédraogo et al., 2019). The volatile rainfall patterns pose a serious threat to farmers, as water is a necessary resource that becomes constrained under such circumstances. Thus, the Government of Zimbabwe (GOZ, 2018; Mujeyi, 2018), in collaboration with research and development organisations, has promoted climate-smart agriculture (CSA). CSA refers to agricultural practices that sustainably increase productivity and resilience (adaptation) and reduce or remove greenhouse gases (mitigation) (FAO, 2013; Ndiritu et al., 2014)

The adoption of CSA is one important route towards improving the welfare of smallholder farming communities in developing countries experiencing a changing climate and reduced land for agricultural expansion (Braimoh, 2013; Khatri-chhetri et al., 2016; Zougmoré et al., 2016). CSA can help farmers to meet the growing demand for food. Generally, CSA contributes to food security, economic development and poverty reduction. Literature suggests that increased agriculture productivity can improve the welfare of households by increasing their income and improving their food security through their own food production (Makate et al., 2016; Sani and Kemaw, 2019). Research and development organisations, in collaboration with government departments, have spearheaded the adoption of various CSA technologies in Zimbabwe (Mujeyi 2018). Productivity and welfare gains from CSA crop and livestock technologies have the empirical support of on-station and on-farm trials. For example, on-farm trials on CA systems that were run by researchers from CIMMYT (Mupangwa et al., 2017) from 2012–2015 in Zambia found that dibble stick, rip-line and direct seeding CA systems had a 6–18%, 12–28% and 8–9% greater maize yield, respectively, compared to the conventional tillage system. The study also found that the rotation of maize with legumes (cowpeas and soya beans) significantly increased the maize yields and net returns (as high as US$312 to $767 ha−1, compared to only US$64 to $516 under conventional practices). Another study by (Wossen et al., 2017) found that the adoption of drought-tolerant maize varieties increased maize yields among the adopters by 13.3% and reduced the down-side risk exposure by 81%.

Soil and water management CSA practices protect the soil (minimum tillage), reduce water losses from runoff and improve water infiltration (mulching), and reduce evaporation and improve soil fertility (intercropping, rotation and manure use) (Bodner et al., 2015; Hallama, 2019). These are complemented by CSA crop practices, such as the use of improved crop varieties (drought-tolerant maize, orange maize and improved legumes). Several studies have assessed the impact of CSA and found both direct results (improved crop and livestock productivity, reduced total variable costs) and indirect results (improved food security through the increased availability of staple crops at the household level and in markets, per capita consumption, increased household income (Fentie and Beyene, 2019) and increased demand for farm labour, which brings about better wage returns for agricultural labour) (Fentie and Beyene, 2019; Kebebe, 2017; Khonje et al., 2015; Ogada et al., 2020a; Teklewold et al., 2019) (Mwungu et al., 2019). Researchers in Kenya used the endogenous switching regression (ESR) to investigate the impact of CSA packages on food security (using Household Food Consumption Score (HFCS) and Household Dietary Diversity as proxies for food security (Wekesa et al., 2018). Other researchers have also used composite indexes which use normalisation and weighting methods such as the Food Insecurity Multidimensional Index which synthesizes the four dimensions of food security i.e. availability, access, utilisation and stability (Taylor and Santeramo, 2015). The study found that farmers who used larger CSA packages comprising of crop management, field management, risk reduction practices and specific soil management practices were 56.83% and 25.44% more food secure in terms Household Food Consumption Score and Household Dietary Diversity Scores respectively compared to their non-adopter counterparts (Wekesa et al., 2018). A study by (Ogada et al., 2020a) found that adoption of CSA such as multiple stress-tolerant crops improved household income by 83%. This in turn improved household asset accumulation.

CIMMYT, in collaboration with government departments and the private sector, has promoted high-yielding and disease- and drought-tolerant maize, orange maize and early-maturing, protein-quality maize (Lunduka et al., 2019; Tesfaye et al., 2017). One research study found that the adoption of drought-tolerant maize (DTM) by smallholder farmers in Zimbabwe significantly enhanced maize productivity and, consequently, the quantities that could be set aside for sale and personal household consumption (Makate et al., 2016). Various donor-funded relief and recovery programs have promoted Conservation Agriculture (CA) since 2004. It has been noted that CA can increase the yields of smallholder farmers through soil fertility improvement, soil and water conservation and organic carbon sequestration (Zheng et al., 2014). Studies in Malawi and Zambia have shown a high yield advantage of over one tonne per hectare (Mupangwa et al., 2017; Thierfelder et al., 2016). Livestock productivity has been enhanced through supplementary feeding with forage legumes, such as the velvet bean *(Mucuna pruriens***)**, cowpea (*Vigna unguiculata* (L.), lablab (*lablab purpureus)* and browse legumes, such as the acacia (*Senegalia* and *Vachellia*), the *Calliandra* and *Leucaena* trees (Gwiriri et al., 2016; Kebebe, 2017) which are promoted by ILRI and World Agroforestry Centre (ICRAF), in collaboration with NGOs and government departments. Researchers have reported increased benefit-cost ratios of 1.12 to 3.03 in Zimbabwe (Franzel et al., 2014).

The CSA technologies are therefore very relevant for countries like Zimbabwe which are considered to be climate change 'hotspots' because of the increased probability of extreme events, such as droughts (Rurinda et al., 2014). Much evidence has been generated on the impact of CSA in Zimbabwe, mainly from on-farm and on-station experiments; however, there is a paucity of rigorous evidence under actual non-researcher-managed smallholder farming conditions across different agro-ecological zones in Zimbabwe. Evidence from long-term regional trials in Zimbabwe, Zambia, Malawi and Mozambique found that CA maintained higher infiltration rates (55%-221% higher than conventional) and conserved soil moisture (14 % or above moisture benefits in CA plots over conventional plots) resultantly leading to increased productivity (a12%–16% (or 592–847 kg ha^{-1}) maize yield benefit in a normal year and 38% and 66% (or 1314–2815 kg ha^{-1}) yield benefits in a dry year) (Thierfelder et al., 2017b) and profitability. The yield benefits were however noticeable over a lag period of 2–5 cropping seasons. There has also been a paucity of insight in peer-reviewed publications, compared to that of other southern African and East African countries like South Africa and Uganda, mainly due to lack of data for Zimbabwe. This study thus bridges the gap and uses quantitative evidence from a cross-sectional dataset. Several studies have measured the impact using a single economic model, such as Propensity Score Matching (PSM) (Kassie et al., 2011; Ahmed et al., Geleta et al., 2017), which is ideal when differences in adopters and non-adopters are captured through only observable characteristics. The results from PSM can however be biased, especially when there are unobservable characteristics such as motivation, a farmer's management ability, farmer-to-farmer networking, informal associations or the transaction costs experienced by the farmers as a result of poor infrastructure. To counter these challenges, this study employs the Endogenous Switching Regression (ESR) model (Di Falco 2014; Ahmed et al., 2017; Teklewold et al. 2013; Kassie et al. 2018; Teklewold et al. 2019) to measure the impact of CSA adoption on the welfare of farmers, using household income and food security.

Thus, the objective of this chapter was to assess the welfare implications of crop and livestock CSA packages in smallholder farming systems. It sought to recommend the characteristics or factors that should be incorporated into the agricultural policies to improve household welfare through the adoption of CSA practices. The rest of the chapter is structured as follows: The next section will discuss the specifications of the empirical Endogenous Switching Regression model, followed by the presentation and discussion of the study results and the final section will show the conclusions and recommendations.

5.3 Data Analysis

Empirical evidence from earlier adoption studies on agricultural technologies guided the choice of variables adopted in the model. These drivers of CSA technologies adoption include household characteristics (Age, gender, education and experience of household head, household size, family labour), asset ownership, institution and technical factors (membership to farmer organisations or group, access to extension, access to credit, training on CSA, ownership to information related assets such as radio, TV and mobile phones), perceived benefits (e.g. productivity enhancement, reduced cash inputs, increased incomes, improved food security, reduced risk of crop and livestock losses), economic factors (household income, off-farm income, tropical livestock unit, size of arable land), market factors (distance to input and produce markets) and farm characteristics (soil fertility, slope, tenure) (Ouédraogo et al., 2019; Tran and Goto, 2019; Abegunde et al., 2019; Mujeyi et al., 2019).

To increase the willingness of farmers to adopt CSA and thus to make a contribution to the household welfare improvement efforts, it is necessary to be aware of the drivers and obstacles that influence the farmers' decisions and choices and to understand factors that influence the welfare variables i.e food security and household incomes. Farm households are assumed to be heterogeneous agents, and their decision to adopt new technologies is constrained by their resources, information and the availability of the technology (Midingoyi et al., 2019). Investment in new technologies is attractive to households if the perceived benefits significantly offset the costs. Therefore, the decision to adopt CSA can be viewed through the lens of constrained optimization where the household chooses the technology if it is available, affordable and its use is expected to be beneficial. The expected benefits are determined by observable and non-observable factors. Any household that adopts at least one CSA was therefore classified as an adopter. This is so because farmers are assumed to be rational and, as such, adopt technologies to suit their objectives and to address the constraints that they encounter during production.

To evaluate the impact of CSA technologies on the welfare of selected households, two indices were used, i.e., the average household income and food security. Welfare refers to the total utility derived from all the goods and services consumed. Researchers have used various outcome indicators to measure welfare, including consumption, expenditure, income, asset-based wealth indices, poverty (the poverty gap and poverty headcount) and food security, (Afolami et al., 2015; Khonje et al., 2015; Larbi et al., 2014; Moratti and Natali, 2012). FAO defines household food security as when all the household members have physical and economic access to sufficient, nutritious and safe food at all times, to meet their dietary needs for active and healthy life (Fentie and Beyene, 2019). Several indicators have been used as proxies of household food security to capture the four major dimensions (access, availability, utilisation and stability), including the Dietary Diversity Score, food insecurity scores, hunger scale, food utilisation (anthropometry as a proxy i.e. height-for-age, weight-for-height, Body mass index (BMI) for age and weight for age (Ballard and Cafiero, 2013; Ahmed and Muhammed 2018; Huluka and Wondimagegnhu, 2019) The Household Dietary Diversity Score (HDDS) was used as an indicator of food security. The HDDS measures the number of food groups that are consumed per given reference period. In this study, the HDDS was generated by using eight food groups (staples, vegetables, fruits, pulses, meat and fish, oils and fats, milk and its products, and other condiments) from a 24-hour dietary recall. The DDS, therefore, ranged from 0 to 8, with the higher scores correlating with a better nutrient intake.

The adoption of CSA practices can increase crop and livestock production, thus more food is available for the household, and the surplus can be sold to generate more income. Some CSA technologies are labour-saving and, as such, they help to avail labour for other off-farm activities that can generate an income for the household. In this case, the food consumed in the previous seven days was considered. The household income was a combination of on-farm (crop and livestock) and off-farm incomes, as well as other income sources (in-kind transfers, gifts and remittances).

In previous studies, adoption has been measured as a binary treatment (the Probit and Logit models) or as a continuous variable (the Tobit and Propensity score methods) according to impact evaluation literature (Danso-abbeam et al., 2018; Khatri-chhetri et al., 2016; Li et al., 2019; Teklewold et al., 2019). For this study, the ESR was used to evaluate the relationship between the outcome variables (household income and food security) and the exogenous variables. The study used the switching of selection bias, which arises from the fact that treated individuals may differ from those who are non-treated, for reasons other than treatment status. The Switching Regression model is a variant of the classical Heckman Selection model. The ESR has two equations that are simultaneously estimated in STATA using the selection and outcome equations.

Selection Equation: Farmers are faced with two choices, namely, to adopt or not to adopt CSA. This equation (the Probit model) determines the relationship between adoption and the possible determinants.

$A_i^* = \beta Z_i + u_i$ ……………………………………………(1)

$A = 1$ if $A_i^* > 0$ $A = 0$ if otherwise i.e. $A_i^* \leq 0$

A_i^* is the latent dichotomous (binary) dependent variable for the adoption of CSA
β is a vector of the unknown parameters
Zi is a vector of the observable characteristics (farmer, farm, etc.) influencing the decision to adopt CSA.
u_i is the error term that captures the unobservable characteristics

Outcome equation:

Regime 1 (CSA Adopters): $Y_{1i}=X_{1i}B_1+\varepsilon_{1i}$ if $A_1=1$……………………(2)

Regime 2 (CSA Non Adopters): $Y_{2i}=X_{2i}B_2+\varepsilon_{2i}$ if $A_1=0$…………………….(3)

Where Y_1 and Y_2 are outcome levels (Food security (HDDS) or gross household income) for adopters and non-adopters, respectively, and X_1 and X_2 are the vectors of factors that affect food security that is to be estimated. ε_{1i} and ε_{2i} are error terms. For the gross household income, a logarithm transformation of income was used and expressed as a linear function of the independent variables. These error terms (ε_{1i}, ε_{2i} and u_i) in Equations 1, 2 and 3 are assumed to have a triumvirate normal distribution, with a zero mean and covariance matrix.

$$\mathbf{Cov(e1i,e2i,\ ui)=}\begin{bmatrix} \boldsymbol{\sigma^2_{e2}} & . & \boldsymbol{\sigma_{e2u}} \\ . & \boldsymbol{\sigma^1_{e1}} & \boldsymbol{\sigma_{e1u}} \\ . & . & \boldsymbol{\sigma^2_u} \end{bmatrix}$$

Where: σ^2_u = variance of the error term in the selection equation

σ^2_{e1} and σ^2_{e2} = variance of the error terms in the outcome equation

σ_{e1u} and σ_{e2u} = covariance of u_i , e_{1i} and e_{2i}

The ESR model is thus used to compare the expected outcome (food security and income) of the household that adopted CSA (Equation 4) to the households that did not (Equation 5) and to investigate the expected food security and incomes in the counterfactual cases (Equation 6) that the CSA adopters did not adopt and that the CSA non-adopters did adopt (Equation 7). There is a high likelihood that some unobserved factors that affect the adoption of CSA could also affect food security or household income (outcome variables). Hence, the error term in the selection equation (Equation 1) and the error terms in the outcome (Equations 2 and 3) may be correlated. To solve this problem, Equations 1, 2 and 3 were estimated simultaneously.

The discussed framework is therefore used to estimate the average treatment effect on the treated and the untreated i.e. the ATT and ATU, respectively. The equations are given as follows:

For CSA adopters with adoption: $\mathbf{E(Y_{i1}|\ A=1,\ x= X_{i1}\beta_1 + \sigma_{1\varepsilon}\lambda_{i1}}$ ……….. **(4)**

For CSA non-adopters without adoption: $\mathbf{E(Y_{i2}|\ A=0,\ x= X_{i2}\beta_2 + \sigma_{2\varepsilon}\lambda_{i2}}$ ……..… **(5)**

For Counterfactuals:

i) CSA adopters, had they not adopted: $\mathbf{E(Y_{i2}| A=1, x = X_{i1}\beta_2 + \sigma_{2\varepsilon}\lambda_{i1}}$ **………… (6)**

ii) CSA non-adopters, had they decided to adopt: $\mathbf{E(Y_{i1}| A= 0, x = X_{i2}\beta_1 + \sigma_{1\varepsilon}\lambda_{i2}}$ **……….. (7)**

Equations 4 and 5 give the actual expectations, as observed from data, while Equations 6 and 7 give the expected outcomes on the counterfactuals. The Average Treatment Effect (ATT) gives a measure of the change in the food security outcome (food security or household income).

ATT= $\mathbf{E(Y_{i1}| A=1,x)- E(Y_{i2}| A=1,x) = X_{i1}(\beta_1 -\beta_2)+ \lambda_{i1} (\sigma_{1\varepsilon}-\sigma_{2\varepsilon})}$ **………………….……………… (8)**

The Average Treatment Effect on the non-adopters

ATU = $\mathbf{E(Y_{i1}| A= 0,x)- E(Y_{i2}| A=0,x) = X_{i2}(\beta_1 -\beta_2)+ \lambda_{i2} (\sigma_{1\varepsilon}-\sigma_{2\varepsilon})}$ **……………………………. (9)**

λ_{i1} **and** λ_{i2} adjust the ATT and ATU, respectively, for the unobserved factors. The ESR model is used to address issues of self-selection and the estimation of treatment effects, when there is a non-random allocation of subjects to treatment and control groups, as is generally the case with observational (as opposed to experimental) data (Lokshin and Sajaia, 2004).

The important determinants of food security from the literature include education, the age of the household head, input availability, technology adoption, the size of the farm, the quality of land, the price of the inputs, gender, the expenditure on food, household size, income levels, access to credit, access to safe water and sanitation, as well as access to markets (Ahmed et al., 2017; Ngema et al., 2018; Abdullah et al., 2019). The formation of the selection and outcome models were based on the hypotheses that were informed by the literature review. The farmer's decision to adopt or reject CSA is influenced by the simultaneous effect of several factors related to the farmer's objectives, constraints and characteristics, the biophysical characteristics of the location, asset ownership and the attributes of the technology (Aryal et al., 2018; Mwungu et al., 2018). It was hypothesized that a farmer's age can either create or reduce confidence in new technology. More experienced farmers can be conservative, thereby avoiding new technologies. On the other hand, experienced farmers can also be willing to try new technologies if they have done it once and obtained positive results. This variable could thus have a positive or negative effect on a farmer's decision to adopt CSA technology. A larger labour size is expected to increase the probability of adopting CSA, as the household can provide timely labour that might be associated with new technologies. Education increases a farmer’s ability to obtain, process and use the information and thus increases the probability that a farmer will adopt CSA. Farm size is expected to be positively associated with the decision to adopt CSA, as farmers with smaller farms are less likely to risk experimenting with new technologies. Access to credit can increase the probability of the adoption of CSA, particularly if new investments are needed for these technologies. Studies by researchers in Ethiopia (Di Falco et al., 2011; Teklewold et al., 2017) found that access to credit, as well as access to extension and information, were the major drivers of adaptation by farmers. It can be noted that adaptation increases food production and that the farm households that did not adapt would benefit the most from adaptation. Researchers in Zimbabwe (Mujeyi et al., 2019) studied multiple CSA technology adoption determinants in smallholder farming systems and found that the gender of the household head, institutional factors (market access, information access and access to credit) and farm characteristics (soil type and labour size) significantly affected adoption. Another study in South Africa by (Abegunde et al., 2019) found that adoption was significantly affected by educational status, farming experience, farm income, membership of an agricultural association or group, farmland size, contact with agricultural extension and exposure to media. The researchers also found statistically significant negative effects of the distance from the farm to the homestead and off-farm income. Another study in Pakistan (Chandio and Yuanshend, 2018) found that the adoption of CSA in rice farming systems was significantly affected by education, farming experience, soil quality, farm machinery ownership, access to market information and contact with extension agents. Other researchers who analysed the factors affecting the adoption of Sustainable Land Management (SLM) and CSA in the Amhara region of Ethiopia found that the household characteristics (e.g. sex, household size), the physical characteristics of the farm (slope of field, tenure), access to credit and access to extension played a crucial role in decisions to adopt adaptation strategies (Miheretu and Yimer, 2017). Higher Livestock Ownership, as measured by TLU, is expected to increase the chances of the adoption of CSA. The availability of off-farm income enables farmers to purchase inputs and it is expected to have a positive influence on adoption. Contact with extension practitioners is hypothesized to increase a farmer’s likelihood of adopting CSA, as they offer a major source of information for farmers regarding production.

Researchers are now using the most advanced and recent econometric methods that are based on counterfactual analysis (Teklewold et al., 2019). Taking the observed characteristics of the adopters and non-adopters of CSA, the analysis will determine what the outcome variable (the household crop and livestock income and food security situation) would be if adopters had observed non-adopters characteristics and resources (land, livestock, education, age, family size, land quality, access and the use of agriculture services, etc.), and vice versa. The Household Dietary Diversity Score (HDDS) was used as a proxy for food security. Dietary diversity is a measure of the variety of foods across and within the food groups that are capable of ensuring an adequate intake of essential nutrients to promote good health, as well as physical and mental development (Swindale and Bilinsky, 2006). A balanced diet consists of various nutrients that come from multiple food sources and, as such, the more food groups included in the daily diet, the greater the probability of meeting the nutrient requirements. Therefore, a sufficiently diverse diet may reflect nutrient adequacy. The dietary diversity scores were created by summing the number of food groups consumed over a reference period.

5.4 Results and Discussion

5.4.1 Descriptive summary of the variables used in the estimations

Table 15 presents the descriptive statistics of the data for the relevant variables included in the estimation of the ESR model. The t-test was used to show the difference between CSA adopters and non-adopters to the relevant continuous variables (i.e. household DDS, log income, education, farming experience, household size, labour size, maize area, TLU, distance to input and output markets, number of local buyers, frequency of extension contact, distance to extension, etc.), while the Chi-square test was used to describe the difference between the two groups to the categorical binary variables (i.e. awareness of CSA, asset ownership, access to credit, access to safe water and sanitation, soil fertility status, access to weather and group membership). Soil fertility was derived from the main soil type on the farm, as identified by the household head and verified by the enumerator during the survey. Red and black clay soils were classified as fertile, whereas sand, sandy loam and loam were classified as infertile, because of their inherent deficiencies in nitrogen and phosphorus, as well as their low nutrient retention, low organic matter and low water-holding capacity (Nyamangara et al., 2000; Nyamangara et al., 2013).

Table 16 shows the differences between the adopters and non-adopters of CSA, as given by the summary statistics of the farm households that were surveyed. The results reveal a few significant variables, namely, that there is a significant difference between adopters and non-adopters in terms of access to sanitation and water, the livestock income share, the ownership of communication assets, access to weather forecasts, area under the staple maize crop and TLU. Non-CSA adopters have 0.99 acres under maize while their CSA counterparts have 1.36 acres. Overall on average, the farmers grow 1.35 acres of maize (0.55 hectares) which is lower than the national average of 0.74 ha (ZIMSTAT, 2019). Farmers who adopted CSA have higher herd sizes, they own ICT gadgets, such as radios, phones and televisions, and they have good access to weather forecast information, safe water and proper sanitation. These results on ICT and information on ownership of relevant devices point towards the knowledge-intensive nature of CSA technologies in the earlier years. The average age of the household head for the whole sample was 49.86 years which is almost similar to the mean age of the head of a household of 50 nationally for communal farmers (ZIMSTAT, 2019). The average farm experience of the household heads was about 18.90 years.

The average size of the labour force for the total sample was about four members. The average distance to inputs and output markets was 14km and 43km respectively. This resonates with the Zimbabwe Vulnerability Assessment Committee (ZimVAC) assessment findings in 2019 where nationally more than 76% of households travelled more than 10km to access inputs and to sell agricultural produce (ZimVAC, 2019).

Table 15: Variables used in the ESR model and summary statistics

Variable	**Non-adopter**		**Adopter**		**Whole sample**		**Test Statistic** t/ chi-square value
	Mean	**Std. Dev**	**Mean**	**Std. Dev**	**Mean**	**Std. Dev**	
HH Food security (DDS)	6.46	2.3	6.67	1.42	6.66	1.48	-0.65
Annual HH Income (US$)	428.23	418.62	865.96	1618.31	841.01	1577.71	1.62
HH education (years)	8.77	4.19	8.25	3.73	8.28	3.75	0.63
HH age (years)	48.45	15.94	49.95	16.49	49.86	16.44	-0.41
HH farm experience (years)	16.23	14.06	19.06	13.79	18.9	13.8	-0.94
Household size (number)	4.5	1.97	4.96	2.48	4.93	2.45	-0.85
HH labour size (number)	3.27	1.52	3.53	2.18	3.51	2.14	-0.54
Arable land size (acres)	2.4	1.94	3.1	2.22	3.06	2.21	-1.45
Soil fertility (1=fertile 0=otherwise)	0.05	0.21	0.15	0.36	0.14	0.35	1.80
Maize area (acres)	0.99	0.47	1.36	1.04	1.35	1.02	3.34*
TLU (number)	0.85	1.95	2.32	3.61	2.24	3.55	-1.89*
Draft livestock (number)	0.18	0.59	0.46	0.99	0.44	0.97	-1.28
Distance output market (Km)	31.15	27.9	43.96	62.61	43.23	61.22	-0.95
Distance input market (Km)	13.22	13.64	14.07	23.47	14.02	23.01	-0.17
Traders buying locally (number)	3.23	4.10	4.23	6.76	4.17	6.63	-0.69
Group membership (1=yes)	0.41	0.50	0.49	0.50	0.48	0.50	0.53
Extension Contact (number)	5.27	4.23	6.43	6	6.36	5.92	-0.89
Distance to extension (Km)	39.56	121.27	18.78	87.65	19.97	89.83	1.05
Access to weather forecast (1=yes 0=no)	0.41	0.5	0.66	0.47	0.65	0.48	5.67**
Awareness CSA (1=yes 0=no)	0.64	0.49	0.63	0.48	0.63	0.48	0.00
Owns Communication Asset (1=yes 0=no)	0.82	0.39	0.93	0.26	0.92	0.27	3.53*
Owns Transport asset (1=yes 0=no)	0.55	0.51	0.41	0.49	0.42	0.49	-1.45

Variable	Non-adopter		Adopter		Whole sample		Test Statistic t/ chi-square value
	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	
Owns Tillage asset (1=yes 0=no)	0.32	0.48	0.37	0.48	0.37	0.48	0.25
Asset index	7.36	3.82	7.92	3.57	7.89	3.58	-0.71
Credit access (1=yes 0=no)	0.18	0.39	0.19	0.39	0.19	0.39	0.01
Crop income US$	114.77	33.32	328.11	62.98	114.77	156.32	-0.83
Livestock income US$	50.46	31.50	138.02	19.71	50.45	147.73	-1.09
Off-farm income US$	263	361.52	399.83	726.99	392.03	711.65	-0.88
Access to safe water (1=yes 0=no)	0.59	0.5	0.86	0.35	0.84	0.37	11.05***
Access to sanitation (1=yes 0=no)	0.73	0.46	0.90	0.31	0.89	0.32	5.82**

*, **, *** significance level at 10%, 5% and 1%, respectively. *HH means Household Head*

5.4.2 Results of the Switching Regression Analysis

The results of the first stage i.e. the selection equation (CSA adoption) revealed that factors such as the soil fertility status of the fields, distance to inputs and output markets, TLU and ownership of communication assets significantly influenced the adoption of CSA in integrated crop-livestock farming systems (Tables 16 and 17). A unit increase in distance to the output market increases the odds of the adoption of CSA by 0,004, and a unit increase in TLU increases the probability of CSA adoption by 0.25. Livestock is a store of wealth in smallholder farming communities and also households who own them are usually less constrained financially. They can sell livestock to generate the income necessary to purchase farm inputs needed for new technologies. An increase in distance to input markets will decrease the odds of adoption by 0.007. This concurs with the findings of other researchers, who found a significant negative association between market (inputs) distance and adoption (Moroda et al., 2018). This is so because longer distances are associated with high transaction costs, due to the high transportation costs. Tables 16 and 17 reports the results of the ESR model.

Table 16: Food security ESR model results

Variable	Selection Equation (CSA adoption)		Outcome Equation (Food security)			
			Non-adopter		Adopter	
	Coefficient.	Robust Std. Err.	**Coefficient.**	**Robust Std. Err.**	**Coefficient**	**Robust Std. Err.**
HH education	-0.05	0.05	0.06	0.17	0.04**	0.02
Household size			0.18	0.41	0.01	0.03
Arable land size	0.10	0.08	0.102**	0.077	-0.01	0.03
Distance output market	0.003**	0.002	0.11	0.11	-4.5	0.002
Extension contact	-0.02	0.03	-0.04	0.40	-0.001	0.02
LogMaizearea			0.21	2.41	-0.19	0.25
Off-farm Income			0.001	0.003	0.00	0.00
TLU	0.25**	0.10	0.29	0.18	0.06***	0.02
Access to safe water			-0.48	1.54	-0.43**	0.17
Access to sanitation			0.03	1.78	0.81***	0.25
Distance extension	-0.01	0.001				
Distance input market	-0.007**	0.004				
HH Age	-0.01	0.02				
HH farm experience	0.02	0.01				
Local traders	0.01	0.03				
Group membership	-0.24	0.33				
Access to weather forecasts	0.56	0.58				
Draft livestock	-0.28	0.22				
HH labour size	-0.02	0.05				
Awareness CSA	0.12	0.70				
Communication asset ownership	0.84	0.92				
Transport asset ownership	-0.67	0.55				
Tillage implement asset	-0.23	0.25				
Fertile soil	0.75*	0.43				
Credit access	-0.16	0.38				
_cons	0.91	0.68	4.17	6.58	5.75***	0.38
/lns0	0.66	1.46				
/lns1	0.31***	0.05				
/r0	-0.57	3.38				
/r1	0.11	0.34				
sigma0	1.93	2.82				
sigma1	1.36	0.07				
rho0	-0.52	2.48				
rho1	0.11	0.33				

*, **, *** a significance level of 10%, 5% and 1%, respectively.

Table 17: Household Income ESR model results

Variable	Selection Equation (CSA adoption)		Outcome Equation (Log Income)			
			Non-adopters		Adopters	
	Coef.	Robust Std. Err.	Coef.	Robust Std. Err.	Coef.	Robust Std. Err.
HH Education	-0.05	0.04	0.05*	0.30	0.02***	0.01
Labour size	-0.03	0.05	0.09	0.06	0.04***	0.01
Arable land size	0.14	0.11	-0.06	0.07	0.02	0.01
TLU	0.25**	0.13	0.03	0.06	0.02**	0.01
Log crop income share			-0.12	0.20	0.01	0.04
Log livestock income share			0.09	0.17	-0.09**	0.04
Log non-agriculture income share			0.15	0.24	0.12**	0.04
Asset index			0.02	0.03	0.04***	0.01
HH Age	0.01	0.02				
HH Farm experience	0.11	0.01				
KM to extension	0.00	0.001				
Distance output market	0.004**	0.002				
Distance input market	-0.01**	0.01				
Local traders	0.02	0.01				
Group membership	-0.34	0.33				
Extension Contact	-0.05**	0.02				
Access to weather forecasts	0.35	0.31				
Draft animals	-0.31	0.25				
Awareness CSA	0.05	0.29				
Communication asset ownership	0.78**	0.32				
Transport Asset Ownership	-0.50**	0.24				
Tillage implements	-0.45	0.43				
Fertile soil	0.99**	035				
Credit access	0.07	0.34				
_cons	1.65	1.17	1.01	0.98	1.81***	0.14
/lns0	-0.77	0.39				
/lns1	-0.78	0.07				
/r0	-1.08	0.69				
/r1	-1.29	0.96				
sigma0	0.46	0.18				
sigma1	1.46	0.03				
rho0	-0.79	0.26				
rho1	-0.86	0.25				

*, **, *** a significance level of 10%, 5% and 1%, respectively.

The second set of outcome equations from the ESR (i.e. food security and household income) analysed the factors that affected the outcome with reference to CSA adoption. The analysis revealed that farmer and farm characteristics, as well as market factors, significantly affected the welfare of the households. The findings in Tables 16 and 17 revealed that the education of the household head, the labour size, size of arable land owned, the TLU and the asset index significantly predicted the household income in the study areas. Unsurprisingly, education had a significant positive effect on income. More educated household heads can engage in better yield-enhancing CSA which will resultantly lead to more products destined for the market. Education enhances the capacity of the farmer to make sound decisions on what enterprises to pursue in light of their potential profitability. A higher labour size also contributes to increased incomes through timely farm operations which increase productivity and some family members can also engage in other non-farm economic activities thereby enhancing household income. TLU had a positive and significant effect on household income. Livestock is indeed a form of savings in rural areas that can easily be liquidated to bridge income gaps that may arise within a household (Ogada et al., 2020a). Asset ownership also has a positive effect on household income. This calls for the need to encourage farmers to invest in agricultural productive assets.

Food security was affected by factors such as the education of the household head, the TLU, access to safe water and access to sanitation which concurs with prior expectations. Education and TLU had a positive impact on food security for adopters. These findings concur with other researchers in the literature. A study in Mudzi rural area in Zimbabwe showed that that household dietary diversity was influenced by the education of the household head and livestock ownership (Mango et al., 2014). Another study in South Africa also found a significant positive relationship between education and household food security(Ngema et al., 2018). Educated household heads can decipher information on innovations such as CSA and they quickly adopt yield-enhancing components that can ultimately boost food security. Studies from 22 low-income countries also showed a correlation between food insecurity with a low level of education (Nwokolo, 2017). This finding also corroborate the findings of (Mota et al., 2019) who reported that educational attainment by the household head could lead better understanding of new technologies. Education enhances the reasoning capability of an individual and enables them to have better awareness of new technologies. It also enables farmers to read and acquire knowledge on agriculture Information Education and Communication (IEC).

There was a positive relation between sanitation and food security. Researchers like (Moroda et al., 2018) while investigating food insecurity in rural households of Ethiopia also reiterated that sanitation contributed significantly to food security by ensuring the increased capacity of the body to absorb and use the nutrients in their food. Sanitation also prevents human faecal pollution thereby reducing the spread of diseases. TLU contribute positively to food security through consumption of the products (milk, meat) and even income generation through sales and the money is used to purchase food during critical times. Farmers can also hire out draught power services and get cash to purchase household food. The draught power also ensures timeliness in farm operations which lead to good yields and this helps farmers to meet food requirements through their production.

There was a negative significant relationship between food security and access to safe water (protected wells and boreholes). While this finding is surprising as it is contrary to expectations that good water access can enhance food security through adequate hygiene practices and consumption of safe drinking water, this might be because boreholes and the protected wells in these communities are provided by government and donor agents such as NGOs through social protection support programs and this does not have links directly to food security. In as much as these facilities might be available, issues of access due to distance and whether these sources have adequate water for the households also become very important. In some communities, boreholes are broken down and there is no technical expertise to repair them, thus the community relies on the District Development Fund (DDF) which takes time to attend. These challenges which contribute to the negative relationship calls for the promotion of rainwater harvesting technologies that would alleviate pressure on underground water sources, allowing protected wells and boreholes to replenish their water supplies. Furthermore more boreholes should be drilled in proximity to homesteads such that households do not need to travel long distances to access water. Mechanisms should also be put in place to rehabilitate broken-down boreholes.

The estimates of the treatment effects of the adoption of CSA on food security and household income are reported in Table 18. The Average Treatment Effect on the Treated (ATT) measures the difference between the welfare of the adopters and what they would have if they had not adopted CSA. The Average Treatment Effect on the Untreated (ATU), on the other hand, assesses the difference between the welfare of non-adopters and their counterfactuals. These estimates account for selection bias, unlike the mean differences reported in Table 18.

Table 18: Average treatment effect of CSA adoption on food security and household income

Index	Income			Food security		
	Estimate	**Std Err**	**t value**	**Estimate**	**Std. Err**	**t value**
ATT	0.713	0.016	43.72***	1.492	0.090	16.604***
ATU	-0.532	0.081	-6.61***	0.370	0.297	1.245
ATE	0.642	0.022	29.52***	1.428	0.087	16.349***

*, **, *** a significance level of 10%, 5% and 1%, respectively.

The ATT shows that food security for the treated is positive (1.49) and statistically significant, and it is also positive and statistically significant for the log household income (0.713). This indicates that adopters would have lost income and become food insecure had they had not adopted CSA. The ATU, however, is -0.53 and statistically significant for the log household income, but it is higher for food security (0.37), although it is not statistically significant. Similarly, the Average Treatment Effect (ATE) outcomes from ESR show that non-adopters would have attained crop income gains had they adopted CSA technologies. These findings reveal that adopters of CSA would have been worse off, in welfare terms, had they not adopted it. Non-adopters would also have benefited, food security-wise, had they adopted CSA. As presented in Table 18, CSA technology adoption significantly affects both the food security and household income of adopters. This finding is in line with previous studies, which point towards the positive contribution of CSA adoption on household welfare (Mwungu et al., 2019; Ogada et al., 2020a; Wekesa et al., 2018). A study in Teso North Sub-county, Busia County in Kenya found that farmers who adopted CSA were more food secure compared to non-adopters (Wekesa et al., 2018). The study demonstrated a robust relationship between food security and CSA adoption. Therefore, CSA interventions that are aimed at improving food security in smallholder farming communities may have significant welfare gains for smallholder farmers. Generally, climate-smart agriculture technologies enhance household welfare through improved agricultural productivity.

5.5 Conclusion and Recommendations

This study examined the impact of CSA on the welfare of households, using the ESR model. Variables relating to the soil fertility status of the fields, access to inputs markets, TLU and ownership of communication assets have emerged as having a significant impact on a farmer's decision to adopt CSA. The ATT is positive and significant which indicates that CSA adoption has resulted in a significantly positive impact on the welfare of the farmers. Several policy implications can therefore be drawn from these findings. The government should consider providing incentives for agro-dealers to invest in agricultural businesses that sell inputs in rural areas. In as much as taxes are good for government revenue, the government could reduce the taxes for rural agro-dealers, so that inputs are supplied and made available closer to where the farmers live, to provide easier access. The government could also provide incentives for financial service providers to avail affordable financial products that are targeted at agro-dealers and to enable them to stock the required inputs in adequate quantities. Alternatively, the incentives can be offered to the manufacturers of inputs, as well as the buyers of agricultural produce, to encourage them to foster flexible and mutually beneficial marketing arrangements with the rural agro-dealers. The study findings show that reducing the distance to input markets will go a long way in increasing the probability of CSA technology adoption, which is associated with improved productivity. Enhanced productivity will, in turn, improve the welfare of households by increasing food security and household incomes. Also, related to the improved and significant impact on food security is the promotion of sanitation. The availability of food alone does not guarantee the food security of households, as it should be complemented by good sanitation and access to safe water. Development practitioners should target educated farmers because of their greater ability to adopt. Information, education and communication materials to suit uneducated farmers should be made available as well to enhance adoption. The study findings have demonstrated that there is a robust relationship between food security and CSA adoption (through positive and significant ATT). Therefore, interventions that are aimed at improving climate-smartness in smallholder farming communities may have significant food security and income benefits for smallholder farmers.

References

Abdullah, Zhou, D., Shah, T., Ali, S., Ahmad, W., Din, I. U., and Ilyas, A., 2019. Factors affecting household food security in the rural northern hinterland of Pakistan. *Journal of the Saudi Society of Agricultural Sciences*, *18*(2), 201–210. https://doi.org/10.1016/j.jssas.2017.05.003

Abegunde, V. O., Sibanda, M., and Obi, A., 2019. Determinants of the Adoption of Climate-Smart Agricultural Practices by Small-Scale Farming Households in King Cetshwayo District Municipality, South Africa. *Sustainability*, *12*(195), 1–27.

Afolami, C. a., Obayelu, A. E., and Vaughan, I. I., 2015. Welfare impact of the adoption of improved cassava varieties by rural households in South-Western Nigeria. *Agricultural and Food Economics*, *3*(18), 1-17. https://doi.org/10.1186/s40100-015-0037-2

Ahmed, M. H., Geleta, K. M., Tazeze, A., and Ahmed, M. H., 2017. The Impact of improved maize varieties on-farm productivity and wellbeing : evidence from the East Hararghe Zone of Ethiopia The Impact of improved maize varieties on-farm productivity and wellbeing : *Development Studies Research*, *4*(1), 9–21. https://doi.org/10.1080/21665095.2017.1400393

Aryal, J. P., Jat, M. ., Sapkota, T. B., Kassie, M., Rahut, B. D., and Maharjan, S., 2017. Adoption of multiple climate-smart agricultural practices in the Gangetic plains of Bihar, India. *International Journal of Climate Change Strategies and Management*, *10*(3), 407–427. https://doi.org/10.1108/IJCCSM-02-2017-0025

Aryal, J. P., Rahut, D. B., Maharjan, S., and Erenstein, O., 2018. Factors affecting the adoption of multiple climate-smart agricultural practices in the Indo-Gangetic Plains of India. *Natural Resources Forum*, *42*, 141–158. https://doi.org/10.1111/1477-8947.12152

Ballard Kepple, A. W., and Cafiero, C., 2013. The food insecurity experience scale: development of a global standard for monitoring hunger worldwide. Technical Paper. Rome, FAO. (available at http://www.fao.org/economic/ess/ess-fs/voices/en/).

Belay, A., Recha, J. W., Woldeamanuel, T., and Morton, J. F., 2017. Smallholder farmers ' adaptation to climate change and determinants of their adaptation decisions in the Central Rift Valley of Ethiopia. *Agriculture and Food Security*, (6), 1–13. https://doi.org/10.1186/s40066-017-0100-1

Bodner, G., Nakhforoosh, A., and Kaul, H., 2015. Management of crop water under drought : a review. *Agronomy for Sustainable Development*, *35*, 401–442. https://doi.org/10.1007/s13593-015-0283-4

Bonga, W., 2018. Trade Balance Analysis in Zimbabwe: Import and Export Examination Using Vector Auto-Regression Model. *Munich Personal RePEc Archive*, Germany. https://mpra.ub.uni-muenchen.de/89002/

Braimoh, A. K., 2013. Global agriculture needs smart science and policies. *Agriculture and Food Security*, *2*(6), 1–2. https://doi.org/10.1186/2048-7010-2-6

Chandio, A. A., and Yuanshend, J., 2018. Determinants of Adoption of Improved Rice Varieties in Northern Sindh, Pakistan. Rice Science. 2018, 25(2): 103−110. http://dx.doi.org/10.1016/j.rsci.2017.10.003

Danso-abbeam, G., Bosiako, J. A., Ehiakpor, D. S., and Mabe, F. N., 2018. Adoption of improved maize variety among farm households in the northern region of Ghana. *Cogent Economics and Finance*, *109*(1), 1–14. https://doi.org/10.1080/23322039.2017.1416896

Di Falco, S., 2014. Adaptation to climate change in Sub-Saharan agriculture: Assessing the evidence and rethinking the drivers. *European Review of Agricultural Economics*, *41*(3), 405–430. https://doi.org/10.1093/erae/jbu014

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), 825–842. https://doi.org/10.1093/ajae/aar006

Enahoro, D., Croz, D. M., Mul, M., Rich, K. M., Robinson, T. P., Thornton, P., and Staal, S. S., 2019. Supporting sustainable expansion of livestock production in South Asia and Sub-Saharan Africa : Scenario analysis of investment options. *Global Food Security*, *20* (May

2018), 114–121. https://doi.org/10.1016/j.gfs.2019.01.001
Fentie, A., and Beyene, A. D., 2019. Climate-smart agricultural practices and welfare of rural smallholders in Ethiopia: Does planting method matter? *Land Use Policy*, *85* (May 2018), 387–396. https://doi.org/10.1016/j.landusepol.2019.04.020
Franzel, S., Carsan, S., Lukuyu, B., Sinja, J., and Wambugu, C., 2014. Fodder trees for improving livestock productivity and smallholder livelihoods in Africa. *Environmental Sustainability*, *6*, 98–103.
GOZ, 2018. Transitional Stabilisation Programme Reforms Agenda : Towards a Prosperous and Empowered Upper Middle Income Society by 2030. *Government of Zimbabwe*. Harare, Zimbabwe.
Gwiriri, L. C., Manyawu, G., Mashanda, P. B., Moyo, S., Chakoma, C., Sethaunyane, H., Maasdorp, B. V., 2016. The potential of replacing conventional dairy supplements with forage legume-based diets in Zimbabwe's smallholder dairy sector. *African Journal of Range and Forage Science*, *0119* (July), 1-9 https://doi.org/10.2989/10220119.2016.1170727
Hallama, M., 2019. Hidden miners – the roles of cover crops and soil microorganisms in phosphorus cycling through agroecosystems. *Plant and Soil International Journal*, 7–45.
Huluka, A. T., and Wondimagegnhu, B. A., 2019. Determinants of household dietary diversity in the Yayo biosphere reserve of Ethiopia: An empirical analysis using sustainable livelihood framework. *Cogent Food and Agriculture, 5*(1690829). https://doi.org/10.1080/23311932.2019.1690829
Hussein, F. M., Ahmed, A. Y., and Muhammed, O. S., 2018. Household food insecurity access scale and dietary diversity score as a proxy indicator of nutritional status among people living with HIV/AIDS, Bahir Dar, Ethiopia, 2017. *PLoS ONE*, *13*(6), 1–9. https://doi.org/10.1371/journal.pone.0199511
Kassie, M., Shiferaw, B., and Muricho, G., 2011. Agricultural Technology, Crop Income, and Poverty Alleviation in Uganda. *World Development*, *39*(10), 1784–1795. https://doi.org/10.1016/j.worlddev.2011.04.023
Kassie, M., Stage, J., Diiro, G., Muriithi, B., Ledermann, S. T., Pittchar, J., Zeyaur, K., 2018. Land Use Policy Push-pull farming system in Kenya : Implications for economic and social welfare. *Land*, *77*(September 2017), 186–198. https://doi.org/10.1016/j.landusepol.2018.05.041
Kebebe, E. G., 2017. Household nutrition and income impacts of using dairy technologies in mixed crop-livestock production systems. *The Australian Journal of Agricultural and Resource Economics*, (61), 626–644. https://doi.org/10.1111/1467-8489.12223
Khatri-chhetri, A., Aryal, J. P., and Sapkota, T. B., 2016. Economic benefits of climate-smart agricultural practices to smallholder farmers in the Indo-Gangetic Plains of India Economic benefits of climate-smart agricultural practices to smallholder farmers in the Indo-Gangetic Plains of India. *Current Science*, *110*(April), 1251–1256. https://doi.org/10.18520/cs/v110/i7/1251-1256
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*, 695 706-706. https://doi.org/10.1016/j.worlddev.2014.09.008
Larbi, A., Hoeschle-zeledon, I., Agriculture, T., Zemadim, B., Tropics, S., and Azzarri, C., 2014. Sustainable intensification of crop-livestock mixed farming systems in the Guinea / Sudan Savanna Zone of West Africa. *Africa RISING Project Document*. IITA.
Li, E., Dang, H. Le, Li, E., Nuberg, I., and Bruwer, J., 2019. Factors influencing the adaptation of farmers in response to climate change : a Factors influencing the adaptation of farmers in response to climate change : a review. *Climate and Development*, (January). https://doi.org/10.1080/17565529.2018.1562866
Lokshin, M., and Sajaia, Z., 2004. Maximum likelihood estimation of endogenous switching regression models. *The Stata Journal*, *4*(3), 282–289.
Lunduka, R. W., Mateva, K. I., and Magorokosho, C., 2019. Impact of adoption of drought-tolerant maize varieties on total maize production in south Eastern Zimbabwe. *Climate and*

Development ISSN:11(1), 35–46. https://doi.org/10.1080/17565529.2017.1372269
Makate, C., Wang, R., Makate, M., and Mango, N., 2016. Crop diversification and livelihoods of smallholder farmers in Zimbabwe : adaptive management for environmental change. *SpringerPlus*, *5*(1135), 1–18. https://doi.org/10.1186/s40064-016-2802-4
Mango, N., Zamasiya, B., Makate, C., Nyikahadzoi, K., and Siziba, S., 2014. Factors influencing household food security among smallholder farmers in the Mudzi district of Zimbabwe. *Development Southern Africa*, *31*(January 20154), 37–41. https://doi.org/10.1080/0376835X.2014.911694
Midingoyi, S. G., Kassie, M., Muriithi, B., Diiro, G., and Ekesi, S., 2019. Do Farmers and the Environment Benefit from Adopting Integrated Pest Management Practices ? Evidence from Kenya. *Journal of Agricultural Economics*, *70*(2), 452–470. https://doi.org/10.1111/1477-9552.12306
Miheretu, B. A., and Yimer, A. A., 2017. Determinants of farmers' adoption of land management practices in Gelana sub-watershed of Northern highlands of Ethiopia. *Ecological Processes*, *6*(1). https://doi.org/10.1186/s13717-017-0085-5
Moratti, M., and Natali, L., 2012. Measuring Household Welfare: Short versus long consumption. Working Papers. UNICEF Office of Research, Florence.
Moroda, G. T., Tolossa, D., and Semie, N,. 2018. Food insecurity of rural households in Boset district of Ethiopia : a suite of indicators analysis. *Agriculture and Food Security,* 1–16. https://doi.org/10.1186/s40066-018-0217-x
Mota, A. A., Lachore, S. T., and Handiso, Y. H., 2019. Assessment of food insecurity and its determinants in the rural households in Damot Gale Woreda, Wolaita zone, southern Ethiopia. *Agriculture and Food Security*, *8*(11), 1–11. https://doi.org/10.1186/s40066-019-0254-0
Mujeyi, A., 2018. Policy and Institutional Dimensions in Climate-Smart Agriculture Adoption : Case of Rural Communities in Zimbabwe. In W. Leal Filho (ed.) (Ed.), *Handbook of Climate Change Resilience*. https://doi.org/10.1007/978-3-319-71025-9_66-1
Mujeyi, A., Mudhara, M., and Mutenje, M. J., 2019. Adoption determinants of multiple climate-smart agricultural technologies in Zimbabwe : Considerations for scaling-up and out. *African Journal of Science, Technology, Innovation and Development, 0*(0), 1–13. https://doi.org/10.1080/20421338.2019.1694780
Muoni, T., Barnes, A. P., Öborn, I., Watson, C. A., Shiluli, M., and Duncan, A. J., 2019. Farmer perceptions of legumes and their functions in smallholder farming systems in east Africa. *International Journal of Agricultural Sustainability ISSN: 17*(3), 205–218. https://doi.org/10.1080/14735903.2019.1609166
Mupangwa, W., Mutenje, M., Thierfelder, C., Mwila, M., Malumo, H., Mujeyi, A., and Setimela, P., 2017. Productivity and profitability of manual and mechanized conservation agriculture (CA) systems in Eastern Zambia. *Renewable Agriculture and Food Systems*, 1–15. https://doi.org/10.1017/S1742170517000606
Mupangwa, W., and Thierfelder, C., 2014. Intensification of conservation agriculture systems for increased livestock feed and maize production in Zimbabwe. *International Journal of Agricultural Sustainability*, *12*(4), 425–439. https://doi.org/10.1080/14735903.2013.859836
Mwungu, C. M., Mwongera, C., Shikuku, K. M., Acosta, M., Ampaire, E. L., Winowiecki, L. A., and Läderach, P., 2019. The Climate-Smart Agriculture Papers. In T. S. Rosenstock (Ed.), *The Climate-Smart Agriculture Papers*. https://doi.org/10.1007/978-3-319-92798-5
Mwungu, C. M., Mwongera, C., Shikuku, K. M., Acosta, M., and Läderach, P., 2018. Determinants of Adoption of Climate-Smart Agriculture Technologies at Farm Plot Level : An Assessment from Southern Tanzania. In W. L. Filho (Ed.), *Handbook of Climate Change Resilience*. Springer International Publishing.
Ndiritu, S. W., Kassie, M., and Shiferaw, B., 2014. Are there systematic gender differences in the adoption of sustainable agricultural intensification practices? Evidence from Kenya. *Food Policy*, *49*(P1), 117–127. https://doi.org/10.1016/j.foodpol.2014.06.010
Ngema, P. Z., Sibanda, M., and Musemwa, L., 2018. Household Food Security Status and Its Determinants in Maphumulo Local Municipality, South Africa. *Sustainability*, *10*, 1–23.

https://doi.org/10.3390/su10093307
Nwokolo, E. E., 2017. The Influence of Educational Level on Sources of Income and Household Food Security in Alice, Eastern Cape, South Africa. *Journal of Human Ecology*, *52*(3), 208–217. https://doi.org/10.1080/09709274.2015.11906944
Nyamangara, J, Mugwira, L. M., and Mpofu, S., 2000. Soil Fertility Status in the Communal Areas of Zimbabwe in Relation to Sustainable Crop Production Soil Fertility Status in the Communal Areas of Zimbabwe in Relation to Sustainable Crop Production. *Journal of Sustainable Agriculture*, *16*(November), 15–29. https://doi.org/10.1300/J064v16n02
Nyamangara, Justice, Masvaya, E. N., Tirivavi, R., and Nyengerai, K., 2013. Effect of hand-hoe based conservation agriculture on soil fertility and maize yield in selected smallholder areas in Zimbabwe. *Soil and Tillage Research*, *126*, 19–25. https://doi.org/10.1016/j.still.2012.07.018
Ogada, M. J., Rao, E. J. O., Radeny, M., Recha, J. W., and Solomon, D., 2020. Climate-smart agriculture, household income and asset accumulation among smallholder farmers in the Nyando basin of Kenya. *World Development Perspectives*, 1–11. https://doi.org/10.1016/j.wdp.2020.100203
Ouédraogo, M., Houessionon, P., Zougmoré, R. B., and Partey, S. T., 2019. Uptake of climate-smart agricultural technologies and practices: Actual and potential adoption rates in the climate-smart village site of Mali. *Sustainability (Switzerland)*, *11*(17). https://doi.org/10.3390/su11174710
Rurinda, J., Mapfumo, P., Wijk, M. T. Van, Mtambanengwe, F., and Rufino, M. C., 2014. Climate Risk Management Sources of vulnerability to a variable and changing climate among smallholder households in Zimbabwe : A participatory analysis. *Climate Risk Management*, *3*, 65–78. https://doi.org/10.1016/j.crm.2014.05.004
Sani, S., and Kemaw, B., 2019. Analysis of households food insecurity and its coping mechanisms in Western Ethiopia. *Agricultural and Food Economics*, *7*(5), 1-20. https://doi.org/10.1186/s40100-019-0124-x
Steenwerth, K. L., Hodson, A. K., Bloom, A. J., Carter, M. R., Cattaneo, A., Chartres, C. J., Jackson, L. E., 2014. Climate-smart agriculture global research agenda : scientific basis for action. *Agriculture and Food Security*, *2*(11), 1–39.
Swindale, A., and Bilinsky, P., 2006. Household Dietary Diversity Score (HDDS) for Measurement of Household Food Access : Indicator Guide (V2). *Food and Nutrition Assistance II Project (FANTA)*. Washington, D.C
Taylor, P., and Santeramo, F. G., 2015. On the Composite Indicators for Food Security : Decisions Matter ! On the Composite Indicators for Food Security : Decisions Matter ! *Food Review International*, (January), 37–41. https://doi.org/10.1080/87559129.2014.961076
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 labour. *Ecological Economics*, *93*, 85–93. https://doi.org/10.1016/j.ecolecon.2013.05.002
Teklewold, H., Mekonnen, A., Salvatore, D. F. and, and Kohlin, G., 2017. Does the adoption of multiple climate-smart practices improve farmers ' climate resilience? Empirical evidence from the Nile basin of Ethiopia. *Climate Change Economics*, *8*(1 (2017) 1750001), 1-30. https://doi.org/10.1142/S2010007817500014
Teklewold, H., Gebrehiwot, T., and Bezabih, M., 2019. Climate-smart agricultural practices and gender-differentiated nutrition outcome : An empirical evidence from Ethiopia. *World Development*, *122*, 38–53. https://doi.org/10.1016/j.worlddev.2019.05.010
Tesfaye, K., Kassie, M., Cairns, J. E., Michael, M., Stirling, C., Abate, T., Gerard, B. (2017). Potential for Scaling up Climate Smart Agricultural Practices : Examples from Sub-Saharan Africa. *Climate Change Management*, 185–203. https://doi.org/10.1007/978-3-319-49520-0
Thierfelder, C., Chivenge, P., Mupangwa, W., Rosenstock, T. S., Lamanna, C., and Eyre, J. X. (2017). How climate-smart is conservation agriculture (CA)? – its potential to deliver on adaptation, mitigation and productivity on smallholder farms in southern Africa. *Food*

Security, *9*(3), 537–560. https://doi.org/10.1007/s12571-017-0665-3
Thierfelder, C., Matemba-Mutasa, R., Bunderson, W. T., Mutenje, M., Nyagumbo, I., and Mupangwa, W., 2016. Evaluating manual conservation agriculture systems in southern Africa. *Agriculture, Ecosystems and Environment*, *222*(February), 112–124. https://doi.org/10.1016/j.agee.2016.02.009
Tran, D., and Goto, D., 2019. Impacts of sustainability certification on farm income: Evidence from small-scale speciality green tea farmers in Vietnam. *Food Policy*, *83*(June), 70–82. https://doi.org/10.1016/j.foodpol.2018.11.006
Wekesa, B. M., Ayuya, O. I., and Lagat, J. K., 2018. Effect of climate-smart agricultural practices on household food security in smallholder production systems : micro-level evidence from Kenya. *Agriculture and Food Security*, *7*(80), 1–14. https://doi.org/10.1186/s40066-018-0230-0
Wossen, T., Abdoulaye, T., Alene, A., Feleke, S., Menkir, A., and Manyong, V., 2017. Measuring the impacts of adaptation strategies to drought stress : The case of drought-tolerant maize varieties. *Journal of Environmental Management*, *203*, 106–113. https://doi.org/10.1016/j.jenvman.2017.06.058
Zheng, C., Jiang, Y., Chen, C., Sun, Y., Feng, J., Deng, A., Zhang, W., 2014. The impacts of conservation agriculture on crop yield in China depend on specific practices, crops and cropping regions. *The Crop Journal*, *2*(5), 289–296. https://doi.org/10.1016/j.cj.2014.06.006
ZIMSTAT, 2012. The Zimbabwe 2012 Population Census National Report. *Zimbabwe National Statistics Agency*. Harare, Zimbabwe.
ZIMSTAT, 2019. Zimbabwe Smallholder Agricultural Productivity Survey 2017 Report. *Zimbabwe National Statistics Agency*. Harare, Zimbabwe.
ZimVAC, 2019. Rural Livelihoods Assessment. Zimbabwe Vulnerability Assessment Committee. *The Food and Nutrition Council*. Harare, Zimbabwe.
Zougmoré, R., Partey, S., Ouédraogo, M., Omitoyin, B., Thomas, T., Ayantunde, A., Jalloh, A., 2016. Toward climate-smart agriculture in West Africa: A review of climate change impacts, adaptation strategies and policy developments for the livestock, fishery and crop production sectors. *Agriculture and Food Security*, *5*(1), 1–16. https://doi.org/10.1186/s40066-016-0075-3

CHAPTER 6: THE ECONOMIC ANALYSIS OF CLIMATE-SMART AGRICULTURE TECHNOLOGIES IN MAIZE PRODUCTION IN SMALLHOLDER FARMING SYSTEMS.

6.1 Abstract

Smallholder farmers who grow the staple maize crop rely mainly on rain-fed agricultural production and yields are estimated to have decreased by over 50% largely due to climate change. As a result, CSA is being increasingly promoted to overcome problems of declining agricultural productivity and reduced technical efficiency. This study analysed profitability and profit efficiency in maize (Zea mays) production as a result of CSA technology adoption using Cost-Benefit Analysis and stochastic profit frontier model. The study used data from a cross-sectional household survey of 386 households drawn four districts in Mashonaland East province located in the North-Eastern side of Zimbabwe. Results from the cost-benefit analysis reveal that maize performs best under CSA technologies. The profit inefficiency model shows that extension contact, number of traders locally and adoption of CSA had a significant negative coefficient implying that as these variables increase, profit inefficiency among maize farmers' decreases. TLU and farming experience had a significant positive coefficient implying that as the farmers' TLU/herd size and farming experience increase, the profit inefficiency of the farmers also increases. This contradicts expectation and might be explained by the fact that experienced farmers are older and unwilling to invest in any new technologies that come around. The findings call for development practitioners to incorporate market linkages that bring buyers closer to the farmers and support for the extension to be able to have frequent contacts with farmers. The results also point out to the potential of CSA in positively influencing profitability as a result of reduced costs and improved productivity.

Keywords: *Cost-Benefit Analysis, return on investment, Profit efficiency, stochastic frontier, Zimbabwe*

6.2 Introduction

Maize (Zea mays L.) is the most important cereal crop in sub-Saharan Africa and is the world's most widely grown cereal crop as well as an essential food source for millions of the world's poor. Farmers grow conventional maize on an estimated 100 million hectares (250 million acres) throughout the developing world (Nsikak and Sunday, 2013). In sub-Saharan Africa, maize is a staple food for an estimated 50% of the population and an important source of carbohydrate, protein, iron, vitamin B, and minerals. The current production of maize is about 8 million tonnes and its average yield is 1.5 tonnes per hectare pointing to some technical inefficiencies. The average yield is lower as compared to the world average of 4.3 tonnes/ha and other African countries such as South Africa with 2.5 tonnes/ha (FAO, 2009). Zimbabwe is an agro-based country and maize is also the main crop in the smallholder farming communities. Smallholder farmers rely mainly on rain-fed production and are often hamstrung by multiple constraints such as reduced soil fertility, limited income to access inputs such as fertilisers, improved seed, herbicides and pesticides, unavailability of lucrative output markets, high cost of inputs and reduced yield due to climate variability (Poole, 2017; Rurinda et al., 2014). Researchers and development practitioners from the United Nations Common Coding System (UNCCS) have reported reductions in agricultural yield due to extreme weather (UNCCS, 2019). These unpredictable seasons have become a major constraint in smallholder crop and livestock production farming systems and as such, the use of Climate-smart agriculture (CSA) technologies becomes essential as a solution. Climate-smart agriculture technologies are innovations that sustainably increase agricultural productivity, help households to adapt and be resilient to climate change and contribute to the reduction in greenhouse gas emissions (Steward et al., 2018).

Adaptation strategies for households can either be reactive (Shongwe, 2014) i.e. soil fertility maintenance through the use of animal manure and inorganic fertilisers, rotations and intercropping to address problems linked to observed climate change impacts or proactive CSA technologies such as the use of new drought-tolerant varieties, use of early maturing varieties policy measures such as insurance policies. Zimbabwe has participated in programs and alliances promoting CSA such as the Department for International Development (DFID) funded Vuna (2015-2018) and the Africa Development Bank's Africa Climate-smart Agriculture (ACSA)

(2018-2025) (Rosenstock, 2018). The Government of Zimbabwe has developed policies and interventions to lessen the impacts of climate change on agriculture. These policies include a child-friendly climate policy that targets education in schools on climate change issues, the Climate-smart agriculture policy which promotes the adoption of CSA by farmers and the National Climate policy which seeks to establish legal structures to guide businesses on becoming greener (GOZ, 2018). Government and NGOs have introduced a range of CSA interventions in Zimbabwe which include conservation agriculture, drought-tolerant maize and legume varieties, cereal-legume intercropping and rotation systems, improved fodder crops among others (Mujeyi, 2018). Assuming economic rationality, smallholder farmers who rely on agriculture for livelihoods would adopt technologies that reduce costs of production while increasing benefits from greater incomes through improved yields. Smallholder farmers are heterogeneous and as such, they adopt different combinations of CSA to address varying constraints that they face. These different technology bundles have different profitability levels because of the different inputs requirements associated with them as well as their potential impact on productivity.

The need to upscale CSA as an adaptation mechanism to improve or maintain high productivity levels in smallholder farming communities can effectively be achieved if the profitability of these technologies is properly understood. This study, therefore, aims to:

1. Estimate profitability and compare benefit-cost ratio (BCR) of maize production in smallholder farming communities across CSA technology bundles and
2. Measure profit efficiency and identify the determinants thereof.

This study aims to contribute to the literature on CSA in Zimbabwe by analysing the profitability of current CSA technology bundles in maize production and technical inefficiency. Furthermore, using the stochastic frontier model, the article aims to identify determinants of efficiency. The results will provide a better understanding of costs and benefits, making it possible to design more economically efficient policies and programs to promote CSA technology adoption. Economic evaluations can provide critical information to those making decisions about the allocation of limited agriculture input resources across enterprises. The chapter provides empirical evidence from actual farmer behaviour in the uncontrolled environment thus adding to studies from on-farm and on-station trials.

6.3 CSA in main cereal crop in Crop Livestock Farming systems

This study particularly chose to do an analysis for maize (Zea mays) as it is the most important crop in smallholder farming systems in the four districts.

Maize is the staple crop in Zimbabwe to 98% of the 12.7 million people in the country and it provides 40–50% of the calories (Kassie et al., 2017). Average maize yield has dropped from a highest (after independence) of 2163.7 Kg/ha in 1985 to 667.8 Kg/ha in 2017 (FAOSTAT, 2019). Maize productivity has been negatively affected by infertile soils, inadequate water due to droughts and erratic rainfall patterns caused by climate change as well as the incidence of pests and diseases. Various CSA technologies have been used in maize production to boost yields. One such is Conservation Agriculture (CA) which consists of three key principles namely minimum tillage, permanent soil cover (mulching with crop residues or cover crop) and crop diversification (either temporal diversification i.e. rotation or spatial diversification i.e. intercropping). CA offers benefits of increased yields. Crop rotation and intercropping improve soil fertility through the nitrogen-fixing characteristics of legumes. Large increases in maize yields in maize-groundnut rotations has been reported by CIMMYT researchers in Zimbabwe from long term trials in smallholder farming systems (Waddington et al., 2007). Cereal-legume rotations also have the benefits of reducing the build-up of pests and diseases. Minimum soil disturbance reduces the rate and amount of soil erosion. Soil cover leads to reduced runoff, reduced soil erosion, increased water infiltration and reduced evaporation of soil moisture. (Michler et al., 2019; Steward et al., 2018; Thierfelder et al., 2017a). Drought-tolerant maize (DTM) varieties have been promoted by organisations such as CIMMYT and these are input-responsive, stress-tolerant, and high-yielding in comparison to traditionally grown commercial hybrids (Mujeyi and Mujeyi, 2018).

6.3. Data analysis

The study employed descriptive statistics and inferential statistics. It explored the economic assessment of CSA technologies through a Costs Benefits Analysis (CBA) and a stochastic frontier. This study precisely probed farmers to state which CSA technologies they had used for various crops in one season and the inputs that were used and grain harvested after such an investment. Information from this economic analysis is important for price setting of commodities by government watchdogs, researchers working to improve the technologies, farmers using them and donors and governments who fund research and development work.

6.3.1 Economic Analysis of CSA

Farmers use different technologies as adaptation strategies and their decisions on which particular technology to adopt under what area depends on its cost-effectiveness (Shingwe, 2014). The cost-benefit analysis thus plays an important role in farmers' decisions with regards to inputs costs e.g. fertiliser, labour, seed, pesticide etc. and was used in the economic analysis. Other researchers have used CBA in analysing CSA technologies (Papendiek et al., 2016; Sain et al., 2017). Cost-Benefit Analysis (CBA) compare inputs and outputs for technology in monetary terms (Shongwe, 2014). CBA for this study focuses on the quantitative evaluation of CSA technologies on the two main crops i.e. maize and groundnut. All benefits and costs are estimated in monetary terms and through calculating net benefits, the most economic efficient CSA are identified. Benefits from maize include grain and stover used to feed livestock. The Net benefits are calculated as follows:

$NB = \Sigma (B\,t - Ct)$……………………………………(1)

$NB = \Sigma Bt - \Sigma Ct$ ……………………………………(2)

Where;

NB represents the net benefits, $\Sigma B\,t$ = Total benefits in year t and ΣCt = Total variable costs (TVC) in year t

Bt is a combination of revenue from the quantity of grain output and stover benefits.

$\Sigma B\,t$ =Total Revenue= Σ (Grain Output (Kg) * Unit grain prices ($/Kg) + (Stover Output (Kg) * Unit stover prices)…………………..(3)

Average local market prices obtained by the farmers were used to compute returns. The farm gate price of the output is the value (price) farmers receive or can receive for their harvested crops. Total variable input costs refer to the sum of all variable input costs and vary from one CSA technology to another.

$TVC = \Sigma Ct = P_{landprep}Q_{landprepr} + P_{basalfertiliser}Q_{basalfertiliser} + P_{topdressingfertiliser}Q_{topdressingfertiliser} + P_{seed}Q_{seed} + P_{labor}Q_{labor} + \ldots + P_nQ_n$……………………………………………………………..(4)

The benefit-to-cost ratio (BCR), a financial ratio that is used to determine whether the amount of money made through a project will be greater than the costs incurred in executing was also computed as follows:

BCR= (Benefit/Costs) ………………………………(5)

For each CSA technology, the total costs incurred when using that strategy and benefits were computed to compute the net benefit for that particular adaptation strategy.

Return on Investment:

Return on investment values helps link the value of technologies to users. The Return on Investment (ROI) value is more powerful than the benefit-cost ratio because the ROI value shows the net return for a $100 investment.

ROI= (Net Benefit/ TVC) *100……………………………….(6)

6.3.2 Stochastic Frontier model

The stochastic frontier models have been used extensively even in agriculture, to model input-output relationships and to measure technical efficiency (Greene, 2010). These were first proposed in the context of production function estimation to account for the effect of technical inefficiency (Wang, 2008). The analytical method has been used to compare the performance of farmers under different technological regimes. For example, the method has been used to examine the impact of technology adoption on the output and technical efficiency of rice farmers (Villano et al. 2015). In this study, the stochastic frontier model is used to compare the technical efficiency of farmers using CSA versus those who are not using any CSA technology. The model is specified as follows:

$y = \beta' x + \varepsilon_i$…………………………………………………………….(7)

where y =observed outcome in this case maize profitability estimated by the Gross margin (goal attainment), x is the logarithm of costs of that input, coefficient β are parameters estimated

ε_i is the error term. The error structure is specified as follows:

$\varepsilon_i=v_i-u_i\varepsilon_i=v_i-u_i$ …………………………………………(8)
$u_i=|\sigma u U_i|=\sigma u|U_i|$where $U_i\sim N(0,1)u_i=|\sigma u U_i|=\sigma u|U_i|$where $U_i\sim N(0,1)$…..(9)
$v_i=\sigma v V_i$ where $V_i\sim N(0,1)v_i=\sigma v V_i$ where $V_i\sim N(0,1)$…………………….(10)
Thus the stochastic model is:

$y = \beta' x + v - u$, ……………………………..(11)

$\beta' x + v$ is the optimal, frontier goal (e.g., maximal production output or minimum cost) pursued by the individual, $\beta' x$ is the deterministic part of the frontier and $v \sim N[0,\sigma v^{2}]$ is the stochastic part. v_j is the stochastic (white noise) error term and u_j is a one-sided error representing the technical inefficiency of firm j. Both v_j and u_j are assumed to be independently and identically distributed

Given that the profitability of each farmer can be estimated as:

$GM_j= \Sigma$ Log $X-U_j$…………………………… (12)

while the efficient level of profitability (i.e. no inefficiency) is defined as:

$GM^*_j= \Sigma$Log X)……………………… (13)

then technical efficiency (TE) can be given by:

GM_{j-} $GM_{j=-}U_j$…………………………………… (14)

Inefficiency model is modelled using farm-specific, market-specific and household characteristics and can therefore be estimated as follows:

$U_j=\alpha+ \alpha_i Z_i+\varepsilon i$……………………………………….(15)

$U_j = \alpha + \alpha_1 Z_{1+} \alpha_2 Z\alpha_{2+} \alpha_3 Z_3 + \ldots\ldots\ldots\ldots\ldots\ldots\alpha_n Z_n + \varepsilon_i$ (16)

Where U_j is technical inefficiency of the j the farm

Z_1 to Z_n are the determinants and ε_i is the disturbance term and the coefficients $\propto$ are parameters estimated. Stochastic frontier models allow analysing technical inefficiency in the framework of production functions. Production units such as households are assumed to produce according to a common technology and reach the frontier when they produce the maximum possible output for a given set of inputs. Inefficiencies can be due to structural problems or market imperfections and other factors which cause countries to produce below their maximum attainable output. The stochastic frontier model decomposes the growth of the output variable into changes in input use, changes in technology and changes inefficiency. All parameters in the stochastic frontier and the technical inefficiency effects model are simultaneously calculated by a single-stage maximum likelihood estimation procedure using sfcross command in Stata (Coelli, 1996). Table 19 gives a summary of all the variables thus used in the stochastic frontier model.

Table 19:Stochastic frontier model variables

Variable	Frontier regression model (Efficiency Factors) dependent variable *yi* is the maize gross margin in US$		
X1	SEEDcosts	Seed Costs in US$	Continuous variable
X2	DFERTcosts	Basal fertiliser costs US$	Continuous variable
X3	ANFERTcosts	Topdressing fertiliser costs US$	Continuous variable
X4	LANDPREPcosts	Land preparation costs in US$	Continuous variable
X5	MANUREcosts	Manure costs in US$	Continuous variable
X6	HERBcosts	Herbicides cost US$	Continuous variable
X7	PESTcosts	Pesticides cost US$	Continuous variable
X8	LABOURcosts	Labour costs in US$	Continuous variable
X9	PACKcosts	Packaging costs in US$	Continuous variable
X10	OTHERcosts	Other costs in US$	Continuous variable
	Mu (Inefficiency model)		
Z1	HHSEX	Gender of the household head	Dummy i.e 1=male 0=female
Z2	HHEXPER	Experience household head (years)	Continuous variable
Z3	MEMBERSHIP	Membership to farmer groups	Dummy i.e 1=yes 0=no
Z4	CREDIT	Access to credit	Dummy i.e 1=yes 0=no
Z5	TRADERS	Number of traders locally	Continuous variable
Z6	TAR	Distance to tar (km)	Continuous variable
Z7	Kmextension	Distance to extension (Km)	Continuous variable
Z8	TLU	Total Livestock Units	Continuous variable
Z9	AGROREGION	Agro ecological region	Dummy i.e. 1=wetter (II) 0=otherwise(drier III and IV)
Z10	EXTNcontact	Frequency of extension contact	Continuous variable
Z11	CSAadoption	Use of CSA in maize production	Dummy i.e. 1=yes 0=otherwise

6.4 Results and Discussion

6.4.1 CSA Adaptation Strategies Employed by Households in maize production

Crop production is negatively affected by climate change and as such adoption of CSA technologies is key to increasing yields. Table 20 shows the CSA currently being used by the farmers.

Table 20: Maize CSA technologies

Maize Technology	Goromonzi	Murehwa	Mutoko	U.M.P	Whole sample	Chi-square
Intercropping	24.0%	21.6%	2.0%	5.4%	16.1%	24.23***
Sole CN	5.5%	7.2%	0.0%	6.5%	5.4%	3.66
Rotation	39.0%	54.6%	66.0%	47.3%	48.4%	12.88**
Minimum Tillage	39.0%	35.1%	48.0%	24.7%	35.8%	8.89**
DT Maize	13.7%	11.3%	36.0%	12.9%	15.8%	17.85***
Manure use	13.7%	21.6%	14.0%	8.6%	14.5%	6.69*
Mulching	4.1%	5.2%	10.0%	0.0%	4.1%	8.59**

The results show that farmers use various CSA in maize production with crop rotation being the highest in Mutoko and Murehwa (66% and 54.6% respectively), minimum tillage and DT maize being highest in Mutoko (48% and 36% respectively). Few farmers (less than 10%) are not using any CSA in maize production. This highlights the importance of CSA in smallholder farming communities. Adoption of CSA such as intercropping, rotation, minimum tillage, DT Maize, manure use and mulching was significantly different across the study districts. Overall CSA use is still low at less than 50%. Farmers highlighted during Focus Group Discussions (FGDs) that manure use had become low as there was an outbreak of theileriosis which led to most households being left with no cattle which are the major source of manure. Manure from small ruminants and poultry are prioritised for use in horticulture gardens. Farmers also cited that technologies such as minimum tillage promoted by NGOs were labour intensive and as such people were shunning them in favour of hiring animal-based tillage services. Mulching and intercropping under maize had the least frequencies. Farmers highlighted that mulching was difficult to come by given that Stover was used to feeding livestock. The study further determined CSA technology combinations in maize production using principal component analysis-clustering. Four distinctive clusters were identified using various technologies i.e. Technology Cluster 1 (dominantly min tillage with lower use of rotation, DT maize, manure and intercrop), Technology Cluster 2 (Dominantly rotation use with lower use of intercrop and very low DT, manure and min-till), Technology cluster 3 (higher use of mulch, manure and DT maize, the average use of minimum tillage and rotation and less intercrop) and Technology cluster 4 (Conventional).

6.4.2 Economic Analysis of Maize

Economic analysis was performed to estimate the net return and benefit-cost ratio in various CSA technology bundles. A comparison of costs and returns from various CSA technology combinations in maize production is presented in Table 21.

Table 21: Results of Cost-benefit analysis

	Maize Technology cluster				
Cost-benefit indicators	**Cluster 1 N=178**	**Cluster 2 n=163**	**Cluster 3 n=24**	**Cluster 4 n=21**	**ALL n=386**
Grain (Kg)	1646.41	1815.61	1833.51	1266.87	1711.02
Grain Revenue ($)	643.94	705.14	752.63	488.18	668.91
Stover (Kg)	823.21	907.80	916.75	633.43	855.51
Stover Revenue ($)	32.93	36.31	36.67	25.34	34.22
Total Revenue	**676.87**	**741.45**	**789.30**	**513.52**	**703.13**
Land Preparation Costs	68.85	65.37	67.81	77.46	67.75
Seed (Kg)	25.72	25.20	26.60	29.76	25.78
Seed Costs ($)	67.60	71.71	69.56	68.73	69.59
Compound D Fertilizer (Kg)	204.97	208.33	247.40	180.58	207.80
Compound D Fertiliser costs	137.76	138.44	151.12	134.94	138.76
Ammonium Nitrate fertiliser (Kg)	184.39	187.66	192.53	178.17	185.99
Ammonium Nitrate fertiliser Costs ($)	137.43	137.46	137.08	141.96	137.68
Manure (carts)	0.00	0.02	0.00	0.00	0.01
Manure Costs ($)	30.39	33.22	47.60	30.16	32.72
Herbicides Costs ($)	1.55	2.01	0.29	0.48	1.61
Pesticide Costs ($)	0.38	0.23	2.08	0.00	0.40
Labour Costs ($)	66.36	72.74	47.67	119.05	70.91
Maize Packaging Costs ($)	5.02	6.68	5.05	4.33	5.71

	Maize Technology cluster				
Cost-benefit indicators	**Cluster 1 N=178**	**Cluster 2 n=163**	**Cluster 3 n=24**	**Cluster 4 n=21**	**ALL n=386**
Other Costs ($)	0.21	0.88	2.03	0.00	0.61
Total Variable Costs (TVC)	**515.56**	**528.75**	**530.30**	**577.11**	**525.74**
Gross Margin	**161.30**	**212.70**	**259.00**	**-63.59**	**177.39**
BCR	**1.42**	**1.50**	**1.69**	**0.90**	**1.44**
ROI	**42.17**	**50.06**	**68.82**	**-9.59**	**44.42**

The result showed that the farmers who used CSA had higher gross margin ranging from $259 (Return on investment of 69%) with a BCR of 1.69 under higher CSA use to $161.30 (Return on investment of 42%) and a BCR of 1.42 under low CSA use compared to a negative gross margin under sole conventional practices (-$63.59) with a BCR of 0.9 but negative ROI of close to 10%. This indicates that farmers get at least more than $40 for every $1 spent in maize production using CSA technologies. The difference in profitability is maybe a result of yield differences in the conventional system versus CSA. There are also reduced labour costs brought about by CSA technologies. These findings are consistent with the findings of some researchers (Sain et al., 2017) who found that the incorporation of the CSA practices increased maize yields by 20% or more in comparison to existing farm management systems and Erenstein et al. (2003) who found that yields differed according to production system and technology used.

6.4.3 Estimated Stochastic Frontier profit function

The analysis was done using the sfcross Stata commands for the estimation of parametric stochastic frontier (SF) models using cross-sectional data (Belloti, 2013; Camilla, 2008). Table 3 shows the maximum likelihood estimates for parameters of the stochastic frontier model. Other clusters did not have more than 50 respondents and as such, a single model with a dummy variable for adopters and non-adopters was run. Almost all inputs have positive relations with maize profitability except for fertilisers, herbicide and labour costs that have negative effects on maize output variable.

Table 22 also shows the determinants of technical inefficiency in maize production. Inefficiency is the dependent variable in the Inefficiency model and as such, variables with a negative (positive) coefficient sign will have a positive (negative) impact on technical efficiency. The inefficiency model found that the frequency of extension contact had a negative and significant effect on inefficiency. This implies that farmers with a high frequency of extension contact are more technically efficient. Extension officers impart skills to farmers through one on one visits, training workshops and promotional events like exchange visits and field days. Farmers can thus learn about new technologies when they are in constant contact with extension. This finding is in line with those of Seyoum et al. (1998), Parikh et al. (1995) and Owens et al. (2001). They are also in line with findings from Mango 2015 who found a negative and statistically significant relationship between technical efficiency and extension contact in smallholder farming systems of Zimbabwe following the fast track land reform program. Another researcher, (Tasila Konja et al., 2019) also found a positive impact of extension contact to technical inefficiency in certified groundnut seed production in Northern Ghana.

Correspondingly, the coefficient for the number of traders available locally was negative and significant. This means that farmers who have access to farm gate traders are technically efficient. Maize farmers in most rural areas are constrained when it comes to capital and hence have difficulties accessing distant markets. Therefore, if traders come to buy locally this acts as an incentive for them to produce that particular crop knowing there is a guaranteed market with low transaction costs. Furthermore, the coefficient of CSA adoption was negative and significant. This means that farmers using CSA are more efficient.

Basal dressing fertiliser has a significant negative effect on maize gross margin. An additional 1% of the compound D basal dressing fertiliser will lead to 166.68% decrease in the gross margin. Discussions with farmers and extension pointed to how farmers are applying basal dressing fertiliser. The majority of farmers do not apply the fertiliser at the planting stage but wait for plants to germinate and apply at around three or four weeks from the day of planting which is already too late.

The Stochastic frontier results showed that fertiliser and other costs have a negative and significant effect on the inefficiency of maize profitability. The negative signs of the variables indicate that as these variables increase the profit inefficiency of maize producers' decrease. This means a unit increase in costs of the basal dressing fertiliser (DFERT) and top dressing (ANFERT) will lead to 166.68% and 40.02% increases in profitability respectively. Basal and top dressing fertilizer applications are very critical for maize profitability and the increase in use as proxied by costs will result in increased profitability. Timely agronomic operations (land preparation, weeding etc.) coupled with the application of fertiliser supplements the soil's nutrient stocks which are necessary for plant growth and grain filling.

Table 22: The stochastic frontier model results

	Variables Frontier regression model (Efficiency Factors)	Coef.	Std. Err	P-value
X1	SEEDcosts	102.41	151.51	0.50
X2	DFERTcosts	-166.68**	67.53	0.01
X3	ANFERTcosts	-40.02	67.85	0.56
X4	LANDPREPcosts	106.57	105.16	0.31
X5	MANUREcosts	11.6	27.17	0.67
X6	HERBcosts	-93.47	74.80	0.21
X7	PESTcosts	15.98	121.90	0.90
X8	LABOURcosts	-28.28	24.82	0.25
X9	PACKcosts	1362.15***	79.66	0.00
X10	OTHERcosts	-208.07**	96.51	0.03
	cons	-642.06	324.50	0.05
	Mu (Inefficiency model)			
Z1	HHSEX	-51.86	72.02	0.47
Z2	HHEXPER	152.62**	69.20	0.03
Z3	MEMBERSHIP	18.08	63.86	0.78
Z4	CREDIT	117.29	76.06	0.12
Z5	TRADERS	-145.16**	60.61	0.02
Z6	TAR	-74.88	85.25	0.38
Z7	Kmextension	100.71	64.87	0.12
Z8	TLU	181.94***	59.94	0.00
Z9	AGROREGION	-60.21	63.55	0.34
Z10	EXTNcontact	-167.5**	82.10	0.04
Z11	CSAadoption	-297.64**	125.80	0.02
	cons	436.91**	201.05	0.03
Usigma				
cons		4.65	7.77	0.55
Vsigma				
cons		11.78***	0.09	0.00
sigma u		10.22	39.70	0.80
sigma v		361.46***	15.36	0.00
lambda		0.03	42.72	1.00

*****, **,* indicates statistical significance at 1%, 5% and 10% respectively**

TLU and farming experience had significant positive coefficients implying that as the farmer's TLU/herd size and farming experience increase, the profit inefficiency of the farmers also increases. This contradicts prior expectation and might be explained by the fact that experienced farmers are older and unwilling to invest in any new technologies.

6.5 Conclusions and Recommendations

The most economic adaptation strategy in the face of climate change would be the adoption of CSA technologies as evidenced by positive gross margins and higher returns on investment when compared to the conventional way of farming. This is further supported by the positive effect of CSA adoption on technical efficiency. Farmers should however note that not all adaptation strategies are economical, thus, record keeping of costs and income for regular computation of costs and benefits is crucial. Farmers can then choose technologies that give higher benefits or those that use fewer inputs given that most of the farmers are financially constrained. Based on variables that significantly influenced profit efficiency, the study makes three recommendations.

Government should continue to allocate resources towards supporting the mobility of extension staff, so that they can continue delivering key information on yield-enhancing CSA technologies to farmers. Policies that promote inorganic fertiliser use to boost soil fertility remain critical. Government should therefore strengthen the capacity of rural agro-dealers so that they can sell fertilisers locally at reasonable prices. Policies that promote farm-gate buying or market centres within wards should also be put in place as they have the potential to increase efficiency once farmers are aware of a guaranteed market with very low transaction costs.

References

Kassie, G. T., Abdulai, A., Greene, W. H., Shiferaw, B., Abate, T., Tarekegne, A., and Sutcliffe, C., 2017. Modelling Preference and Willingness to Pay for Drought Tolerance (DT) in Maize in rural Zimbabwe. *World Development*, *94*, 465–477. https://doi.org/10.1016/j.worlddev.2017.02.008

Michler, J. D., Baylis, K., Arends-Kuenning, M., and Mazvimavi, K., 2019. Conservation agriculture and climate resilience. *Journal of Environmental Economics and Management*, *93*, 148–169. https://doi.org/10.1016/j.jeem.2018.11.008

Mujeyi, A., 2018. Policy and Institutional Dimensions in Climate-Smart Agriculture Adoption : Case of Rural Communities in Zimbabwe. In W. Leal Filho (ed.) (Ed.), *Handbook of Climate Change Resilience*. https://doi.org/10.1007/978-3-319-71025-9_66-1

Mujeyi, K., and Mujeyi, A., 2018. Fostering Climate Smartness in Smallholder Farming Systems : Business Promotional Approaches for Improved Maize Varieties in Eastern and Southern Africa. In *W. Leal Filho (ed.), Handbook of Climate Change Resilience, https://doi.org/10.1007/978-3-319-71025-9_24-1*. Springer International Publishing AG, part of Springer Nature.

Papendiek, F., Tartiu, V. E., Morone, P., and Venus, J., 2016. *Assessing the economic profitability of fodder legume production for Green Biore fi neries e A cost-benefit analysis to evaluate farmers profitability*. *112*, 3643–3656. https://doi.org/10.1016/j.jclepro.2015.07.108

Poole, N., 2017. Smallholder Agriculture Market Participation. Rugby, UK: *Food and Agriculture Organization of the United Nations and Practical Action*. http://dx.doi.org/10.3362/9781780449401

Rurinda, J., Mapfumo, P., Wijk, M. T. Van, Mtambanengwe, F., and Rufino, M. C., 2014. Climate Risk Management Sources of vulnerability to a variable and changing climate among smallholder households in Zimbabwe : A participatory analysis. *Climate Risk Management*, *3*, 65–78. https://doi.org/10.1016/j.crm.2014.05.004

Sain, G., María, A., Corner-dolloff, C., Lizarazo, M., Nowak, A., Martínez-barón, D., and Andrieu, N., 2017. Costs and bene fi ts of climate-smart agriculture : The case of the Dry Corridor in Guatemala. *Agricultural Systems*, *151*, 163–173. https://doi.org/10.1016/j.agsy.2016.05.004

Steward, P. R., Dougill, A. J., Thierfelder, C., Pittelkow, C. M., Stringer, L. C., Kudzala, M., and Shackelford, G. E., 2018. The adaptive capacity of maize-based conservation agriculture systems to climate stress in tropical and subtropical environments: A meta-regression of yields. *Agriculture, Ecosystems and Environment*, *251*(September 2017), 194–202. https://doi.org/10.1016/j.agee.2017.09.019

Tasila Konja, D. T., Mabe, F. N., and Alhassan, H., 2019. Technical and resource-use-efficiency among smallholder rice farmers in Northern Ghana. *Cogent Food and Agriculture*, *5*(1), 1–15. https://doi.org/10.1080/23311932.2019.1651473

Thierfelder, C., Chivenge, P., Mupangwa, W., Rosenstock, T. S., Lamanna, C., and Eyre, J. X., 2017. How climate-smart is conservation agriculture (CA)? – its potential to deliver on adaptation, mitigation and productivity on smallholder farms in southern Africa. *Food Security*, 1–24. https://doi.org/10.1007/s12571-017-0665-3

UNCCS, 2019. Climate action and support trends. *United Nations Climate Change Secretariat*. Bonn, Germany.

Waddington, S. R., Karigwindi, J., and Chifamba, J., 2007. The sustainability of a groundnut plus maize rotation over 12 years on smallholder farms in the sub-humid zone of Zimbabwe. African Journal of Agricultural Research Vol. 2 (8), pp. 342-348, August 2007. https://doi.org/10.5897/AJAR.9000733

Kassie, G. T., Abdulai, A., Greene, W. H., Shiferaw, B., Abate, T., Tarekegne, A., and Sutcliffe, C., 2017. Modelling Preference and Willingness to Pay for Drought Tolerance (DT) in Maize in

rural Zimbabwe. *World Development*, *94*, 465–477. https://doi.org/10.1016/j.worlddev.2017.02.008

Michler, J. D., Baylis, K., Arends-Kuenning, M., and Mazvimavi, K., 2019. Conservation agriculture and climate resilience. *Journal of Environmental Economics and Management*, *93*, 148–169. https://doi.org/10.1016/j.jeem.2018.11.008

Mujeyi, A., 2018. Policy and Institutional Dimensions in Climate-Smart Agriculture Adoption : Case of Rural Communities in Zimbabwe. In W. Leal Filho (ed.) (Ed.), *Handbook of Climate Change Resilience*. https://doi.org/10.1007/978-3-319-71025-9_66-1

Mujeyi, K., and Mujeyi, A., 2018. Fostering Climate Smartness in Smallholder Farming Systems : Business Promotional Approaches for Improved Maize Varieties in Eastern and Southern Africa. In *W. Leal Filho (ed.), Handbook of Climate Change Resilience, https://doi.org/10.1007/978-3-319-71025-9_24-1*. Springer International Publishing AG, part of Springer Nature.

Papendiek, F., Tartiu, V. E., Morone, P., and Venus, J., 2016. *Assessing the economic profitability of fodder legume production for Green Biore fi neries e A cost-benefit analysis to evaluate farmers profitability*. *112*, 3643–3656. https://doi.org/10.1016/j.jclepro.2015.07.108

Poole, N., 2017. Smallholder Agriculture Market Participation. Rugby, UK: *Food and Agriculture Organization of the United Nations and Practical Action*. http://dx.doi.org/10.3362/9781780449401

Rurinda, J., Mapfumo, P., Wijk, M. T. Van, Mtambanengwe, F., and Rufino, M. C., 2014. Climate Risk Management Sources of vulnerability to a variable and changing climate among smallholder households in Zimbabwe : A participatory analysis. *Climate Risk Management*, *3*, 65–78. https://doi.org/10.1016/j.crm.2014.05.004

Sain, G., María, A., Corner-dolloff, C., Lizarazo, M., Nowak, A., Martínez-barón, D., and Andrieu, N., 2017. Costs and bene fi ts of climate-smart agriculture : The case of the Dry Corridor in Guatemala. *Agricultural Systems*, *151*, 163–173. https://doi.org/10.1016/j.agsy.2016.05.004

Steward, P. R., Dougill, A. J., Thierfelder, C., Pittelkow, C. M., Stringer, L. C., Kudzala, M., and Shackelford, G. E., 2018. The adaptive capacity of maize-based conservation agriculture systems to climate stress in tropical and subtropical environments: A meta-regression of yields. *Agriculture, Ecosystems and Environment*, *251*(September 2017), 194–202. https://doi.org/10.1016/j.agee.2017.09.019

Tasila Konja, D. T., Mabe, F. N., and Alhassan, H., 2019. Technical and resource-use-efficiency among smallholder rice farmers in Northern Ghana. *Cogent Food and Agriculture*, *5*(1), 1–15. https://doi.org/10.1080/23311932.2019.1651473

Thierfelder, C., Chivenge, P., Mupangwa, W., Rosenstock, T. S., Lamanna, C., and Eyre, J. X., 2017. How climate-smart is conservation agriculture (CA)? – its potential to deliver on adaptation, mitigation and productivity on smallholder farms in southern Africa. *Food Security*, 1–24. https://doi.org/10.1007/s12571-017-0665-3

UNCCS, 2019. Climate action and support trends. *United Nations Climate Change Secretariat*. Bonn, Germany.

CHAPTER 7: OPTIMAL ENTERPRISE MIX IN CROP-LIVESTOCK INTEGRATED FARMING SYSTEMS OF ZIMBABWE: IMPLICATIONS FOR HETEROGENEOUS CLIMATE-SMART AGRICULTURE TECHNOLOGY ADOPTION

7.1 Abstract

Smallholders in integrated crop-livestock farming systems of Mashonaland East province in Zimbabwe, who rely on rain-fed agriculture, have reduced arable and grazing land due to population growth. Besides, they have been experiencing low agricultural productivity due to climate change, which has translated into low incomes and rising food insecurity. Development and research organisations have promoted several CSA technologies as mitigation strategies in communities. These technologies have varying costs and benefits as such adoption requires appropriate investment decisions by farmers. Choosing the optimal enterprise mix becomes one of the most significant challenges facing farmers who have to satisfy multiple objectives and are constrained by key resources such as land, cash and labour among others. Farmers fitted into three distinct bundles based on the extent of their use of CSA. A multi-objective goal programming model with three crops, three livestock enterprises and five constraints, was employed in analysing data from a household survey of 386 farmers in four districts using the e-constraint method across the three technology bundles. Results indicate that only mixed (i.e., crop-livestock integration) entered the feasible plan for all the farmers. The optimal enterprise combinations across the three technology bundles had the following combinations: (i) one hectare under horticulture plus three cattle (technology bundle I), (ii) one hectare under horticulture and two cattle (technology bundle II) and one hectare of groundnuts and three cattle (technology bundle III). This study's policy implication is that government extension staff must educate farmers on the importance of highly profitable enterprises like horticulture. Government must also develop programs to enhance low-input livestock productivity, requiring enterprises like cattle production that emerged in the optimal solution for all technology bundles. Lead or progressive farmers in communities can set up demonstrations to showcase the potential benefits of CSA on integrated crop-livestock farms. The government can also extend credit lines to farmers practising CSA on crop-livestock integration as an incentive for adoption.

Keywords: multiple objective programming models, ε-constraint, scarce resources, optimum enterprise mix, Zimbabwe

7.2 Introduction

Rural smallholder farmers are largely dependent on agriculture, where they dominantly practice crop-livestock integration. Their agricultural enterprises are interlinked and they interact through the exchange of inputs and outputs (Stark et al., 2018; Ng'ang'a et al., 2016; Tui and Valbuena, 2015). Livestock such as cattle and donkeys provide draught power for crop production operations such as ploughing, ridging and weeding (Mkuhlani et al., 2018), while crops can supply supplementary livestock feed as grain, hay or stover. Studies on integrated farming systems have shown that cattle derive 45 per cent to 80 per cent of their feed intake from crop residues of cereals and grain legumes. The cattle are grazed in situ or supplemented from storage racks during the dry season when the rangeland nutrient value is low. (Hellin et al., , 2013; Jaleta et al., 2015; Rusinamhodzi et al., 2015). Manure from livestock plays a pivotal role in maintaining and increasing soil fertility at relatively significantly lower costs than inorganic fertilizers. Crop and livestock enterprises supply food (meat and non-meat products from livestock, grain, tubers, etc. from crops) and generate income (Valbuena and Tui, 2014). Furthermore, livestock serves as security and capital reserve for smallholder farmers as funds from sales can be used to purchase farming inputs in economically risky environments where the currency is not stable and is affected by inflation. Farmers reap various benefits from crop-livestock interactions, including improved yields from timeliness in farming operations from animal traction, enhanced soil fertility from manure, land use efficiency, cushioning against commodity price variability due to diversification and household food security (Asai et al., 2018; Mekuria and Mekonnen, 2018; Teklewold et al., 2019).

Crop and livestock production in these communities are overwhelmed by many constraints, such as limited land resources due to increasing human population and low yield levels. The most prominent challenge negatively affecting productivity is inadequate and variable rainfall for production due to climate change. Climate change effects such as rising temperatures coupled with altered rainfall patterns have reduced productivity of crop-livestock integrated smallholder farming systems that rely on rain-fed cultivation of crops and rangeland for livestock feed (Wineman and Crawford, 2017). Livestock productivity has declined mainly due to reduced grazing areas, poor quality rangeland, and shortage of feed during the dry winter season. Similarly, crop productivity has also declined due to soil fertility loss, inadequate rains and excessive temperatures. Recent technological development by various organisations has prioritised climate-smart agriculture (CSA) as a panacea to increasing crop and livestock productivity in the face of climate change (Teklewold et al., 2019). CSA technologies refer to the innovations that sustainably increase agricultural productivity, help households adapt and be resilient to climate change, and reduce greenhouse gas emissions, thereby ultimately contributing to household food security (Steward et al., 2018). In collaboration with NGOs and international research organisations, Zimbabwe's government has promoted livestock CSA technologies such as fodder production to complement the existing feeding regime (rangeland, crop stover, and crop residue feeding). Crop-based CSA technologies such as conservation agriculture, drought-tolerant maize (*Zea mays*) varieties, nitrogen-fixing legume varieties, cereal-legume intercropping, and rotation systems have also been promoted (Mujeyi, 2018).

The adoption of CSA into crop-livestock integrated systems leads to a complementary relationship between enterprises. Such a relationship is not without challenges. It requires decision-making on allocating scarce resources such as land, capital and labour in a system that faces multiple constraints. The system seeks to optimize various production objectives, including maximising profit or minimising costs (Herrero and Thornton, 2009; Hosu and Mushunje, 2013). Research by (Hettig et al., 2016) on factors necessary for the allocation of resources such as land shows that determinants include technology (6%), markets (15%), demography (11%), household characteristics and endowments (labour, physical capital, human capital, social capital) (45%), infrastructure (15%) and institutions (5%). Farmers have a chance to alter enterprise combinations depending on factors such as natural (e.g., climate, soil condition), asset ownership (e.g., size of arable land holding, productive assets), amount of capital available to purchase inputs needed for technologies adoption and even labour availability for farming. Optimal farm plans can help farmers identify the appropriate enterprises for the farms and efficiently allocate scarce resources (Ndip et al., 2019). Studies have shown that in as much as farmers in their ways allocate resources, they usually end up with suboptimal plans and inefficiency of resource use. Mathematical programming can develop the optimal enterprise mix using heterogeneous CSA technology packages for a given set of resource constraints. Understanding the optimum enterprise mix for farmers given their constraints is crucial for guiding the adoption of innovations and policy for enhancing agricultural productivity and rural development. The findings of this research can therefore benefit development agencies and extension services working in rural areas. These practitioners can use the results to support farmers when making decisions on selecting crop and livestock enterprises. Although development agents have promoted several CSA technologies in crop-livestock integrated smallholder farming systems, there is little knowledge regarding the enterprise mix, which gives high returns under different technology combinations. This study, therefore, was done to fill this gap. Thus, this study's objective is to construct an optimization model for different technology combinations and generate optimal enterprise combinations for smallholder farmers practising integrated crop-livestock farming systems.

7.3 Adoption and Enterprise Planning

Although literature widely acknowledges the importance of CSA in smallholder farming, there is relatively little understanding of optimal enterprise plans under different adoption bundles in an integrated crop-livestock farm context. Smallholder farmers are characterized by low investment capacity, scarce resources, low agricultural productivity, and varying incomes and are currently being affected by climate change (Mujeyi, 2007). The adoption of CSA can increase productivity and enhance farmer's food security and income. However, any new technology will bring about changes in resource use across crop and livestock enterprises. Farmers are bound to re-organise resource use to accommodate the new technologies adopted. Adopting CSA technology is expected to increase productivity for resource-constrained (land, cash) farmers. Therefore, the farmer will attempt to minimize costs and/or maximise gross margin with a given level of input costs. The presence of multiple objectives in the face of competition on the use of inadequate resources, such as land, capital and labour makes multiple objective-programming (MOP) models an appropriate tool (Franscico, 2005). The MOP model generates efficient solutions in a multi-criteria decision-making paradigm. The model allows optimization of several objective functions to design an optimal plan to pursue at different technology adoption levels. This study seeks to fill the knowledge gap on determining the enterprise combination that gives high returns to smallholder farmers practising crop-livestock integration system in Zimbabwe.

7.4.1 Smallholder CSA technology bundles and crop-livestock enterprises

CSA technologies are used as a joint package to address the multiple constraints that smallholder farmers face (Teklewold et al., 2019). Therefore, this study constructed technology bundles using a k-means clustering method. The clusters considered nine dummy variables for CSA technology adoption, i.e., crop rotation, intercropping, mulching, and improved legumes drought-tolerant maize, fodder crops, minimum tillage, use of purchased livestock feed and adoption of fodder trees. PCA categorised farmers into the following three technology bundles:

i. Labour saving and soil fertility enhancing CSA: These farmers are characterized by the use of three CSA technologies on the crop (rotation, minimum tillage and use of animal manure)
ii. Yield increasing and soil fertility enhancing CSA: These farmers are characterized by the use of CSA practices (intercropping, rotation, minimum tillage, mulching, drought-tolerant maize, improved legumes and use of animal manure)
iii. Traditional/non-CSA technology: These farmers use conventional farming techniques with very limited use of CSA. Only crop rotation was dominating for the category.

7.4.4 Data Analysis

The designing of optimum solutions in integrated crop-livestock farming systems has widely used optimization models to show feasible farm plans in the presence of technical, economic (land, labour, and capital) and agronomic constraints (Sintori and Tzouramani, 2019). Optimization models for resource allocation are crucial in investigating how to make the best use of available but limited resources to achieve the best results. Resource allocation plans can be arrived at by using mathematical programming. Various studies have used Linear Programming (LP) (Finley and Brown, 1960), Goal Programming (GP) and multiple objective programming (Jones and Tamiz, 2003). The earlier researchers used single objective optimization models such as Linear Programming. LP is a mathematical optimisation method to achieve the best outcome, e.g., maximum profit, lowest cost (objective function) subject to linear equality and linear inequality constraints. The LP objective function is specified as:

Maximize the objective function $Z=\sum C_i X_i$ *(1) subject to*

Constraints; $\sum A_{ij} X_i \leq b_j$ (2)

Non negativity constraint; $X_i \geq 0$ (3)

where *Z* is e.g. the farm profit; *C* is the net profit for enterprise X and AX shows the A inputs used for X enterprise and b is the amount of resources available on the farm. i=1,2,3…….n representing number of variables while j=1,2,3,….m representing the number of constraints. Linear Programming can be used to determine the most profitable cropping or livestock systems, design least cost livestock feeds, solve resource requirements for given income expectations and even test stability of farm operations through sensitivity analysis (e.g. changing prices, climate or policy). (Butterworth, 1985) used Linear integer programming model to design optimum crop and livestock mix for Bedfordshire farm subject to land, labour, machinery, buildings and capital constraints. Another study (Sumpsi et al., 1997) used LP to design a cost minimisation model in livestock ration feed formulation. The conventional LP mathematical is inadequate to deal with real agricultural planning problems when multiple goals and objectives are important elements. This model is rigid as it does not reflect the real-life scenarios where farmers usually have multiple objectives and constraints that they face in production and marketing. Researchers realise that farmers usually have multiple objectives that can either be minimized or maximised and thus started applying multi-objective optimization. The farmers' goals include maximising profits, minimising working capital requirements, minimising management difficulties, achieving food security etc. (Sumpsi et al., 1997) and has led to the emergence of Goal Programming (GP). GP, originally developed by Charnes and Cooper in 1961, is an important class of multi-criteria decision models widely used to analyse and solve applied problems involving conflicting objectives (Colapinto et al., 2017; Gunantara, 2018). Different fields use GP, e.g., accounting (budgeting, cost allocation, corporate social reporting, asset management, and portfolio selection), marketing (sales operation, media planning), operations (inventory management, transportation) and natural resources. The multiple Goal Programming model can be specified as follows:

$$\text{Max } Z(x) = (Z_1(x), Z_2(x), Z_3(x), \ldots, Z_k(x),$$

$$Z_1(x) = Z_1(x_1, x_2, x_3, \ldots, x_n),$$

$$Z_2(x) = Z_2(x_1, x_2, x_3, \ldots, x_n),$$

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$$Z_k(x) = Z_k(x_1, x_2, x_3, \ldots, x_n),$$

Subject to constraints: $g(x_i) \leq b_i$

X_1 to X_n are the resource constraints that should be less or equal to b_i = available resources on the farm.

A non-negativity constraint $x_i>0$, where i=1,2,3……..,n

Where:

$Z = (Z_1, Z_2, Z_3 \ldots, Z_k)$ is the vector of objective functions with elements; Z_i,

$i = 1, 2, 3, \ldots, k$, are individual objective functions;

X_i, $i = 1, 2, \ldots, n$, is the area allocated to the cultivation of crop enterprise i. Examples of multiple objectives could include maximising farm revenue, minimising production costs, achieving food security, and avoiding risk among others. These objectives may involve multiple goals and involve a hierarchy of goals, which might be potentially conflicting.

Pitakpongjaroen and Wiboonpongse (2015) used Multiple Goal Linear Programming (MGLP) to maximize four-goal, i.e., maximizing income, and ensuring rice sufficiency for household consumption, minimizing chemical and fertiliser costs subject to constraints that included land, labour and capital. A study in New York State designed the optimal mixed crop-livestock options using multi-objective mixed-integer nonlinear fractional programming (MINLFP) problem, which consisted of the fractional objective function and nonconvex nonlinear constraints in light of the adoption of sustainable agriculture practices (Liang et al., 2018). Researchers in Argentina used Multi-Criteria Decision Modelling (MCDM) to design land allocation to crops and extensive livestock production (Cabrini and Calcaterra, 2016). Soltani et al. (2011) used a Fuzzy Goal Programming (FGP) model, goal programming (GP), and linear programming (LP) models to model optimal cropping patterns, where the objective was to maximize crop production and net returns, and resource use. Results indicated that the optimum cropping pattern suggested by the FGP gave maximum net return. (Okoruwa and Jabbarht, 1996) designed optimum enterprise mixes for West Africa farmers practising crop-livestock mixed farming using a multiple objective Programming model. The model maximised profit from the farming operations (four livestock activities; cattle caretaking, cattle owning, sheep Owning, goat owning,) and six crop production activities (sole maize, maize-cassava mixed, maize-sorghum-yam mixed, pepper-tomato mixed, maize-yam mixed, and sole okra), subject to land, labour, capital, manure and minimum amount of food crops in tonnes produced for family consumption constraints. Other researchers in South Africa used the multi-objective linear programming (LP) model to determine crop and livestock enterprises that maximise total gross margin among small farms in the Eastern Cape Province

(Hosu and Mushunje, 2013). In Ethiopia, Mellaku and Reynolds (2018) used an LP model with the objective of profit maximization and satisfying food crop production under two hypothetical land-allocation scenarios subject to ecological constraints (total land available cannot be exceeded), budget constraints (estimated based on prior household expenditures and assuming no access to credit outside resources), and food crop production requirements constraint.

Several ways can generate optimal solutions for the GP model:

i. ***The multi-objective simplex method*****:** Optimal solutions are obtained by moving from one extreme solution (point) to the adjacent extreme solution (point) by a simplex 'pivoting' operation. lf the extreme point is efficient, it is stored, otherwise, it is eliminated (Okoruwa and Jabbarht, 1996).

ii. ***The weighted Sum method:*** The method scalarise a set of objectives into a single objective by adding each objective pre-multiplied by an agreed weight subject to set constraints. The method converts multiple objectives into a combined objective function by multiplying each objective function by a weighting factor and summing up all weighted objective functions. The weight of an objective is chosen in proportion to its relative importance.

$$Max\ F(x) = \sum_{m=1}^{m} Wmf_j(X),$$

Subject to constraints: $g_j\ (x_1, x_2, \ldots, x_n) \leq b_i$ where $j=1,2,3,\ldots,j$

$x_i > 0$, where $i=1,2,3\ldots\ldots.,n$

This method is simple but has the challenges of not finding Pareto-optimal solutions in a non-convex objective. It is difficult to set weights to obtain a Pareto optimal solution. The weighted sum goal programming method is ideal when all the objectives are compared directly and the decision-maker can assign weights that reflect the relative importance of the objectives. This method is a powerful tool when the decision-maker is interested in a solution that gives a pure overall lowest sum of weighted deviations from the goals rather than an overall balance between achieving those goals as it will show the trade-offs between the objectives. The drawbacks of the weighted sum method are that the optimal solution distribution is often not uniform and that optimal solutions in non-convex regions are not detected. The combined weighted sum transforms the optimization problem into a single objective, which is not necessarily equivalent to the original multi-objective problem. The extra weighting coefficients could be arbitrary. In contrast, the final solutions still depend on these coefficients. Furthermore, there are so many ways to construct the weighted sum function i.e., linear, and there is no easy guideline to choose which form is the best for a given problem (Yang, 2014).

iii. ***The Epsilon constraint (ε-constraint) method:*** In this method, the multi-objective is converted into a single-objective optimization problem. This is achieved by retaining the objective function with the highest priority. All the other objective functions are converted into additional constraints (Zhang and Reimann, 2014; Hartillo-Hermoso et al., 2020). The method has the advantage of being applicable to both convex and even non-convex problems. In this method, the k^{th} objective function is optimised and the remaining k-1 objectives converted to constraints represented as follows:

Max $Z_k\ (x_a, x_2, x_3,\ldots x_n)$,

Subject to:

$Z_1(x_1, x_2, x_3,\ldots, x_n) \geq b_1$

$Z_2(x_1, x_2, x_3,\ldots, x_n) \geq b_2$

$Z_3(x_1, x_2, x_3,\ldots, x_n) \geq b_3$

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$Z_{(k-1)}\ (x_1, x_2, x_3,\ldots, x_n) \geq b_{(k-1)}$ and

$x_i > 0$,

Where b_1, b_2, b_3,…. $b_{(k-1)}$ is the limit on objectives now converted to constraints in the optimisation model

iv. ***Lexicographic/ pre-emptive Goal Programming:*** This method is ideal when the decision-maker has a natural ordering of the objectives (Jones and Tamiz, 2003). The method is used when the decision-maker cannot provide the relevant relative importance of the objectives using weights. The method assumes the decision-maker has a strictly ordered preemptive preference system among objectives with fixed target levels. Goals will be dealt with in strict sequential order starting with higher goals. Under the method, the deviational variables are assigned into several priority levels and minimised while maintaining the minimal values reached by all higher priority level minimisations.

v. ***The Chebyshev/ Minmax Goal Programming:*** In this method, the maximum deviation from amongst the weighted deviations is minimized, rather than the sum of the deviations. The weights used should reflect the importance of the objective to the decision-maker and as such, the maximum deviation is penalised. The method provides a balance between the objectives' levels rather than a strict minimisation of their sum(Jones and Tamiz, 2003). This study adopted a simple yet efficient constraint method. The farmers' objectives were mainly to maximise profits (measured by gross margin) from crop and livestock enterprises. The other objective was to achieve food security through own production by dedicating at least one acre of land to maize production and this was converted into a constraint in the model. The Multiple Objective Goal Programming model used in this study is thus:

Objective function:

$$Max\ GM = \sum_{j=1}^{m} GM_j \qquad \text{subject to constraints discussed in the section below (1)}$$

Where;

GM_j is the sum of Gross Margins, in US$, of all activities (livestock plus crops), i.e., j=1, 2, 3,….*m* enterprises. This study considered the top three crop and top three livestock enterprises.

Constraints

The resource restrictions included in the integrated crop-livestock model had labour, land, capital, manure and food security as informed by literature. A study in Bangladesh used the LP model to maximize the contribution obtained from cropping in a single-crop year plus imported crops subject to land, food requirements and capital to determine the optimum land capital allocation (Sarker, 1997). Researchers in India used a dynamic non-linear programming bio-economic model to get the optimal mix for the crop, livestock, and forest activities subject to a set of constraints, such as land area according to quality, seasonal labour requirements, and capital availability (Sharma et al., 2010). Labour is a significant input into smallholder farming systems and it is critical for ensuring timeliness in production operations such as planting and weeding. A delay in weeding leads to high competition for nutrients and water between crops and weeds, which ultimately leads to potential yields losses ranging from 25% to 100% (Dahlin and Rusinamhodzi, 2019). Cropland in a communal area is fixed and a farmer decides on how to use it. Pastures are also specified in size but communally owned. Capital owned by a household is crucial since it helps farmers purchase inputs such as herbicides for the cropping enterprises and vaccines, feed, or any veterinary services for livestock. Sources of income for farmers include crop and livestock sales, pensions, remittances and livestock, a wealth store. Manure from livestock is used for organic fertilization (Asai et al., 2018). Cattle manure is typically used in maize fields, while manure from small ruminants such as goats and poultry are used in gardens for horticulture crops. Besides, the food security objective was converted into a constraint through the staple maize, production as per the e-constraint method of Goal Programming.

Constraint 1: Cropping Land

The land is a vital factor in an integrated crop-livestock production system where the amount of land available for a cash crop, food crop, and fodder crops is directly related to the amount of available land on the farm. The land is the most critical limiting factor and is the main resource of production. Land for the cultivation of crops is expressed on a hectare basis. The land constraint limits the total available area of land allocated to different cropping enterprises. Relatively minor crops are not considered for modelling purposes. Thus, crops grown on more than half a hectare of the land area were included in the model. The constraint is given by:

$$\sum_{i=1}^{n} \mathrm{Li} \leq \mathrm{A}$$

Where Li is the land under crop i. The crop enterprises are from 1 to n possible options. The model considered three enterprises, i.e., maize, groundnuts and horticulture. *A* is the total arable farmland in hectares

Constraint 2: Grazing Land

Rangeland pastures are the source of feed for livestock and are communally owned. The available grazing used was based on the stocking rates in these areas.

$$\sum_{i=1}^{m} \mathrm{Lvi} \leq \mathrm{Lgrazing}$$

where Lvi is the land requirement for the livestock enterprises while $L_{grazing}$ is the total grazing land available. The grazing capacities determined this. The number of grazing animals converted in livestock units (LU) per grazing area over a given reference period (annually, grazing season). The farmers in these districts highlighted that while grazing was communally owned, extensive livestock production is now constrained in communal areas. The rise in population has led to encroachment into grazing areas. Limited grazing land means more labour for herding during the summer season which is already a scarce resource. Therefore, the herd sizes have been declining due to periodic droughts and loss of grazing lands.

Constraint 3: Labour

Family supply labour for agriculture activities and then hires labour during peak periods. The farmers indicated during FGDs that households work for approximately five days a week (the two days are weekends committed for religion e.g. church while a day is also culturally regarded as sacred and no farm operation is done on this day.

$$\sum L_{crop} + \sum L_{Livestock} \leq L_h \text{……………………….(3)}$$

where L_{crop} and $L_{Livestock}$ is the labour required for the crop and livestock enterprises and L_h is the labour available for use (family labour plus hired annually)

Constraint 4: Capital

$$\sum K_{crop} + \sum K_{Livestock} \leq K_h \text{………………………..(4)}$$

where K_{crop} and $K_{Livestock}$ capital requirement for the crop and livestock enterprises while K_h is the capital available (estimated by household income and assets such as livestock that can easily be sold to generate money for inputs purchase. Capital is important for purchasing farming inputs such as organic fertilisers, certified hybrid and open-pollinated seeds, pesticides, herbicides, etc. Households also need capital allocation for buying spray dip chemicals to prevent tick-borne diseases such as January diseases that can lead to deaths among cattle. The farmers relied on proceeds from previous harvests and were involved in other off-farm activities. The optimisation model was run in GAMS (General Algebraic Modelling System) software.

Constraint 5: Manure

$\sum M_{crop} \leq M_{h}$……………………….(5)

where M_{crop} is total manure used in all the crops which should be less or equal to the manure available from the household that is produced from livestock owned.

Constraint 6: Food Security Constraint

$\sum F_{maizeKg} \geq M_{zh}$ ……………………..(6)

where $F_{maizeKg}$ is the total amount of maize produced in Kg, which should be greater or equal to household maize cereal requirements annually, i.e.,. M_{zh}…Per capita consumption of corn is estimated at 110kg per annum. Smallholder farmers put importance on food security that is achieved through the own production of maize, the staple food crop in these communities.

Constraint 7: Non Negativity Constraint

All inputs costs should be positive, e.g., labour costs >0

7.5 Results and Discussion

Tables 23 and 24 presents descriptive results. Table 23 shows the percentage of households growing a particular crop and rearing certain livestock across technology bundles. The results show that there is a significant difference in the percentage of households growing groundnuts, horticulture crops, rearing of poultry and goats across the technology bundles.

Table 23: Existing crop and livestock enterprises

	Technology bundle			
Household growing/rearing	**Tech bundle I (%)**	**Tech bundle II (%)**	**Tech bundle III (%)**	**Pearson Chi-Square Tests**
Maize	95.9	99.1	96.4	2.38
Groundnuts	75.1	74.8	53.6	16.76***
Cowpea	13.6	12.1	6.4	3.69
Mucuna	4.1	0.9	5.5	3.40
Lablab	1.8	0.9	1.8	0.37
Field cash crops	3.6	3.7	1.8	0.86
Horticulture	20.7	53.3	14.5	48.25***
Cattle	42.0	42.1	35.5	0.49
Poultry	77.5	59.8	62.7	11.78**
Goats	45.6	57.9	36.4	10.24*
	1.2	5.6	1.8	5.45
Donkey	1.8	3.7	1.8	1.29
Rabbits	5.9	3.7	1.8	2.88

***, **, *, indicates significance level at 1%, 5% and 10% Source: Survey Data

The dominant crops across all the technology bundles are maize (more than 90%) and groundnuts (more than 50%), while technology bundle II farmers also grew a lot of horticulture crops (53.3%). Maize is the staple crop and as such, farmers have a goal to achieve food security through their production.

Overall, the area under maize averages 1.36 hectares and that of groundnuts average 0.59 hectares (Table 24). Other minor crops grown by very few households (less than 5%) include mucuna, lablab and cash crops such as tobacco. Mucuna and lablab are relatively new fodder crops that have been introduced in crop-livestock integrated farming systems to address the challenge of livestock feed shortage during the winter season. Adoption is still low as shown by the figures. As such, more work on scaling technology is still needed. The households' top three livestock enterprises are poultry, goats and cattle reared under an extensive system i.e. grazing on communally owned pastures during the day and feeding on crop residues such as groundnuts and maize stover during the dry season. The most important livestock and crop enterprises' profitability under different technology bundles was measured using the gross margin technique.

Table 24: Numbers of livestock owned and hectares under different crops

	Technology Bundle				
	Bundle I	**Bundle II**	**Bundle III**	**ALL**	**F value**
Numbers owned by Household					
Goats	1.81 (2.47)	2.39 (2.85)	1.58 (2.76)	1.91(2.68)	2.71**
Poultry	21.40 (23.45)	19.53 (23.01)	17.65(16.63)	19.97(21.74)	0.69
Cattle	1.80(2.86)	2.43(3.53)	1.59(3.19)	1.92(3.16)	2.11
Donkeys	0.03 (0.23)	0.11(0.59)	0.03(0.21)	0.05(0.36)	2.05
Pigs	0.08(0.76)	0.16(0.73)	0.09(0.86)	0.10(0.78)	0.38
Rabbits	0.26(1.34)	0.23(1.49)	0.15(1.14)	0.22(1.33)	0.22
The area under crop enterprise					
Maize	1.36 (0.89)	1.42(1.13)	1.30 (1.15)	1.36 (1.04)	0.32
Groundnut	0.54(0.51)	0.75 (0.42)	0.48 (0.45)	0.59 (0.48)	7.19***
Cowpeas	0.48(0.43)	0.43 (0.23)	0.56 (0.32)	0.48 (0.36)	0.33
Mucuna	0.96(0.75)	1.00	0.83 (0.41)	0.91 (0.57)	0.08
Lablab	0.00(0.04)	0.05 (0.48)	0.01 (0.05)	0.02 (0.26)	1.01
horticulture crops	0.66(0.84)	0.68 (0.4)	0.58 (0.56)	0.66 (0.59)	0.36
Field cash crops	0.03(0.11)	0.11 (0.48)	0.03 (0.14)	0.05 (0.28)	2.05
Other food crops	0.12(0.14)	0.14 (0.3)	0.04 (0.26)	0.10 (0.31)	1.78

***, **, *, indicates significance level at 1%, 5% and 10% Source: Survey Data. Figures in parentheses are standard deviation.

Multiple Goal Programming Results

The model used three crops (maize, groundnut and horticulture) and three livestock activities because of their cultivation prevalence and importance among surveyed districts. The household decision problem is how much land to allocate to each crop and the number of livestock to keep, given the set objectives and available resources.

Profit Performance under Technology Bundle 1

The optimum enterprise combination under technology bundle 1 is formulated using the equations in Table 25.

Table 25: Multiple objective programming model for technology bundle 1 farmers in Mashonaland East Province, Zimbabwe

Objectives/Constraints	Equations
Maximise Gross margin	Max 200.44x1 + 465.71x2 + 1141.82x3 + 849.27x4 + 18.47x5 + 25.77x6 s.t
Land area (hectares)	x1 + x2 + x3 <= 1.36
Food security proxy (maize requirements) for consumption (Kg)	1852.13x1 >= 531.78
Household labour (man-days)	21.75x1 + 46.37x2 + 52.76x3 + 80.55x4 + 26.82x5 + 17.34x6 <= 482.57
Household capital (US$)	512.49x1 + 398.19x2 + 600.78x3 + 150.35x4 + 44.91x5+ 55.57x6 <= 1335.66
Manure (carts)	6.93x1 + 10.55x3 <= 11
Grazing area (hectares)	7.95x4 + 1.58x5 + 1.77x6 <= 25
Non negativity	x1 >= 0, x2 >= 0, x4 >= 0, x5 >= 0, x6 >= 0

The multiple objective goal optimisation model results show that an average farmer under technology 1 who has adopted labour saving and soil fertility enhancing CSA should have 0.32 Ha groundnuts, 1.04 Ha horticulture and rear three cattle to maximise whole farm profit at $4 008.96 annually.

Table 26: Multiple programming optimum enterprise combinations against the existing plan for technology 1

Variable	**Enterprise**	**Technology bundle I**		
		Existing Plan	**Optimum plan**	**Difference (increase / decrease)**
X_1	Maize (ha)	1.36	0	-1.36
X_2	Groundnuts (ha)	0.54	0.32	-0.22
X_3	Horticulture (ha)	0.66	1.04	0.38
X_4	Cattle (numbers)	1.8	3.15	1.35
X_5	Goats (numbers)	1.81	0	-1.81

Variable	Enterprise	Technology bundle I		
		Existing Plan	**Optimum plan**	**Difference (increase / decrease)**
X_6	Poultry (numbers)	21.4	0	-21.4
z	Profit to be maximised		4008.98	

Profit Performance under Technology Bundle 2

The optimum enterprise combination under technology bundle 2 is formulated using the equations in Table 27.

Table 27: Multiple objective programming model for technology bundle 2 farmers in Mashonaland East Province, Zimbabwe

Objectives/Constraints	Equation
Maximise Gross margin	Max 137.52x1 + 243.4x2 + 909.49x3 + 1047.29x4 + 103.8x5 + 23.52x6 s.t
Land area (hectares)	x1 + x2 + x3 <= 1.42
Food security proxy (maize requirements) for consumption (Kg)	1370.08x1 >= 580.84
Household labour (man-days)	18.69x1 + 29.11x2 + 33.05x3 + 108.33x4 + 27.87x5 + 15.82x6 <= 413.07
Household capital (US$)	416.2x1 + 258.17x2 + 613.17x3 + 202.22x4+ 46.66x5+ 50.7x6 <= 1400.79
Manure Carts	5.81x1 + 10.43x3 <= 13
Grazing area	12.15x4 + 2.39x5 + 1.95x6 <= 25
Non negativity	x1 >= 0, x2 >= 0, x3 >=0, x4 >= 0, x5 >= 0, x6 >= 0

The optimum tech bundle II plan shows that the average farmer in that category should concentrate on two crops and one livestock enterprise. These are 0.174 ha of groundnuts, 1.25 ha horticulture and two cattle to maximise profit to a level of $3,357 annually. Horticulture is a high-value enterprise and the farmers in the four districts have the advantage of having access to a ready market within districts and to the biggest open market in Zimbabwe located in Harare i.e. Mbare Musika, where commodities are sold for cash daily throughout the year. Horticulture has great potential for farmers who have water to irrigate throughout the year as this enterprise can provide increased returns in the short run. Farmers can use the income generated from horticulture to meet the staple food requirements by purchasing maize from fellow farmers or maize meals from shops. Results for this technology bundle II are supported by researchers such as (Liang et al., 2018) who also found out that it was economical to cultivate high-value crops and raise a moderate number of cows.

Table 28: Multiple programming existing and optimum Enterprise combinations against the existing plan for technology bundle II

Variable	Enterprise	Technology Bundle II		
		Existing Plan	Optimum plan	Difference (increase / decrease)
X_1	Maize (ha)	1.3	0	-1.3
X_2	Groundnuts (ha)	0.48	0.174	-0.306
X_3	Horticulture (ha)	0.58	1.246	0.666
X_4	Cattle (numbers)	1.59	2.06	0.47
X_5	Goats (numbers)	1.58	0	-1.58
X_6	Poultry (numbers)	17.65	0	-17.65
z	Profit to be maximised		3357	

Profit Performance under Technology Bundle 3

The optimum enterprise combination under technology bundle 3 is formulated using the following equations:

Table 29: Multiple objective programming model for technology bundle 3 farmers in Mashonaland East Province, Zimbabwe

Objectives/Constraints	Equation
Maximise Gross margin	Max 168.07x1 + 493.62x2 + 1312.11x3 + 923.51x4 + 109.36x5 + 21.25.77x6 s.t
Land area (hectares)	x1 + x2 + x3 <= 1.3
Food security proxy (maize requirements) for consumption (Kg)	1721.95x1 >= 522
Household labour (man-days)	23.53x1 + 51.88x2 + 63.09x3 + 84.13x4 + 29.36x5 + 14.3x6 <= 445.88
Household capital (US$)	501.66x1 + 464.79x2 + 1332.29x3 + 157.05x4+ 49.16x5+ 45.82x6 <= 1082.71
Manure Carts	2.17x1 + 8.61x3 <= 9.55
Grazing area	7.95x4 + 1.58x5 + 1.77x6 <= 25
Non negativity	x1 >= 0, x2 >= 0, x3 >=0, x4 >= 0, x5 >= 0, x6 >= 0

The optimisation model results show farmers in the technology bundle III (traditional non CSA adopting farmers) will maximise profits by combining two enterprises, i.e. groundnuts and cattle. An average farmer under technology bundle III can optimise profit at $3,529.49 by growing 1.27 ha groundnuts and rearing three cattle. The optimised solutions all included crop and livestock enterprises highlighting the importance of crop-livestock integration. The model suggested reducing the maize area from 1.3 to 0.3 ha and nearly doubling the groundnut area.

Table 30: Multiple programming existing and optimum enterprise combinations against the existing plan for technology bundle III

		Technology Bundle III		
Variable	**Enterprise**	**Existing Plan**	**Optimum plan**	**Difference (increase / decrease)**
X_1	Maize (ha)	1.42	0	-1.42
X_2	Groundnuts (ha)	0.75	1.267	0.517
X_3	Horticulture (ha)	0.68	0	-0.68
X_4	Cattle (numbers)	2.43	3.145	0.715
X_5	Goats (numbers)	2.39	0	-2.39
X_6	Poultry (numbers)	19.53	0	-19.53
z	Profit to be maximised		3529.49	

Overall, the models show that farmers do better by intensification rather than extensification for the groundnut enterprise (Figure 4). The farmers can get optimal returns by reducing the land under groundnuts and increasing that under high-value enterprises, like horticulture. The Multiple Objective model also showed a considerable shift to large ruminants only, i.e., cattle.

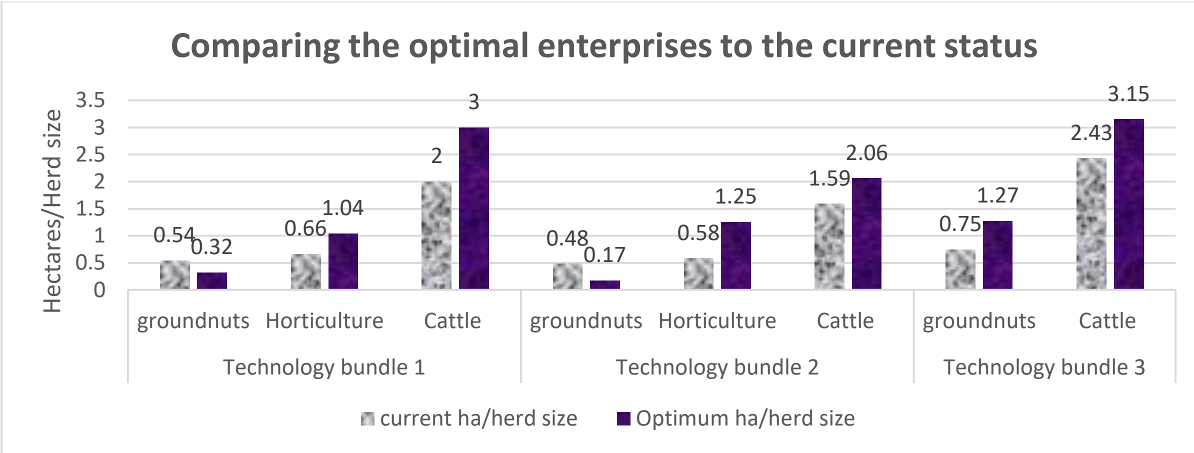

Figure 4:The optimum enterprise combinations (current versus optimal solution)

Poultry, goats and maize are not part of the efficient optimal solutions. This shows that in as much as maize is the staple it cannot currently compete with groundnuts and horticulture. A possibility of maize being part of the optimal solution given that smallholder farmers usually want to meet the maize production through their own production can be achieved through some technology changes that enhance yields. The same applies to poultry which is kept under free-range and goats that are reared under tethering grazing. Goat under tethering has compromised productivity as they have access to grass low in protein and very limited or no access to forage species. CSA technology such as fodder production (mucuna and lablab) could go a long way in supplementing tethered goats thereby increasing the productivity and increasing chances of the enterprise being part of the optimal solution.

7.6 Conclusion and Recommendations

In smallholder crop-livestock integrated farming systems, where the farmers are being exposed to various CSA technologies to address the negative impacts of climate change, they need to make decisions on what crops to grow and area to commit to each crop and herd/flock in line with the scarce resources. Answers to this question can be generated through modelling to get optimal solutions. Results from the Goal Programming optimisation model have shown that the smallholder farmers in crop-livestock farming systems are not efficiently utilising resources. They could improve efficiency by reducing the number of enterprises in a particular season. Extension policy strategies should educate farmers on the importance of intensification and adoption of high-value crops. Farmers with enough water for horticulture can generate extra income enough even to achieve food security through purchases. To make horticulture even more profitable, the farmers could be capacitated to access better-paying markets such as linkages to certain food chains rather than total reliance on the open markets. This study recommends that extension and advisory services promote sustainable intensification. Based on these findings, training programs should focus on equipping farmers with knowledge on the efficient allocation of existing resources to realise optimum benefits.

References

Asai, M., Moraine, M., Ryschawy, J., Wit, J. De, Hoshide, A. K., and Martin, G., 2018. Land Use Policy Critical factors for crop-livestock integration beyond the farm level : A cross-analysis of worldwide case studies. *Land Use Policy*, *73*(November 2017), 184–194. https://doi.org/10.1016/j.landusepol.2017.12.010

Butterworth, K., 1985. Linear / Integer Programming In Agriculture. *Journal of Operational Research Society*, *36*(2), 99–107.

Cabrini, S. M., and Calcaterra, C. P., 2016. Modelling economic-environmental decision making for agricultural land use in Argentinean Pampas. *Agricultural Systems*, *143*, 183–194. https://doi.org/10.1016/j.agsy.2015.12.016

Colapinto, C., Jayaraman, R., and Marsiglio, S., 2017. Multi-criteria decision analysis with goal programming in engineering, management and social sciences: a state-of-the-art review. *Annals of Operations Research*, *251*(1–2), 7–40. https://doi.org/10.1007/s10479-015-1829-1

Dahlin, A. S., and Rusinamhodzi, L., 2019. Yield and labour relations of sustainable intensification options for smallholder farmers in sub - Saharan Africa. A meta-analysis. *Agronomy for Sustainable Development*, *39*(32), 1–18. https://doi.org/10.1007/s13593-019-0575-1

Finley, R., and Brown, D., 1960. EC60-815 Linear Programming. A New Farm Management Tool. *The University of Nebraska-Lincoln Extension*. 3681.

Gunantara, N., 2018. A review of multi-objective optimization: Methods and its applications. *Cogent Engineering*, *5*(1), 1–16. https://doi.org/10.1080/23311916.2018.1502242

Hartillo-Hermoso, M. I., Jiménez-Tafur, H., and Ucha-Enríquez, J. M., 2020. An exact algebraic ϵ-constraint method for bi-objective linear integer programming based on test sets. *European Journal of Operational Research*, *282*(2), 453–463. https://doi.org/10.1016/j.ejor.2019.09.032

Hellin, J., Erenstein, O., Beuchelt, T., Camacho, C., and Flores, D., 2013. Maize stover use and sustainable crop production in mixed crop-livestock systems in Mexico. *Field Crops Research*, *153*, 12–21. https://doi.org/10.1016/j.fcr.2013.05.014

Herrero, M., and Pk, T., 2009. Production systems for the future : balancing trade-offs between food production, efficiency, livelihoods and the environment. *Current Opinion in Environmental Sustainability, 1 (2) 2009, 111-120, https://doi.org/10.1016/j.cosust.2009.10.003.*

Hettig, E., Lay, J., and Sipangule, K. (2016). Drivers of households' land-use decisions: A critical review of micro-level studies in tropical regions. *Land*, *5*(4). https://doi.org/10.3390/land5040032

Hosu, S., and Mushunje, A., 2013. Optimizing resource use and economics of crop-livestock integration among small farmers in semiarid regions of South Africa. *Agroecology and Sustainable Food Systems, 37*(9), 985–1000. https://doi.org/10.1080/21683565.2013.802755

Jaleta, M., Kassie, M., and Erenstein, O. (2015). Determinants of maize stover utilization as feed, fuel and soil amendment in mixed crop-livestock systems, Ethiopia. *Agricultural Systems*, *134*, 17–23. https://doi.org/10.1016/j.agsy.2014.08.010

Jones D.F., Tamiz M. (2003) Analysis of Trends in Distance Metric Optimisation Modelling for Operational Research and Soft Computing. In: Multi-Objective Programming and Goal Programming. Advances in Soft Computing, vol 21. Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-540-36510-5_2

Liang, Y., Wai Hui, C., and You, F., 2018. Multi-objective economic-resource-production optimization of sustainable organic mixed farming systems with nutrient recycling. *Journal of Cleaner Production*, *196*, 304–330. https://doi.org/10.1016/j.jclepro.2018.06.040

Mekuria, W., and Mekonnen, K., 2018. Determinants of crop-livestock diversification in the mixed farming systems : evidence from central highlands of Ethiopia. *Agriculture and Food Security*, *7*(60), 1–15.

Mellaku, M. T., and Reynolds, T. W., 2018. Linear Programming-Based Cropland Allocation to

Enhance Performance of Smallholder Crop Production : A Pilot Study in Abaro Kebele, Ethiopia. *MDPI Resources*, *7*(76). https://doi.org/10.3390/resources7040076
Mkuhlani, S., Mupangwa, W., Macleod, N., Gwiriri, L., Nyagumbo, I., Manyawu, G., and Chigede, N., 2018. Crop-livestock integration in smallholder farming systems of Goromonzi and Murehwa, Zimbabwe. *Renewable Agriculture and Food Systems*. https://doi.org/10.1017/S1742170518000558
Mujeyi, A., 2018. Policy and Institutional Dimensions in Climate-Smart Agriculture Adoption : Case of Rural Communities in Zimbabwe. In W. Leal Filho (ed.) (Ed.), *Handbook of Climate Change Resilience*. https://doi.org/10.1007/978-3-319-71025-9_66-1
Ndip, F. E., Molua, E. L., Shu, G., and Mbiafeu, M. F., 2019. Farm Planning for Short-term Optimal Food Crop Combination in the Southwest Region of Cameroon. *Journal of Food Security*, *7*(3), 72–79. https://doi.org/10.12691/jfs-7-3-2
Ng'ang'a, S. K., Bulte, E. H., Giller, K. E., Ndiwa, N. N., Kifugo, S. C., McIntire, J. M., Rufino, M. C., 2016. Livestock wealth and social capital as insurance against climate risk: A case study of Samburu County in Kenya. *Agricultural Systems*, *146*, 44–54. https://doi.org/10.1016/j.agsy.2016.04.004
Zhang, W., & Reimann, M. (2014). A simple augmented ∊-constraint method for multi-objective mathematical integer programming problems. European Journal of Operational Research, 234(1), 15–24. doi:10.1016/j.ejor.2013.09.001
Okoruwa, V., and Jabbarht, M. A., 1996. Crop-Livestock Competition in the West African Derived Savanna : Application of a Multi-objective Programming Model *. *Agricultural Systems*, *52*(August 1994), 439–453.
Pitakpongjaroen, T., and Wiboonpongse, A., 2015. Optimal Production Systems in Highland Communities in Chiang Mai Province. *Agriculture and Agricultural Science Procedia*, *5*, 22–29. https://doi.org/10.1016/j.aaspro.2015.08.004
Rusinamhodzi, L., van Wijk, M. T., Corbeels, M., Rufino, M. C., and Giller, K. E., 2015. Maize crop residue uses and trade-offs on smallholder crop-livestock farms in Zimbabwe: Economic implications of intensification. *Agriculture, Ecosystems and Environment*, *214*, 31–45. https://doi.org/10.1016/j.agee.2015.08.012
Sharma, R. K., Sankhayan, P. L., and Singh, R., 2010. Land-use changes and forest degradation in a Himalayan watershed: Analysis and policy alternatives1. *Journal of Natural Resources Policy Research*, *2*(3), 263–280. https://doi.org/10.1080/19390459.2010.486150
Sintori, A., and Tzouramani, I. (2019). Greenhouse Gas Emissions in Dairy Goat Farming Systems : Abatement Potential and Cost. *MDPI Animals*, *9*.
Soltani, J., Karbasi, A. R., and Fahimifard, S. M., 2011. Determining optimum cropping pattern using Fuzzy Goal Programming (FGP) model. *African Journal of Agricultural Research*, *6*(14), 3305–3310. https://doi.org/10.5897/AJAR11.585
Stark, F., González-García, E., Navegantes, L., Miranda, T., Poccard-Chapuis, R., Archimède, H., and Moulin, C. H., 2018. Crop-livestock integration determines the agroecological performance of mixed farming systems in Latino-Caribbean farms. *Agronomy for Sustainable Development*, *38*(1). https://doi.org/10.1007/s13593-017-0479-x
Steward, P. R., Dougill, A. J., Thierfelder, C., Pittelkow, C. M., Stringer, L. C., Kudzala, M., and Shackelford, G. E., 2018. The adaptive capacity of maize-based conservation agriculture systems to climate stress in tropical and subtropical environments: A meta-regression of yields. *Agriculture, Ecosystems and Environment*, *251*(September 2017), 194–202. https://doi.org/10.1016/j.agee.2017.09.019
Sumpsi, J. M., Amador, F., and Romero, C., 1997. On farmers' objectives: A multi-criteria approach. *European Journal of Operational Research*, *96*(1), 64–71. https://doi.org/10.1016/0377-2217(95)00338-X
Teklewold, H., Gebrehiwot, T., and Bezabih, M., 2019. Climate-smart agricultural practices and gender-differentiated nutrition outcome : An empirical evidence from Ethiopia. *World Development*, *122*, 38–53. https://doi.org/10.1016/j.worlddev.2019.05.010
Tui, S. H., and Valbuena, D., 2015. Economic trade-offs of biomass use in crop-livestock systems :

Exploring more sustainable options in semi-arid. *Agricultural Systems*. https://doi.org/10.1016/j.agsy.2014.06.009

Valbuena, D., and Tui, S. H., 2014. Conservation Agriculture in mixed crop-livestock systems : Scoping crop residue trade-offs in Sub-Saharan Africa and South ... *Field Crops Research*, *132*(February 2012), 175–184. https://doi.org/10.1016/j.fcr.2012.02.022.

Wineman, A., and Crawford, E. W., 2017. Climate change and crop choice in Zambia: A mathematical programming approach. NJAS - Wageningen Journal of Life Sciences, 81, 19–31. doi:10.1016/j.njas.2017.02.002

CHAPTER 8: CONCLUSIONS AND RECOMMENDATIONS

8.1 Introduction

The preceding chapters to this research covered four broad areas to understand how CSA can integrate mitigation and adaptation strategies for smallholder farmers in integrated crop-livestock farming systems. These included discussing climate change effects, CSA technologies that can be used to adapt and mitigate the negative effects, adoption (patterns, determinants and impacts) and modelling the optimal enterprise mix for various CSA technology combinations. This final chapter summarises empirical results in objectives. Furthermore, the chapter discusses the contributions of the research and areas for further investigations.

8.2 Summary and Key findings

Chapter 1 introduced the CSA concept that has been promoted in Sub Saharan Africa to address the negative impacts caused by climate change and variability. The government of Zimbabwe in collaboration with research and development organisations has promoted CSA given 70% of the population rely on agriculture for their livelihood. The smallholder farmers rely on rain-fed production and in addition to climate change face other constraints such as limited resources and inappropriate technologies. Chapter 2 reviewed knowledge on climate change and how it is negatively affecting agriculture productivity in crop and livestock enterprises. The results showed that Sub Saharan Africa including Zimbabwe is vulnerable and farmers can choose from a basket of CSA technologies to mitigate climate change impacts. Conservation agriculture has been the dominant CSA technology in Zimbabwe in addition to drought-tolerant crop varieties and fodder production for supplementary feeding of livestock. Existing empirical research was limited to discussing adoption patterns and modelling optimal enterprise mix for farmers adopting different CSA technology combinations. The chapter laid the theoretical foundation on the adoption and impact of CSA technologies. Empirical CSA research, while providing evidence on adoption and impact, mainly focuses on the adoption of single technologies for single enterprises. In reality, farmers adopt multiple technologies to suit various constraints. There is hardly any modelling on the optimal enterprise mix for farmers adopting different bundles of CSA technologies. The discussions in this chapter formed the basis of the research papers covered by the study.

The research mapped adoption patterns of climate-smart agriculture (CSA) technologies among diverse smallholders' farmers in chapter 3. Analysis using a multivariate analysis approach which combined PCA and cluster analysis generated household typologies and technology bundles. Results showed that patterns of CSA varied across the household typologies with resource endowed and experienced farmers adopting more CSA technologies such as crop rotation and minimum tillage that require more resources while resource-constrained clusters shunned resource-intensive ones. Famers are heterogeneous and will select and adopt different CSA technologies to address constraints and to meet different livelihood objectives. Some of the CSA can be complementary while some compete for the farm's resources. This leads to different technology bundles that were observed in the study. Understanding such patterns is crucial to extension as it helps in tailoring awareness and promotional strategies for different target farmers who favour certain CSA bundles. An example would be promoting complementary technologies together rather than independently.

The other key message in chapter 3 derived from the Cragg double hurdle model is that factors such as distance to the tarred road, access to weather information, livestock income share and ownership of transport asset are key to making adoption decisions. Adoption intensity is then further affected by factors such as sex of household head, labour size, frequency of extension contact, access to credit, access to weather forecasts, off-farm income, distance to input and output markets, number of traders and asset ownership. Chapter 4 established the determinants of multiple CSA technologies in Zimbabwe. Analysis revealed that gender of household head, farm characteristics (soil type and labour size) and institutional factors (market access, information access and access to credit) are the main factors that determine the adoption of various CSA technology combinations. The chapter concluded that government should design policies aimed at improving farmers' knowledge of CSA technologies. This could include early warning systems and programs that enhance access to information, markets and credit to facilitate scaling up of CSA in smallholder farming communities.

The policy implications point towards continued infrastructure construction (tarred road), the need to ensure access to weather forecasts information, coupled with frequent access to extension officers by farmers and access to credit. Good all-weather roads help in ensuring easy access to inputs and outflow of outputs to markets. Transport charges are also cheaper for tarred roads in comparison to gravel roads. Frequent access by farmers to extension officers enables access to agricultural production information through extension-farmer visits, field days, exchange visit and agricultural shows. This interaction reduces uncertainty about CSA technologies and improves the technical know-how needed for the innovations. This calls for motivated well equipped (motorised for mobility, with IEC materials to distribute) extension officers. These factors are vital in ensuring the effective and timely dissemination of information to farmers.

The work of the ward-based government extension officers can be complemented through Public-Private Partnerships (PPPs). The private sector and commodity associations can also provide extension services for key commodities that they promote. In addition, farmer associations (such as Zimbabwe Farmers Union and Commercial Farmers Union (CFU)) can also provide extension services to their members to cover training for technologies such as CSA. The private sector can also facilitate the capacity building of extension through refresher courses. Joint hosting of events like field days and shows will help to provide up-to-date information to farmers to enable them to make sound agricultural management decisions. With the ownership of android mobile devices by farmers, the extension can also make use of e-extension to disseminate agronomic and animal husbandry information to farmers through phones. Partnerships with private profit and private non-profit sectors have great potential in reaching out to more farmers and can complement government efforts.

Weather forecast information can be used by farmers to decide on what varieties to plant (short season versus long season varieties) and even what technologies to use depending on whether a drought, normal rainfall season or flood is anticipated. Access to credit provides farmers with capital to buy an initial investment that might be associated with new CSA equipment, seeds or access to information.

Chapter 5 investigated the impact of CSA on household welfare indicators i.e. Household income and food security. The analysis found evidence of increased food security and household income as a result of adopting CSA. The key message of this chapter was that adopters are benefiting and households that did not adopt CSA would also benefit if they adopted. CSA can contribute to food security and income through increased productivity.

Chapter 6 further analysed profitability and profit efficiency in the staple maize (Zea mays) crop production as a result of CSA technology adoption. The analysis revealed that maize performs best under CSA technologies. The profit inefficiency model showed that profit inefficiency decreased with an increase in extension contact, the number of traders locally, and the adoption of CSA. Findings of this chapter call for development practitioners to incorporate market linkages that bring buyers closer to the farmers and support for an extension to be able to have frequent contacts with farmers. Results also point out the potential of CSA in positively influencing profitability as a result of reduced costs and improved productivity.

Choosing the optimal enterprise mix is one important challenge for farmers integrated farming systems doing both crop and livestock and facing multiple objectives and yet are constrained by key resources such as land, cash and labour, among others. The final chapter 7, designed an optimal enterprise mix using a multi-objective goal programming model. Results indicate that only mixed (i.e. crop-livestock integration) entered the feasible plan for all the farmers adopting different CSA technology bundles. The empirical implication to policy points to the need for extension workers to capacitate farmers on the importance of highly profitable enterprises like horticulture in combination with livestock enterprises. The government must develop programs to enhance low-input livestock productivity, requiring enterprises like cattle. Up-scaling adoption could involve the use of progressive farmers in communities to set up demonstrations to showcase the potential benefits of CSA on integrated crop-livestock farms. Credit lines can also be extended to farmers practising CSA on crop-livestock integration as an incentive for adoption.

8.3 Contributions to new knowledge

Despite the potential of CSA technologies, and efforts to promote them among smallholder farmers in integrated crop-livestock farming systems, adoption has been low. Research has mainly focused on investigating the determinants of singular CSA yet in most cases farmers adopt a combination to suit their needs. This dissertation, therefore, analysed the popular patterns in adoption i.e. bundles by different farmer typologies. Furthermore, the study investigated the factors affecting the adoption of these popular technology combinations. Several studies have addressed the impact of CSA and few and none in Zimbabwe have gone further to model optimal enterprise mix for these popular technology combinations. This study modelled the optimal solutions for farmers of popular technology bundles.

8.4 Future possible research areas

There are quite many future research areas involving CSA that need attention. The empirical findings of the study are based on cross-sectional farm-level data. Future studies could improve conclusions based on such methods considering collecting panel data. In addition, future studies should analyse CSA technologies in smallholder horticulture value chains as well as identify which crops, in particular, are highly profitable. There is also a need to study the effects of various policies on CSA adoption. Also, given differing input and output price ranges and resource availabilities for different households over time, it might be useful to consider doing some simulation analysis (variable price and variable resource programming) to suggest wider possibilities of farm plans.

Appendix 1: Household Survey Questionnaire

Household Survey Questionnaire on Climate-smart agriculture practices in four districts of Zimbabwe

MODULE 0: INTRODUCTION

Start with greetings in the local language.

Please read out aloud the following for the respondents

Angeline Mujeyi is a student at the University of KwaZulu Natal in South Africa. She is doing a research project entitled **"Adoption and Impact of Climate-smart Agriculture Practices (CSA technologies) in Crop Livestock Integrated Farming Systems in Zimbabwe".** We have randomly selected 400 households in 4 districts (Goromonzi, Murehwa, Mutoko, and UMP) of the country regarding farmers' attitudes to climate-smart agriculture technologies in crop and livestock production. The information generated in this study will be kept in a secure place and will be used only for this research. Answers will be kept confidential, and analysis will not involve individual names. There is no way anyone will be able to identify you by what you have said in this interview.

Thank you for your willingness to participate in this study. You have the right to terminate this interview at any time, and you have the right to refuse to answer any question you might not want to respond to. ***(Enumerator give participant time to read the consent form)*** If the household does not consent to the interview, thank them and get a replacement from the supervisor. If the Household consent to the interview, let them sign the consent form and proceed with the interview.

MODULE 1: PRELUDE

	Question	**Response**		**Question**	**Response**
1	Date		5	Village	
2	Interviewer name		6	Name of Respondent (first + initial of surname)	
3	District		7	Relation of the respondent to the household head 1=household head 2=wife 3=Other family member	
4	Ward		8	Record Sex of respondent 1=Male 2=Female	

MODULE 2: HOUSEHOLD CHARACTERISATION

	Questions	**Code**	**Response**
1	Household head marital status	1=married 2=widowed 3=divorced 4=single	
2	Residence of HH head	1=resident 2=non resident	
3	Sex of household head	1= male 2=female	
4	Age of household head		

5	Education of household head in years		
6	Household head specialised agricultural training or education	1=certificate 2=degree 3= Master Farmer training 4= course 5= courses > 40 hours 6= courses < 40 hours 7=none	
8	Principal Economic Activity (1 only)	1= Farming 2=Trading 3= Formal employment	
9	The main farming activity of the household (Choose 1 only)	1= perennial dryland crop production 2= horticulture 3= small livestock 4=dairy, 5=cattle (beef), 99=other specify	
10	Type of a farmer	1= fulltime 2=part time	
11	Farming experience (years)		
12	What is the total number of people residing in this homestead? (Household size)		
13	Number of members who provide Family labour permanently		
14	Number of members who provide Family labour on a part-time basis		
15	Number of hired labour per year		

2.2 Indicate characteristics of the main house

16	Floor type 1=earth 2=cement 3=tiles 99=other (specify	
17	Wall material 1=earth/mud 2=wood/bamboo/iron sheets 3=cement/bricks 99=other (specify)	
18	Roof type 1=grass 2=iron sheets/asbestos 3=tiles 99=other (specify)	
19	The main source of water 1=borehole 2=piped water 3=communal tap 4 unprotected well/river/stream 5 protected well/spring	
20	Toilet 1=blair/pit 2=flush 3=bush	
21	Number of rooms	

MODULE 3 ACCESS TO SERVICES, SOCIAL CAPITAL, NETWORKING, AND ASSET OWNERSHIP

3.1 Access to services, social capital, and networking

Distance from homestead to extension information sources (Km)……………………..
Distance from homestead to main input market (Km)…………………………..
Distance from homestead to the nearest main output market (Km)……………….
Distance from homestead to the tarred road (Km)……………………………………….
Is the household a member of any groups (farmer associations/ agricultural marketing/savings and credit) **1=yes 0=no ………………**
Are Climate-smart agriculture technologies discussed in these groups? **1=yes 0=no ………**
How many people in this village do you rely on for critical support in times of need? (Relatives and non-relatives)………
How many traders outside this village buy your agriculture products? (Crop and livestock)………………

Specify the number of contacts with extension in the last 12 months ……………………………
Do you have access to weather forecasts? **1=yes 0=no**……………………………………..

3.2 Asset ownership

	Asset Category	**Asset type**	**a.Total No. owned**	**Current Value ($)**
11	Domestic	Sofa set		
12		Sewing machine		
13		Refrigerator		
14		Chair		
15		Grinding mill		
16	Farm implements	Sickle		
17		Hoe		
18		Spade or shovel		
19		Axe		
20		Knapsack sprayer		
21		Wheelbarrow		
22		Ox-plough		
23		Water pump		
24		Tractor		
25	Transport	Pushcart		
26		Bicycle		
27		Motorbike		
28		Donkey/oxen cart		
29		Car/truck		
30	Communication	Radio		
31		Mobile phone		
32		TV		
33	Other (specify)			

3.4 Livestock ownership

34 Does household own any livestock **0=No 1=yes …………**

If yes indicate the numbers of animals kept by the household in the table to follow.

	Livestock Species	**Category**	**Number Owned now**	**Number Owned 3 years ago**
35	Indigenous cattle	Bull		
36		Cow/steer/oxen		
37		Immature		

	Livestock Species	Category	Number Owned now	Number Owned 3 years ago
38		Calves		
39	Crossbred/exotic cattle	Bull		
40		Cow/steer		
41		Immature		
42		Calves		
43	Draft power	Draft animals		
44	Local Goats and Sheep	Kids< 5 months		
45		Adult goats		
46	Exotic Goats and sheep	Kids< 5 months		
47		Adult goats		
48	Poultry (local and improved)			
49	Pig			
50	Donkeys			
51	rabbits			
52	Other (specify)			

MODULE 4: HOUSEHOLD CREDIT, SAVINGS, INCOMES AND EXPENDITURE ACTIVITIES DURING 2016/17

4.1 Credit and Savings

1	Did the household get Credit in the last 12 months? **1=yes 0=no**	
2	**Value of credit** Livestock related credit $ Crop related credit $ Personal credit $	…………………… ……………… ………………
3	Who gave you the credit 1=bank 2=informal money lender 3=family and friends 4 buyers 5 government 99=other specify	
4	Amount of savings by household in a year (bank, Mobile account Saving (Ecocash/Telecash/One Wallet) /merry go round) $	

4.2 What was your household's income from the following sources during the past 12 months? **(Include the income of all household members)**

	Income source	Income for the past 12 months (Cash + In-kind (cash equivalent)
5	Sale of livestock and livestock products	
6	Crop sales	
7	Salaried employment	
8	Casual labour (on-farm and off-farm)	
9	Non-agricultural businesses	

10	Remittances	
11	Other sources (specify)…………	

4.3 What is the household expenditure for the past 12 months?

	Item	**Amount $**
12	Food	
13	Clothing	
14	Health	
15	Education	
16	Productive assets purchase	
17	Other	

MODULE 5: LAND OWNERSHIP, CROP AND ANIMAL PRODUCTION: 2016/17 SEASON

1. What is the total arable household landholding? …………………………………….. (acres)

2. Main soil type **1= black clay 2= red clay 3=sandy 4=loam 5= sandy loam** …………….

	Input and output	**Unit**	**ma ize**	**Groun dnuts**	**Cow peas**	**Muc una**	**Lab lab**	**Other food crops**	**Field cash crops**	**Hortic ulture**
3	Area	acre s								
4	Seed	Kg								
5		Cost s ($)								
6	Ploughing	costs US$								
7	Compoun d D	Kg								
8		costs US$								
9	Ammoniu m Nitrate	Kg								
10		costs US$								
11	Manure	carts								
12		costs US$								
13		Kg								

	Input and output	Unit	ma ize	Groun dnuts	Cow peas	Muc una	Lab lab	Other food crops	Field cash crops	Hortic ulture
14	Other fertiliser	costs US$								
15	Herbicides	Litres								
16		costs US$								
17	Pesticides	costs (US $								
18	Labour	costs US$								
19	Packaging and transport	costs US$								
20	Insurance									
21	Other costs									
22	**Total grain harvested**	Kg								
23		Price/Kg								
24	Total hay/silage	Kg								
25		Value $								
26	Value of harvest	$								
	CSA technologies (separate answers by commas) **Code**									
	Code 1=intercropping 2=crop rotation 3=minimum tillage 4=fodder 5=drought tolerant maize 6=Improved legume varieties 7=manure use 8=mulching 9=orange maize 10=bought feeds 11=artificial insemination 12=insurance 99=other specify									

Let us discuss the **Livestock enterprise** Costs and incomes in the past 12 months

	Inputs per year	**Amount**
27	Hired labour	$
28	Family labour	$
29	Homegrown feed	$
30	purchased feed	$
31	Veterinary costs	$
32	transportation	$
33	Miscellaneous/ other	$
	Income/year	Amount

34	Fresh milk amount (l)	
35	Price /L (fresh)	
36	Sour milk amount (l)	
37	Price/L (sour)	
38	Livestock sales	$
39	Hiring out draft	$
40	Manure (carts)	
41	Price/cart (manure)	
42 43	Hides and skins Other (specify)	

MODULE 6: ACCESS TO AND USE OF CROP AND LIVESTOCK CSA technologies

6.1 Technologies adoption

												If No		
	Technology	Ever head	Year heard	Ever used	Year first use	Area (acres) Year 1	Area (acres) Now	How many years have you been consistently using this technology?	Information source	Who decides to adopt?	Who decides on the area to adopt?	Reasons no adoption	Will you adopt in Future?	Why will you not adopt it?
	Code	A		A					C	B	B			
1	Intercropping													
2	Crop Rotation													
3	Minimum Tillage													
4	Drought Tolerant maize hybrid varieties													
5	Improved legume varieties													
6	Manure													
7	Mulching													
8	Orange maize													
9	Agroforestry													
10	Livestock feeding (fodder)													
11	Livestock feeding (bought feed)													
12	Artificial Insemination													
13	Agriculture insurance													
	Codes	**A 1=yes 0= no** **B** 1= men 2 =women 3=Joint **C: Information source:** 1=Government extension 2= Farmer Coop/Union 3= Farmer group 4=NGO 5=Research centre 7. Relative/ Neighbour 9=Radio/newspaper/TV 99=Other, Specify												
14	What is the main reason that motivated you to adopt CSA technologies? **1= Profit orientation 2=protecting the natural Environment 3= risk minimization 4=food security orientation**													

6.2 let us discuss the impact of adopting CSAP by scoring using the following Likert scale:

0=neutral ***1= strongly disagree*** ***2=disagree*** ***3= Agree*** ***4= strongly agree***

	CSAP	**Intercropping**	**Crop rotation**	**Minimum tillage**	**Drought-tolerant maize**	**Improved legume varieties**	**Manure**	**Mulching**	**Orange maize**	**agroforestry**	**Fodder**	**Bought feeds**	**Artificial insemination**	**Agriculture Insurance**
15	Income has increased													
16	Household Consumption has increased													
17	Crop production (yields) have increased													
18	Animal Productivity has increased													
19	Soil fertility has increased													
20	Costs of production have decreased													
21	The cost of production has increased													
22	Labour requirements have increased													
23	Labour requirements have decreased													
24	Food security has increased													
25	Poverty has reduced													
26	**Years from adoption to reaping benefits**													

6.3 let us discuss resource use changes as a result of technology adoption

	Variable	unit	before CSA technologi.es	after CSA technologies
27	milk per day	litres/cow		
28	animal deaths/year	numbers		
29	Disease Incidence per year	number of times		
30	Milk consumed by household per day	Litres/day		
31	Income from livestock sales	$/year		
32	Income from draft hiring out	$/year		
33	Calving interval	months		
34	Maize yield	50Kg bags/acre		
35	Household income/year	$/year		
36	Fertiliser 50Kg bags (basal)	Number/acre		
37	Fertiliser 50Kg bags (top)	Number/acre		
38	**Land allocation (share out of 10 stones)**			
39	Food crops			
40	Cash crops			
41	Fodder crops			
42	Garden crops			
43	Other crops			
			Total (10)	**Total (10)**
	Inputs Investment (share out of 10 stones)			
44	Food crops			
45	Cash crops			
46	Fodder crops			
47	Other crops			
48	Livestock			
			Total (10)	**Total (10)**
	Labour allocation (share out of 10 stones)			
49	Food crops			
50	Cash crops			
51	Fodder crops			
52	Other crops			
53	Livestock			
			Total (10)	**Total (10)**

6.4 Let's discuss the technologies that you are no longer using but which you were using before?
2

	CSA Technologies 1=intercropping 2=crop rotation 3=minimum tillage 4=fodder 5=drought tolerant maize 6=Improved legume varieties 7=manure use 8=mulching 9=orange maize 10=bought feeds 11=artificial insemination 12=insurance 99=other specify	**For how long did you use it? (years)**	**Why did you stop using it (2 reasons using (code A)**	**Will you use the technology again in the future 1=yes 0=No**
54				
55				
56				
	Code A 1= no chance to give feedback to technology promoters 2=technology unprofitable 3= no enough technical expertise to support technology 4=heavy investment needed for the technology 5=technology have a higher failure risk in the area 6=unavailability of markets for the products			

57	If you expect insufficient rain throughout the season, which CSA do you use **(code 1)**	
58	If you expect sufficient rain throughout the season, which CSA do you use?	
59	Rate your awareness of CSA technologies **1=poor 2=good 3=excellent**	
	Code 1 1=intercropping 2=crop rotation 3=minimum tillage 4=fodder 5=drought tolerant maize 6=Improved legume varieties 7=manure use 8=mulching 9=orange maize 10=bought feeds 11=artificial insemination 12=insurance 99=other specify	

MODULE 7: HOUSEHOLD FOOD SECURITY

7.1 Dietary Diversity Score

		1 adult male			1 adult female			1 child below 5 years		
	food type	how was the item mainly obtained **code 1=own produced 2=bought 3=gift 99=other (specify)**	in the last 24 hours, have you consumed **1=yes 0=no**	in the last 7 days, how many times have you consumed these?	how was the item obtained **code 1=own produced 2=bought 3=gift 99=other (specify)**	in the last 24 hours, have you consumed **1=yes 0=no**	in the last 7 days, how many times have you consumed these?	how was the item obtained **code 1=own produced 2=bought 3=gift 99=other (specify)**	in the last 24 hours, have you consumed **(1=yes 0=no)**	in the last 7 days, how many times have you consumed these?
1	staples (millet,sorghum,maize,rice,wheat, bread, noodles)									
2	vegetables									
3	fruits									
4	pulses (bean,peas,cowpeas,nuts)									
5	meat and fish (beef, pork, lamb, goat, wild, poultry etc.)									
6	oils and fats									
7	milk and milk products									
8	other condiments (e.g. coffee, tea)									

7.2. Food Insecurity Access Scale

		response 0=no 1=yes	If yes specify the frequency of occurrence **(code)**
1	In the past four weeks, did you worry that your household would not have enough food?		
2	In the past four weeks, were you or any household member not able to eat the kinds of foods you preferred because of a lack of resources?		
3	In the past four weeks, did you or any household member have to eat a limited variety of foods due to a lack of resources?		
4	In the past four weeks, did you or any household member have to eat some foods that you did not want to eat because of a lack of resources to obtain other types of food?		
5	In the past four weeks, did you or any household member have to eat a smaller meal than you felt you needed because there was not enough food?		
6	In the past four weeks, did you or any other household member have to eat fewer meals in a day because there was not enough food?		
7	In the past four weeks, was there ever no food to eat of any kind in your household because of a lack of resources to get food?		
8	In the past four weeks, did you or any household member go to sleep at night hungry because there was not enough food?		
9	In the past four weeks, did you or any household member go a whole day and night without eating anything because there was not enough food?		
	CODE Frequency of Occurrence 1 = Rarely (once or twice in the 2 = Sometimes (three to ten times in the past four weeks)past four weeks) 3 = Often (more than ten times in the past four weeks		

10	How many meals per day do the following people normally have? 1. Adults……………… 2. Children…………….	
11	On average how many meals per day has this household been consuming over the past 7 days?	
12	In the last 12 months, did you have enough food to eat during all the months? **0=No 1=Yes**	
13	If no how many months did you not have enough food to meet your needs?	
14	Specify the months you did not have enough food to meet your needs?	
15	How did you overcome this food shortage? 1=food aid 2=sold cattle 3=sold goats/sheep 4=remittances 5=food or cash for work 99=Other (specify)	
16	Taking into consideration ALL food sources (own food production + food purchase + help from different sources), assess your family's food consumption in the past 12 months. 1= Food shortage through the year 2=Occasional food shortage 3=No food shortage but no surplus 4=Food surplus	
17	Who sources the food in this household in times of food shortage? 1=Mother 2=Father 3=joint 4 children 99=other (specify	

Any comments
…………………………………………………………………………………………………
…………………………………………………………………………………………………
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Thank you so much for your time!

Appendix 2 Consent form

CONSENT FORM

PROJECT TITLE: Adoption and impact of Climate-Smart agriculture technologies in crop-livestock integrated farming systems of Zimbabwe

RESEARCHER
Full Name: Angeline Mujeyi
School: Agriculture, Earth, and Environmental Sciences
College: Agriculture, Science and Engineering
Campus: Pietermaritzburg
Proposed Qualification: PhD
Contact: +263 773 199 804
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SUPERVISOR
Full Name of Supervisor: Prof Maxwell Mudhara
School: Agriculture, Earth and Environmental Science
College: Agriculture, Science, and Engineering
Campus: Pietermaritzburg
Contact details: 033 2605518
Email: mudhara@ukzn.ac.za

HSSREC RESEARCH OFFICE
Full Name: Mr Prem Mohun
University of Kwazulu Natal
Research Office Ethics
Tel: 031 260 4557
Email: mohunp@ukzn.ac.za

I, Angeline Mujeyi, Student no. 216077004, am a PhD candidate, at the School of Agricultural, Earth and Environmental Sciences, at the University of KwaZulu-Natal. You are invited to participate in a research project entitled: **Adoption and impact of Climate-Smart agriculture technologies in crop-livestock integrated farming systems of Zimbabwe**

I guarantee that your responses will not be identified with you. Your participation is voluntary and there is no penalty if you do not participate in the study. You may refuse to participate or withdraw from the survey at any time with no negative consequence. There will be no monetary gain from participating in this survey. Please sign the consent form if you agree to take part in the survey to show that you have read and understood the contents of this letter. The questionnaire will take approximately 45 minutes to complete.
If you have any questions or concerns about completing the questionnaire or about participating in this study, you may contact me or my supervisor at the numbers listed above.

Sincerely,

Angeline Mujeyi

This page is to be retained by participant (written in English and Vernacular (Shona)

DECLARATION OF CONSENT (Bvumidzo)

I (*Ini*) ………………………………………………………………………………………… (Full Name/ Zita) hereby confirm that I have read and understood the contents of this letter and the nature of the research project has been clearly defined before participating in this research project (*ndinobvuma kuti ndaverenga nekunzwisisa nezviri mutsamba uye kuziviswa chinangwa che tsvagurudzo ndisati ndatanga hurukuro navo).*
I understand that I am at liberty to withdraw from the project at any time, should I so desire (*ndinonzwisisa kuti ndinogona kurega kuenderera mberi nehurukuro iyi panguva yandingade)*.

Participants Signature (Saini): ………………………………………………………………………………………

Date (*Musi*):……………………………………………………………………….

Appendix 3: Ethical clearance

UNIVERSITY OF KWAZULU-NATAL
INYUVESI YAKWAZULU-NATALI

19 February 2018

Mrs Angeline Mujeyi 216977004
School of Agriculture, Earth and Environmental Sciences
Pietermaritzburg Campus

Dear Mrs Mujeyi

Protocol reference number: HSS/0112/018M
Project title: Adoption and impact of Climate Smart Agriculture Technologies in crop - livestock integrated farming systems of Zimbabwe

Full Approval – Expedited Application

In response to your application received 12 February 2018, the Humanities & Social Sciences Research Ethics Committee has considered the abovementioned application and the protocol has been granted **FULL APPROVAL.**

Any alteration/s to the approved research protocol i.e. Questionnaire/Interview Schedule, Informed Consent Form, Title of the Project, Location of the Study, Research Approach and Methods must be reviewed and approved through the amendment /modification prior to its implementation. In case you have further queries, please quote the above reference number.

PLEASE NOTE: Research data should be securely stored in the discipline/department for a period of 5 years.

The ethical clearance certificate is only valid for a period of 3 years from the date of issue. Thereafter Recertification must be applied for on an annual basis.

I take this opportunity of wishing you everything of the best with your study.

Yours faithfully

[redacted]

Professor Shenuka Singh (Chair)
Humanities & Social Sciences Research Ethics Committee

/pm

cc Supervisor: DR Maxwell Mudhara
cc Academic Leader Research: Professor Onisimo Mutanga
cc. School Administrator: Ms Marsha Manjoo

Humanities & Social Sciences Research Ethics Committee
Professor Shenuka Singh (Chair)
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Website: www.ukzn.ac.za

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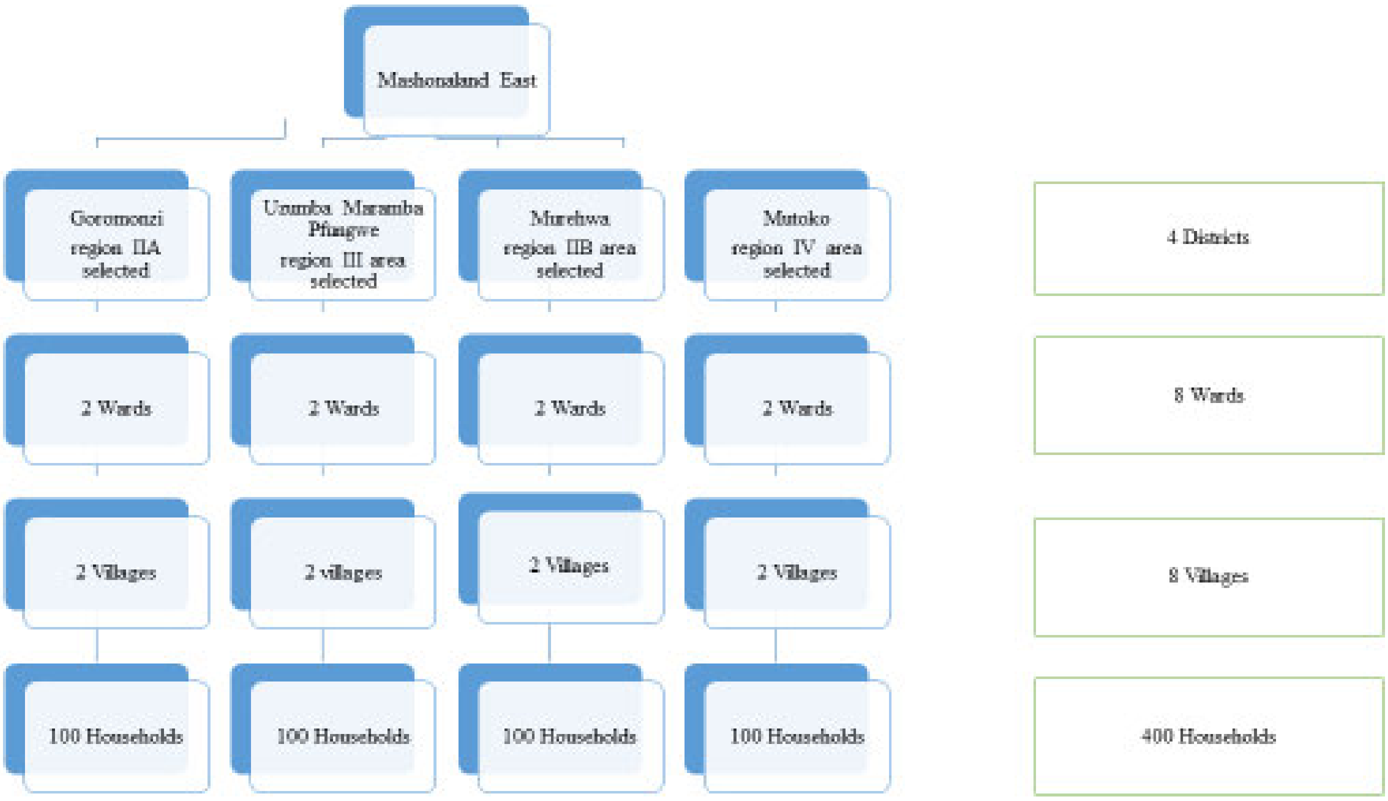
Appendix 4: Recruitment strategy of Participants

The study will be conducted in 4 districts (Goromonzi, Murehwa, Mutoko, and Uzumba Maramba Pfungwe (UMP)) of Mashonaland East province. A stratified random sampling technique will be used to sample farmers. Units (households) are sampled randomly from each of the stratums (villages). The sample size in each stratum varies proportionately depending on the number of households in that strata.

Mashonaland East province was purposively selected as the area has been exposed to CSA technologies. The province has four agro-ecological zones i.e. IIA, IIB, III, and IV and a district from each region has been selected. Two wards each from the four districts will be chosen to give eight wards in total (Figure 1). Determining sample size from each ward was done based on the number of households in each ward as reported in the last national census. The desired sample size of 400 was obtained using the survey monkey and raosoft sample size calculator (15511 households, 5% margin of error, 95% confidence level = 375 households + 25 to allow for any non-responses). The sample size was determined proportionately.

One village will then be randomly selected from each ward from a list provided by the extension officers of villages where CSA technologies have been promoted over the lasts 20 years. Households from each village in each ward will then be randomly selected from the village head lists.



Appendix 5: Turnitin Report

turnitin

Digital Receipt

This receipt acknowledges that Turnitin received your paper. Below you will find the receipt information regarding your submission.

The first page of your submissions is displayed below.

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File size:	1.47M
Page count:	186
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Adoption and Impact of Climate-smart Agriculture Technologies in Integrated Crop-Livestock Farming Systems

by

Angeline Mujeyi

A thesis submitted in fulfilment of the requirements of the degree
Doctor of Philosophy (Agricultural Economics)

School of Agricultural, Earth and Environmental Sciences
College of Agriculture, Engineering and Science
University of KwaZulu-Natal
Pietermaritzburg
South Africa

December 2020