Does the uptake of multiple climate smart agriculture practices enhance household savings, food security and household vulnerability to climate change? Insights from Zimbabwe

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Boscow Okumu[*], Herbert Ntuli[†], Edwin Muchapondwa[‡], Gibson Mudiriza[§] and Alfred Mukong[¶]

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Abstract

Climate change and variability poses a significant hindrance on agricultural productivity. The adverse effects are particularly concerning in many African countries that rely more on rainfed subsistence agriculture for livelihood. The promotion of climate smart agriculture technologies as a pathway to enhancing food security, farmer's welfare, and providing climate adaptation and mitigation benefits is one of the several interventions aimed at improving agricultural productivity. However, there has been a dearth of evidence on the determinants of adoption of climate smart agriculture practices as well as the impact of climate smart agriculture practices on food security and household welfare. This paper contributes to this knowledge gap by using the probit model to explore the drivers of uptake of climate smart agriculture practices and the inverse probability weighting regression model and the instrumental variable approach to assess the impact on food security and household savings and household vulnerability. We find that the adoption of climate smart agriculture practices among smallholder farmers is influenced by land ownership, climatic variables, land terrain, and household sociodemographic characteristics. The study further revealed that adoption of climate smart agriculture

[*]The National Treasury and Planning, Treasury Building, Harambee Avenue, P. O. Box 30007-00100, Nairobi, Kenya, Environment for Development (EfD) Centre, School of Economics, University of Nairobi, Kenya, Corresponding author: kodhis2000@gmail.com or okmbos002@myuct.ac.za.

[†]School of Economics, University of Cape Town, Private Bag, Rondebosch 7701, Cape Town, South Africa, WWF South Africa, South Africa, ntlher001@myuct.ac.za

[‡]Professor, School of Economics, University of Cape Town. edwin.muchapondwa@uct.ac.za

[§]School of Economics, University of Cape Town, South Africa. Email: gmudiriza@gmail.com

[¶]Department of Economics, University of Namibia, Windhoek, Namibia; School of Economics, University of Cape Town, Cape Town, South Africa, mukalf83@gmail.com

practices leads to reduction in household savings and household vulnerability but leads to improved food security. The findings suggest the need to promote climate smart agriculture practices aimed at livestock management, enhanced agricultural extension work and reduced resource constraints that inhibit farmer's capacity to adopt complementary practices among others.

Key Words: Climate Smart, food security, Savings, Vulnerability
JEL Classification: Q01, Q18, Q54, O13

1 Introduction

Globally, climate change and variability poses a significant hindrance on agricultural productivity and agricultural transformation with increased experiences of unpredictable and erratic rainfall and severe temperature that threaten food security and rural livelihoods (see Ching *et al.,* 2011; Williams *et al.,* 2017; Fadairo *et al.,* 2019). The adverse effects are particularly concerning in many African countries that rely more on rain fed subsistence agriculture for livelihood. The predictions of climate models vary from one region to another and depend on the type of economy with cooler temperate regions experiencing mild impacts, but with some benefits, while drier regions such as Sub-Saharan Africa (SSA) suffer severe impacts (Kurukulasuriya and Mendelsohn 2008; Gbetibouo and Hassan 2005).

In developing countries, agriculture remains the mainstay of most economies (Adhikari *et al.,* 2015, Martey *et al.,* 2021). In particular, the smallholder agricultural system in the SSA region has been identified as one of the world's economic subsectors that are most at risk of climate change because it depends heavily on natural resources and rain fed agriculture (Tibesigwa *et al.,* 2020). This developing region is characterized by very poor economies that have little or no capacity to deal with climate shocks (Kurukulasuriya and Mendelsohn 2008). A significant proportion of the African population still resides in marginalized rural areas. Little land for agricultural production, low adaptive capacity of famers coupled with current climate-related stressors such as drought, floods, high temperature and rainfall variability, make African farmers highly susceptible to the impacts of climate change and variability. This leaves smallholder farmers and their households with persistent low agricultural productivity and limited transformation of the food system to ensure reduced household vulnerability, improved food security and livelihood (Martey *et al.,* 2021). Over the years, several development interventions aimed at improving agricultural productivity as a pathway for enhancing the welfare of farmers have emerged. High on the list of adaptation strategies to reduce vulnerability to climate change is the use of climate smart agriculture (CSA) practices. CSA has also emerged as a framework to capture the concept that agricultural systems can be developed and implemented to simultaneously improve food security, rural livelihoods, and provide climate adaptation and mitigation benefits (Scherr *et al.,* 2012).

FAO (2010) define CSA as agriculture that sustainably increases productivity, resilience to climate change, reduces greenhouse gas emissions (mitigation), and enhances the achievement of national food security and development goals. Lipper *et al.,* (2014; 2018) defines CSA as an approach for transforming and reorienting agricultural development under the new realities of climate change. Smallholder farmers have subsequently enhanced their efforts towards adapting to changing climate. However, they require support to lift the limitations they face in putting their knowledge into practice. Despite the increased promotion of CSA technologies, there is still limited consensus on its effectiveness. Little is also known about the links between CSA and livelihood diversification strategies and climate resilience in vulnerable settings. Thus, it is inherent to investigate the drivers of CSA adoption among smallholder farmers to understand how to put the know how into practice. It is also important to understand the effectiveness of CSA technologies in enhancing food security and livelihood of smallholder farmers.

There is growing interest by researchers across the globe to understand the impacts of climate change on agricultural systems in Africa (Kurukulasuriya and Mendelsohn 2008; Gbetibouo and Hassan 2005). Other studies have also assessed the reasons for low adaptive capacity of the smallholder agricultural sector (Amadu *et al.,* 2020; Komba and Muchapondwa 2018; Di Falco 2014; Di Falco 2011), and how climate stressors, in turn, affect the national food security, household welfare and development goals in the region (Adhikari *et al.,* 2015). Hence, knowledge about the impacts of climate change and the drivers of adaptation strategies has improved significantly over the past few decades. However, the linkage between CSA practices and household vulnerability, food security and welfare still need further research in order to provide policymakers and development practitioners with relevant information. For instance, there is very little evidence demonstrating whether the adoption of CSA by smallholder farmers in Africa is welfare enhancing or not. As a result, most donor funded projects and policy interventions in the region are fervently endorsed based on weak evidence (Tibesigwa *et al.,* 2020). In addition, existing studies have either assessed the effect of CSA on household livelihood using individual specific CSA practices or constructed an index of CSA practices (Amadu *et al.,* 2020; Collins-Sowah 2018; Bezu *et al.,* 2014; Asfaw *et al.,* 2012). The diversity and heterogeneity of climate and agricultural practices among countries in Africa suggest the need for context specific evidence.

This paper adopts a different approach that looks at a portfolio of CSA practices and management options on production risk within a developing country perspective. We consider water management and land management practices as adaptation strategies that offers insurance against the risk associated with yield loss from the changing climate and growing conditions. Using a sample of 14,585 smallholder farmers in 8 provinces of Zimbabwe and instrumental variable and inverse probability weighting regression models, we contribute to the body of knowledge on CSA practices and their effect on household vulnerability, food security and household welfare. Zimbabwe presents an interesting case study to examine this relationship given that a huge proportion of rural households are beneficiaries of the fast-track land reform programme which started around 1999 and depended heavily on rainfed agriculture for survival. Furthermore, some of these farmers come from a very poor background with limited ability to invest in CSA. As a result, the government and NGOs have come up with intervention programmes to assist farmers to adapt to climate change, yet there is no evidence to show that these projects are working or not. Given this background, we ask the following questions, i) What influences the uptake of CSA practices among smallholder farmers in Zimbabwe? ii) What is the impact of adopting CSA practices on household savings, food security and household vulnerability to climate change?

The paper contributes to the scant literature on impact of adoption of a portfolio of CSA technologies in the face of changing weather conditions and in the context of climate change adaptation. The paper considers a combination of adaptation measures that builds upon risk reducing options through fertilizer application, improved crop varieties and agricultural water management. Specifically, the study uses a different approach by employing the Principal Component Analysis to identify adopters and non-adopters of CSA practices. Then assess the impact on three major outcome variables namely; household savings, food security and household vulnerability to climate change using quasi experimental approaches. Moreover, in a resource scarce region, establishing the summative impact of different CSA practices is critical for targeted interventions.

The remainder of this paper is organized as follows: Section 2 presents the study context while section 3 provides a review of literature on climate change and smallholder farms. Section 4 explains the estimation strategy and the various identification tests. Section 5 provides the results and discussions while Section 6 concludes the paper.

2 Setting the context

The economy of Zimbabwe is mainly agro-based, with 80% of its land classified as arable, although the bulk of this land is limited by rainfall and availability of water to irrigate crops and livestock (Moyo and Chambati 2013). Figure 1 shows the agro-ecological zones of the country partitioned into five regions from the wettest and coolest to the hottest and driest, while the quality of the land resource declines from natural region (NR) marked I through to NR marked V (Moyo 2000). Upon independence in 1980, the country inherited a vibrant dual agricultural system comprising of both a commercial sector, which occupied over 80% of the agricultural land with more than 80% of the population employed in the smallholder agricultural sector occupying less than 20% of the arable land (Moyo 2013; Rukuni *et al.,* 2006). The former grew crops for the export market to generate the much needed foreign currency, while the latter grew maize to feed the nation and a limited amount of cash crops (Moyo and Chambati 2013). According to the authors, both sectors complemented each other well. The smallholder agricultural sector subdivided further into communal farmers, small-scale commercial farmers and the old resettlement schemes (referred to as *minda mirefu* back then) thereby giving four categories of tenure together with the white commercial farmers under freehold tenure (Moyo 2013).

With the onset of the land reform programme, code named "the fast track land reform programme" (FTLRFP), which was highly politicized, more than 70% of the commercial farms were redistributed and given to black Africans to relieve pressure in communal areas, to advance poverty alleviation and to recruit a new breed of black Africans into farming. In addition to eroding the sanctity of the freehold tenure, the onset of the FTLRFP also marked the beginning of the economic decline in Zimbabwe which persisted up to this period (Moyo and Chambati 2013). This occurrence brought about new farmers under two additional tenure categories namely A1 and A2 farmers with little knowledge of farming and limited resources. Most scholars viewed this move as a negative technical change as it resulted in subdivisions, tenure insecurity and loss of productivity (Moyo, 2011). The addition of the new category of farmers strained the already overburdened extension service which was also crumbling down due to declining economic conditions after the land reform. In the face of climate change, it becomes imperative from a policy perspective to investigate how these different farmers are performing in terms of adaptation and use of CSA technologies and how the adopted technologies have affected their livelihoods.

3 Literature review

3.1 Determinants of CSA adoption among smallholder farmers

Although the adoption of CSA practices has been shown to have significant influence on agricultural productivity, household food security, welfare, and reducing household vulnerability in developing countries, the evidence is still scanty to inform policy interventions in Sub-Saharan Africa. Climate smart policies have also been shown to improve decision making, enhance resilience and adaptive capacity to changing agro-climate conditions and adoption of feasible technologies and post-harvest practices at farm level (McCarthy *et al.,* 2018). These policies have proved effective in managing climate risk and potentially mitigating effects of climate change leading to reduction of poverty, increased food security and reduced economic vulnerability (Caron *et al.,* 2018; Collins-Sowah 2018). According to Bhardwaj (2012) and Deuter (2014), biophysical effects and socio-economic factors are some of the drivers of agricultural responses to high level climate change. Mayaya *et al.,* (2015) cited inadequate resources, weak technical and institutional capacity and cost of adoption of technologies as the main barriers to smallholder household adaptation. In addition, they also cited costly farm inputs, delays in meteorological information, lack of subsidies, inadequate credit facilities, poor access to agricultural extension service and agricultural markets, limited farm size and inadequate labour as the barriers to adaptation strategies.

At the household level, several studies have tried to tease out the drivers of adoption of CSA practices as well as their impact on household livelihood using a variety of approaches. Using Principal Component Analysis, Wekesa *et al.* (2018) found that adoption of CSA practices in Kenya was influenced by gender, farm size and value of productive assets and with impact of CSA adoption being greater in households that adopted more CSA practices. Di Falco *et al.* (2003) and Cutforth *et al.* (2001) also showed that adoption of CSA practices like crop diversification is influenced by land suitability, income level, risk avoidance and contact with extension officers. In addition, Mukankusi *et al.* (2015) found yield to be the major driver of adoption of CSA practices. Distance to market and nearest extension center, weather variability, education and labour have also been found to be some of the drivers of the choice of CSA practices adopted (Teklewood *et al.,* 2020). In Tanzania, Kassie *et al.* (2013) found that rainfall, insects and disease shocks, provision of extension services tenure status of plot, social capital and household assets, influence farmer's investments in sustainable agricultural practices. While in Southern Africa, Makate *et al.* (2019) found that multiple adoption of innovations is influenced by access to credit, income, information, education level and household land size. Contrary to these studies, access to information, inadequate supply of seeds, and perception about the new cultivars were found to be significant constraints of technology adoption in Tanzania and Ethiopia (Asfaw *et al.,* 2012).

3.2 Impact of CSA adoption

Globally, a number of studies have tried to tease out the impact of adoption of CSA practices among smallholder farmers (Tibesigwe *et al.,* 2021; Teklewood *et al.,* 2020; Asfaw *et al.*, 2016; Mendola 2007). In Bangladesh, Mendola (2007) using non-parametric propensity score matching analysis and found robust positive effects of adoption of modern seed technology in improving income and decreasing propensity to fall into poverty. Teklewood *et al.* (2020) used multinomial treatment effects framework and found that on controlling for weather variables at key stages of growth, a portfolio of CSA practices is viewed as a risk insurance strategy that can increase farmers' resilience to production risk. The adoption of modern inputs such as inorganic fertilizers and modern seeds is also positively associated with crop productivity and income (Asfaw *et al.,* 2016). Tibesigwe *et al.* (2021) assessed the impact of multi-season cropping system and found that plots that adopt multi-season cropping systems produce higher quantities, earn more crop revenue and are less likely to be affected by rainfall variability in comparison to plots that engage in single season cropping systems.

Looking at the CSA practices independently, Tesfaye *et al.* (2021) used endogenous switching regression model to handle selectivity issues and farmer heterogeneity in conservation agriculture choice. They found that conservation agriculture practices namely; minimum tillage and cereal legume and a portfolio of the two can accelerate efforts to reduce rural poverty and improve climate risk management.

In Tanzania and Ethiopia, Asfaw *et al.* (2012) after addressing selectivity issues, found that adoption of improved agricultural technologies had positive impact on household welfare, while a study by Bezu *et al.* (2014) in Malawi found that adoption of improved maize has greater impact on welfare of poorer households. Using endogenous switching regression model and control function approach, Amado *et al.* (2020) found that adoption of CSA practices led to a 53% increase in maize yield in Malawi. In China, Liang *et al.* (2021) found that adoption of both adaptive and mitigatory CSA practices increases rice yield and rice net income. However, while exploring the impact of CSA adoption on nutritional outcomes in Ethiopia, Teklewold (2019) found that farmers adopting a combination of CSA practices were more nutritionally secure than those adopting a single practice.

While assessing the impact of adoption of CSA practices on multidimensional poverty, Habtewold *et al.* (2021) found significantly higher impact in several deprived households. The impact of adoption of CSA practices was found to be through increased income or consumption via the non-food expenditure pathway. An assessment of the impact of CSA practices on livelihood outcomes by Ogada *et al.* (2020) using matching methods and simultaneous equations revealed that adoption of multiple stress tolerant crops improves household income which in turn improve household asset accumulation. They also found that adoption of improved livestock breeds significantly reduces household income and attributed this to the possibility of income being invested in the form of livestock rather than household assets a more resilient measure compared to investment in domestic household assets.

Another study by Tong *et al.* (2019) found that crop rotation and zero tillage improves technical efficiency, while crop insurance has no significant effect on technical efficiency. In the southern Africa region, Makate *et al.* (2019) found that concurrent adoption of conservation agriculture, stress adapted legume varieties and drought tolerant maize have greater dividends on productivity and income than when considered individually. They, however, found that the impact of multiple adoption of practices are heterogeneous across geographical regions and by gender. Fentie *et al.* (2019) assessed the impact of row planting as a climate smart agriculture practice on welfare of rural household in Ethiopia using Propensity Score Matching and semi parametric local instrumental variable version of the generalized Roy model. They found that adoption of row planting technology has a positive and significant impact on per capita consumption and on crop income per hectare. Using multinomial endogenous treatment effects model to assess the determinants of adoption of sustainable agricultural practices, Manda *et al.* (2016) found that household and plot-level characteristics influence a household's adoption decisions. However, their findings showed that adoption of a combination of sustainable agricultural practices raises both maize yields and income of smallholder farmers. In support of findings by Manda *et al.* (2016), Abdallah *et al.* (2021), also found that adoption of sustainable agriculture practices as a package rather than a single practice enables farm households to derive significant welfare benefits.

An overview of the literature revealed significant differences in terms of applied methodology, definition of variables and contextual factors. Previous studies have assessed the impact of adoption of single CSA practices on welfare (Tong *et al.,* 2019; Ogada *et al.,* 2020; Fentie *et al.,* 2019). However, farmers may adopt a portfolio of CSA practices (Teklewold *et al.,* 2019; Makate *et al.,* 2019; Amadu *et al.,* 2020) to maximize household welfare and agricultural output. In addition, most of these studies have focused on single outcome mainly food security or welfare measured by different methods that may be prone to measurement errors. We extend this literature by assessing the impact of adopting a portfolio of CSA practices on a vector of outcomes linked to household livelihoods, namely food security, household vulnerability and household savings. The study contributes to the literature by first analyzing the impact of employing adaptive and mitigatory CSA practices on the outcome variables and further explore the potential synergies between adaptation and mitigation practices.

3.3 Climate Smart Agriculture Impact pathways

CSA aims to contribute to a climate resilient nation that is food and nutrition secure and that has equitable access to livelihood opportunities for all, while improving natural resource systems and ecosystem services (FAO 2013a). This is done by building capacity of farmers to adapt and prosper in the face of shocks and long-term stresses. The principal goal of CSA is identified as food security and development (FAO 2013a; Lipper *et al.,* 2014); while productivity, adaptation, and mitigation are identified as the three interlinked pillars necessary for achieving this goal. The adoption of CSA practices is expected to sustainably increase agricultural productivity and incomes from crops, livestock and fish, without having a negative impact on the environment (Lipper *et al.,* 2014). This, in turn, is believed to increase agricultural productivity, increase food and nutritional security, reduce household vulnerability, increase household income and savings through sale of agricultural produce, and increase household adaptive capacity and resilience to both idiosyncratic and covariate shocks. Contrary to conventional agricultural development, CSA systematically integrates climate change into the planning and development of sustainable agricultural systems (Lipper *et al.,* 2014). Figure 1 shows the envisaged impact pathways.

In addition, wherever and whenever possible, CSA should help to reduce greenhouse gas (GHG) emissions. This implies that we avoid deforestation from agriculture, reduce emissions for each calorie of food and fuel that we produce and that we manage soils and trees in ways that maximize their potential to acts as carbon sinks and absorb CO_2 from the atmosphere. To achieve the objective of CSA, crop management entails the use of improved storage and processing techniques, mulching, composting and organic fertilizer, intercropping, crop rotation, new crop varieties and crop diversification among others. It is also envisaged that adopting more CSA practices leads to better national food security and attainment of development goals.

4 Estimation Strategies

The paper employs a mix of econometric techniques to investigate the determinants of smallholder farmer's adoption of CSA practices and the impact of

CSA practices on household livelihood including food security, vulnerability, and savings. The standard probit model is used to identify the determinants of household adoption of CSA practices (Wooldridge 2010).

4.1 Impact of CSA adoption

4.2 Theoretical framework

CSA adoption is grounded in the theory of technology adoption. The theory is well established having its roots from the early days of when researchers modelled the farmers behavior based on the cost-benefit analysis framework (also referred to as the rational choice theory) which assumes rationality in undertaking an action. As we will discuss later, CSA adoption improves food security and nutrition through increased agricultural productivity and farm incomes. The basic framework used in microeconomics and agricultural production economics are based on the farmer's profit maximization behavior (Varian 1992; Debertin 2012), i.e., assuming a single input (x) and single output $(y = f(x))$ the farmer's profit function can be written as follows:

$$\pi(pw) = \max pf(x) - w??$$

where the output and input prices are p and w respectively. This framework can be extended to a model with more than one output and inputs assuming a vector of outputs and inputs $(Y_t^j X_{it})$ and prices (p_{it}, ω_{it}). Letting x_{it} be one element of the vector of inputs X_{it}, the first-order condition of the farmer's maximization would be:

$$p_{it} \frac{\partial Y_t^j}{\partial x_{it}} = \omega_{it}$$

i.e., a farmer chooses input decisions based on the marginal value product. Essentially, adopting a CSA practice can potentially change the marginal product curve of a farmer's land. This means that CSA adoption can either change the slope or change the intercept of the marginal product curve. There are other important pathways through CSA adoption either improves food and nutrition or increases farm productivity and incomes, i.e., through a decrease in production costs and mitigation of production risk due to crop failure. Thus, CSA adoption is also likely to affect the marginal value product if it directly leads to changes in quantity of inputs demanded.

However, there are short comings of the rational choice model, and because of these limitations different theories exist to explain human behavior such as technology adoption. Rogers (1995) popularized the five stages of the adoption cycle referred to as innovators, early adopters, early majority, late majority and laggards. Several theories also emerged at the same time to explain how individual make adoption decisions such as the Theory of Reasoned Action (Fishbein and Ajzen 1975), Theory of Planned Behaviour (Ajzen 1985), different versions of Technology Acceptance Model (Davis et al., 1989) and Bounded Rationality (Esther-Marjam 2017) which addresses the discrepancy between the assumed perfect rationality of human behavior and the reality of human cognition. The theory of Bounded Rationality assumes that humans do not take a full cost-benefit analysis to determine the optimal decisions because people's decisions are limited by variables such as information. These different frameworks help us to identify other variables that affect the farmer's decision.

4.2.1 Econometric framework

The econometric framework is grounded on Roy (1951) occupational choice model which assumes that smallholder farmers adopt CSA practices to maximize benefits and utility and thus assignment to treatment is non-random. For example, define V_{ij} as the utility of household i=1 2...N in treatment regime j= {0, 1}, with 1 representing adoption of CSA technologies and 0 otherwise and hence $D_i = 1$ if $V_{i1} > V_{i0}$. Y_{ij} is a vector of potential outcomes such as household savings (total value of livestock holding), household food security and household vulnerability. Therefore, $Y_{i1}$is thepotential outcome for adopters of CSA practices and Y_{i0} is the potential outcome for non-adopters. The difference between Y_{i1} and Y_{i0} differential impact on the potential outcome.

Rubin (1973) posits that program impact is the difference between the observed and the counterfactual outcome. The main challenge is that counterfactual is not observable, and an individual cannot be in both states at the same time. A quasi-experimental approach is, therefore, more appropriate for identifying the counterfactual given that adoption of CSA practices is non-random. Controlling for adoption decision is therefore important to tease out the impact of CSA adoption and also taking cognizant of the fact that potential outcomes for CSA adopters can be due to unobserved heterogeneity. Failure to distinguish between the causal effects of adoption of CSA practices and effect of unobserved heterogeneity may lead to misleading conclusion and policy implication. Farmers may also self-select themselves to adopt CSA practices based on education level, access to information and income levels among other factors. The adoption of CSA practices is also potentially endogenous to the outcome variables.

This paper, therefore, employed a range of econometric approaches namely, the Inverse Probability Weighting (IPW) regression model to handle selection issues and the instrumental variable regression model to handle the endogeneity issues.

4.2.2 Inverse Probability Weighting Regression Model

Assuming that the distribution of the outcomes is independent of treatment i.e. adoption of CSA technology, given a vector of covariates, a propensity score matching estimator for the average treatment effects on the treated can be estimated. The intention of matching is to create a control group of non-CSA adopters that is similar as possible as the adopters of CSA technologies although the groups may be significantly different. The inverse probability weights mimic the matching intuition through reweighting to make the adopters and non-adopters distribution look as similar as possible. However, identification of average effect of adoption of CSA within this framework requires both strict ignorability of treatment, $(Y_{1i,}\ Y_{01} \perp D_i P(X_i))$ and the propensity score overlap, $0 < P(X_i) < 1$ (Dehejia *et al.,* 2002; Rosenbaum *et al.,* 1983). Another assumption is the common support in which similar individuals have positive probability of being both adopters and non-adopters of CSA technologies (Heckmann *et al.,* 1999). The IPW regression model where the probability is derived from a logit model in line with the propensity scores is specified as follows:

$$Prob\,(D_i = 1|X_i) = \wedge(X\Gamma)$$

Farm, distance to the market and household socioeconomic and demographic characteristics are other controls included in the model. The IPW regression model was applied, where the propensity scores are used to reweight the data. In the model, propensity scores are first estimated to create the weights and define overlaps between comparison and control groups and then the weighted regression is estimated (Cameron *et al.,* 2005; Wooldridge, 2003).

The estimated model is a standard treatment effects regression, wherein the outcome variable of interest is regressed on the treatment together with controls from the propensity score regression presented in equation (1) (Cameron *et al.,* 2005; Wooldridge 2003; Dehejia *et al.,* 2002; Heckmann *et al.,* 1999; Rosenbaum *et al.,* 1983). This is done to control for any lingering covariate imbalance that could influence the estimates.

4.2.3 Instrumental Variable Regression Model

The standard ordinary least squares (OLS) regression model could be appropriate if the adoption of the CSA practices was random. Thus, OLS model could yield consistent estimates, if the adoption of CSA practices is independent of the error term or of unobservable covariates that impact on the outcome variables. However, the adoption of CSA practices is likely dependent on the error term since CSA practices are likely conditional on unobservable covariates that are correlated with the error term (e.g. inert ability), a source of endogeneity of CSA adoption. The identification of the causal effect through nonlinear functional forms is however plausible, but more robust estimates can be archived through non-trivial exclusion restriction or instrumental variable (Heckman and Navarro-Lazano, 2004; Heckman Vytlacil, 2005). This requires obtaining variables that are correlated with the choice of CSA practices but are, conditional on exogenous variables in the outcome equation. In this paper, we adopt the use of long-term historical climate variables that capture rainfall and temperature patterns as identifying instruments (Asfaw *et al.,* 2016). The motivation for the choice of this instrument is that as farmers form expectations on climatic conditions of their area based on experiences, the instruments are assumed not to affect the outcome variables (food security, household vulnerability and savings (value of livestock holding)) directly, but only through the choice of CSA practices.

4.2.4 The Data

Data for the analysis is based on the agricultural productivity module of the poverty, income, consumption and expenditure survey (2017) conducted by the Ministry of Agriculture, Mechanization and Irrigation Development (MAMID). The data we use covers 8 provinces in Zimbabwe namely: Manicaland; Mashonaland Central; Mashonaland East; Mashonaland West; Matabeleland North; Matabeleland South; Midlands; and Masvingo. Harare and Bulawayo which are more of cities with limited agricultural activities are excluded. The provinces reflect different agro-ecological settings and are characterized with varying topology and altitude as well as varied temperature and rainfall patterns and farmers practice mixed farming systems. The cross-sectional data provide information on a representative sample of 14,585 households. It combines household level information on both children and adults living within households. However, this paper considers information given by the adult household head. The household survey involved collection of data on household characteristics, including, assets, agricultural produce, livestock ownership, agricultural practices, frequency, and method of land preparation as well as sociodemographic characteristics. Information was also gathered on land topography soil type, quality, and details on crop management among others.

Temperature and rainfall data are obtained from the climatic data provided by the Climatic Research Unit (CRU) at the University of East Anglia (Harris *et al.,* 2020). The climate data combines data from more than 4000 weather stations around the world and satellite data, to get high-resolution monthly estimates of temperature and rainfall over the period 1901-2020. The advantage of this database is that it is provided at fine spatial resolution (0.5x0.5 degree) grids which allows us to aggregate the data to different geographical levels. Using the provincial shapefile for Zimbabwe, we extract monthly average temperature and rainfall data between 2011 and 2020 for each of the eight provinces used. We used ten-year monthly average rainfall and for temperature, computed the coefficient of variation since variance in temperature in the short term is just as important as the mean temperature. The paper assessed 9 CSA practices identified from the literature namely: irrigation; water harvesting; border trees, erosion control structure; cover crops; organic manure; intercropping; zero tillage; and fallow farming.

The paper constructed an index for adopters of CSA practices using principal component analysis (PCA). The PCA was preferred to the additive index because it produces a more effective measure by recovering the underlying latent variable (Darnell, 1994). The Kaiser-Meyer Olkin (KMO) measure of sampling adequacy revealed that CSA practices had an overall KMO measure of 0.5 allowing for the use of PCA. The PCA results revealed that the first two components had eigenvalues greater than one - dominating in terms of eigenvalues and proportion of variance. The first component also makes more economic sense since none of the coefficients was negative. The first component vector also contains positive weights for all the CSA practices an evidence of aggregate variation as a result of variation in adoption levels by households (Fujiie *et al.,* 2005). We therefore, classified households based on PCA scores with PCA scores greater than zero as adopters of CSA and those with less than or equal to zero as non-adopters. The Household Dietary Diversity index (HDD)[1] a proxy for food security was constructed through an additive index of dummies whether household ate sadza, potatoes, beans, fruits, beef, milk in the last 24 hours. On the other hand, household vulnerability index was also constructed as an additive index obtained by summing up the dummies whether the household was worried about food, ate few foods, ate less, skipped meal, missed food or was out of food among others. The other controls adopted in the study were selected based on related literature. This helped identify a comprehensive set of controls that are known to affect smallholder farmer decision to adopt CSA practices (see Makate et al. 2019; Asfaw et al. 2012; Teklewold 2019; Ogada et al. 2020; Fentie et al. 2019; Bezu et al. 2014; Kassie et al. 2013; Liang et al. 2021).

5 Empirical Results and Discussion

5.1 Descriptive statistics

Table 1 presents summary statistics and description of variables for the full sample, adopters, and non-adopters of CSA practices. The results revealed that the average household dietary diversity index was approximately 8 out of a maximum of 12 for whole sample as well as the disaggregated sample of CSA technologies. The vulnerability index was slightly lower for adopters than it is for non-adopters showing that adopters of CSA practices were less vulnerable compared to non-adopters. However, the household savings (value of livestock holding) was lower for adopters than non-adopters. This shows that most adopters of CSA practice could be more involved in crop farming than livestock farming which dominates in much drier regions where the potential to grow crops is limited by rainfall. Overall, the statistics also revealed that the ownership of livestock for the whole sample was on average 14% of the total sample. Non-adopters of CSA technologies on average owned more livestock than adopters of CSA explaining the low value of livestock holding for adopters.

A summary of adoption of CSA practices by gender of household head and province is presented in Table 2 and Table 3 respectively. Table 2 shows that use of erosion control, border trees, and intercropping were the predominant CSA practices with male headed households being the greatest adopters of these practices compared to their female headed households. This could be because most CSA practices require physical energy and more household income which translate into increased on-farm financial investments common in male headed households (Kassie *et al.,* 2013). However, as expected female headed households dominated the adoption of intercropping. This is because most agricultural practices are done by women and intercropping is less physically intensive

[1] Household dietary diversity score is defined as the number of different foods/food groups consumed by households over a given period. It is derived by grouping all food items consumed by a household over a a period of 24 hours into 12 food groups (Swindale and Bilinsky, 2006)

and also synonymous with female headed households as they strive to maximize out of the small parcel of land they may own (Manda *et al.,* 2016).

Speaking to the topography, vegetation and aridity of the landscapes, the distribution of CSA adoption by region presented in Table A1 in the annex revealed that Manicaland dominated adoption of border trees followed by Matabeleland North, Mashonaland West and Midlands in that order. Erosion control structures were predominant in Masvingo, Manicaland, Mashonaland central and Mashonaland East. Intercropping was also found to be predominant in Matabeleland South and Masvingo.

5.2 Test of significant differences between adopters and non-adopters of CSA practices

Table 4 presents the results of the mean difference in household characteristics and livelihoods of adopters and non-adopters of CSA practices based on the student t-test statistic. The variables include the three-outcome variables, namely, food security (HDD), household vulnerability, savings (value of livestock holding) other controls namely: human capital, physical capital, access to services constraints and climatic variables among others.

The results show that there was significant mean difference in HDD and value of livestock holding between adopters and non-adopters of CSA practices. As expected, CSA adopters have high dietary diversity index and a low vulnerability index compared to non-adopters. This result is not surprising given the diversity of income generating activities and food sources under the former category, which might also help to reduce vulnerability (Manda *et al.,* 2016). However, non-adopter had high value of livestock holding than non-adopters and this could be because most non-adopters owned more livestock than adopters of CSA practices since they are located in drier regions where crop production is less viable. Overall, the significant mean differences for some covariates suggest that the observed outcomes for non-CSA adopters may not provide good counterfactual for adopters. This implies that estimation assuming random treatment assignment would produce biased results calling for an alternative impact evaluation approach.

5.3 Who adopts CSA practices?

Table 5 presents coefficients and marginal effects estimates of CSA from the probit model. The study revealed that the adoption of CSA practices increases with age until age 56 years, whereby further increase in age limits physical strength and hence the lower likelihood of adoption of CSA practices. This shows that the physical energy of youths and their knowledge accumulation increases the likelihood of adopting CSA practices (Martey *et al.,* 2021). Smallholder farmers are more likely to adopt CSA practices where they have forest soil or loam soil compared to other soils like sand, clay etc. This result confirms the result in Table 3 that Manicaland dominated adoption of border trees as the province has forest soil.

The results also revealed that households that received residential input subsidy or vulnerable input subsidy are less likely to adopt CSA practices. Rukuni *et al.* (2006) likened this behaviour of the vulnerable group to the donor dependence syndrome and could be much pronounced in developing countries than previously thought. On the other hand, households that hired labour and have rights to sell their land were more likely to adopt CSA practices. Since some of the CSA technologies are labour and capital intensive, the relatively wealthy households can afford to hire extra labour. Interestingly, those who own land were also found to be less likely to adopt CSA practices compared to those who do not own land. Barrows and Roth (1990) found that in West and East African countries land ownership pushes one to work harder so that they can acquire their own assets such as land to be self-reliant. Similar reasoning could be applied in the Zimbabwean case under a communal setup or the newly resettled farmers because of the tenure insecurity.

Experience of erosion problem was found to positively influence CSA adoption decisions of smallholder households. There is plenty of evidence in the literature in support of the fact that soil erosion is one of the main factors influencing the adoption of CSA practices as it directly and quickly translates into reduced yield if not taken care off immediately (Makate *et al.,* 2019; Manda *et al.,* 2016; Kassie *et al.,* 2013; Mendola 2007). Climatic variables were found to influence adoption of CSA practices. These results support findings by Di Falco *et al.* (2003); Cutforth *et al.* (2001); Kassie *et al.* (2013); Mayaya *et al.* (2015); Manda *et al.* (2016); Wekesa *et al.* (2018); Makate *et al.* (2019) and Teklewood *et al.* (2020) among others. In particular, the likelihood of adopting CSA practices increases with rainfall and decreases with increase in temperature. This confirms the idea that households are more likely to adopt CSA practices in wetter regions and less likely to do so in drier climates as they can easily switch from crop cultivation to livestock production (Kassie *et al.,* 2013). Further, in terms of gender, the results revealed that, Male headed households that owned plots, received vulnerable input subsidy, had sell rights to their land and also received residential input subsidy were more likely to adopt a portfolio of CSA practices compared to their female counterparts. As already alluded to, investment in some of the CSA technologies could be labour and/or capital intensive which usually falls in the domain of employed males (Manda *et al.,* 2016).

5.4 Impact of CSA adoption on household livelihood

As previously stated, if treatment assignment i.e., adoption of CSA practices was completely random, then a simple ordinary least square regression model or a comparison of the mean difference in the outcomes would suffice. However, since adoption of CSA practices is voluntary and a household could self-select into adopting CSA practices based on maybe level of education or access to information, a random treatment assignment may not apply in this case. We therefore, adopted the IPW regression model to address the selectivity issues.

Before discussing the results, the underlying premises of IPW i.e., confoundedness and overlap must be met. The results depicted sufficient overlap although there are few propensity scores closer to either one or zero. This implies that the regions too close to zero or one will not be within the common support. We also assessed the balance although we do not report them here. The primary IPW estimates are presented in Table 6, 7, and 8.

The results in Table 6, 7 and 8 could be sensitive to inclusion of additional covariates. The results show that there is evidence of treatment effect in agreement with the mean differences in Table 4. Despite the sensitivity to choice of counterfactual, the direction as well as size of the program impacts may not be particularly sensitive to the inclusion of a broader set of covariates. The results confirmed that the impact of CSA adoption was significant and positive on household dietary diversity i.e., food security but significantly reduced household vulnerability and household savings as proxied by value of livestock holding. The results were consistent even when we considered male and female headed households separately except for the household vulnerability as shown in Table 7 and Table 8 for male and female headed households, respectively.

In addition, since adoption of CSA practices could be potentially endogenous to food security, household vulnerability and value of livestock holding, we first tested for endogeneity of CSA adoption. The control function approach[2] was employed to test for endogeneity. The approach was conducted in two phases. In the first phase, the endogenous variable (CSA adoption) was regressed on the instrumental variable Coefficient of variation of rainfall and temperature and the other explanatory variables and the predicted residuals saved.[3] In the second phase, the three outcome variables were regressed on the endogenous variables (CSA adoption), other explanatory variables and the residuals (Wooldridge 2010). The test revealed that CSA adoption was not endogenous to Household dietary diversity as the null hypothesis of exogeneity is not rejected with a p-value of 0.789. However, the null hypothesis of exogeneity was rejected for value of livestock holding and household vulnerability index with a p-value of 0.025 and 0.000 showing that adoption of CSA practices is endogenous to value of livestock holding and household vulnerability index. This implies that we cannot proceed to estimate a standard OLS model for value of livestock holding and household vulnerability index. Due to evidence of endogeneity of adoption of CSA practices to livestock holding and vulnerability index we proceeded to estimate an instrumental variable regression model to address the endogeneity concerns. The results were obtained using the ivreg2 Stata command for an extended instrumental variable regression model are presented in Table 9.

Since adoption of CSA, practices was not endogenous to household food security i.e., HDD, but was found to be endogenous to household livestock value and household vulnerability index, the discussion henceforth will be based on

[2] The approach is almost similar to the 2SLS approach but the only difference is that it allows for testing of endogeneity of CSA adoption. However, it hinges on the assumption of exogeneity of the instrument.

[3] The proportion of predicted probabilities outside the unit interval was computed. Finding only 1.3 % of the predicted residuals were outside the unit interval, the Linear probability model was preferred over the probit or logit model. This is because LPM would still produce consistent and unbiased estimates (Horrace &Oaxaca, 2006). The LPM model was also found to be significant with an F-value 32.94 and a p-value of 0.000.

the OLS model estimates for HDD (column 1) and IV model estimates for value of livestock holding and household vulnerability index in columns (3) and (4) respectively. Conditioned on a set of covariates, the results revealed that, adoption of CSA practices has a positive effect on household food security as revealed by the OLS model, while adoption of CSA practices has a negative effect on value of livestock holding and household vulnerability index. The results revealed that adopters of CSA practices experience increased HDD by 0.21 points holding other factors constant. On the other hand, CSA adopters were found to experience reduction in vulnerability by 11 points compared to non-adopters. However, CSA adopters experienced reduction in value of livestock holding by about US $208 compared to non-adopters. Although we expected the adoption of CSA practices to have a positive impact on household savings as proxied by value of livestock holding since most rural smallholder farmers save through purchase of livestock, this could have been because investment on some CSA practices could be costly therefore households may be forced to shed off some livestock to buy say inorganic manure or build gabions or invest in irrigation infrastructure. This was also evident from the descriptive statistics since CSA adopters had very few livestock.

The results of the OLS and IV models are therefore in tandem with results of the IPW models showing that CSA adoption has significant impact on HDD, value of livestock holding and household vulnerability index. It, therefore, implies that CSA adopters were well off economically than non-adopters of CSA practices. The evidence of reduction in household vulnerability implies that ideally adopters of CSA practices had improved welfare as they could now easily be able to meet their daily livelihood needs. The results support findings by Asfaw *et al.* (2012); Bezu *et al.* (2014); Teklewold (2019); Fentie *et al.* (2019); Wekesa *et al.* (2020); Ogada *et al.* (2020); Abdallah *et al.* (2021); Tesfaye *et al.* (2021); and Habtewold *et al.* (2021) among others who found adoption of CSA practices to have positive impact on household welfare. Taking a closer look at both models, the impact analysis results agree with each other after addressing the selectivity issues in the IPW regression model and after taking care of endogeneity using IV estimation. Previous theoretical and empirical accounts also suggest a positive relationship between the adoption CSA practices and food security (Amadu *et al.,* 2020; Fentie and Beyene 2019; Asfaw *et al.,* 2012), while a negative relationship is established between CSA adoption with either household vulnerability (Habtewold 2021; Makate *et al.,* 2019). However, the evidence in Sub-Saharan Africa is still shaky by the fact that adoption of some CSA practices is not widespread as smallholder farmers are still experimenting with the technologies (McCarthy *et al.,* 2018; Collins-Sowah 2018). According to the theory, the process of adoption has several stages starting from the time the farmer receives the information about a new technology, followed by observing the performance of other farmers using the technology in question as a means of consolidating more information, then learning on a small scale and finally deciding to adopt (Montes de Oca Munguia *et al.,* 2021; 2020).

In addition to the time element, the decision-making process involves an element of risk or uncertainty and weighing the real benefit and costs of adopting

CSA practices under the rationality assumption, while the benefit and cost functions are made up of both observable and latent variables (Wauters and Mathijs 2014). The cost of adopting a CSA can be greater than the benefits in the short-run considering real costs, the opportunity costs of land (if land can be used for different purposes) and labour (for labour intensive technologies), and other variables that are unobservable, while in the long-run the benefits can be greater than the costs. Therefore, the length of time that is required by farmers to realize the benefits from adopting CSA practices might too long for certain technologies which also brings in the issue of patience (Liu et al. 2018). In the literature, the behaviour of peasant farmers is assumed to be myopic or short sighted and impatient (Wauters and Mathijs 2014).

The negative relationship between CSA adoption and household savings as proxied by livestock holdings was not expected which makes this result interesting. Manure management mitigation options have a high potential in landless systems but a much more limited potential in land-based systems (FAO 2013). Since most non-adopters were livestock farmers in arid regions, another plausible explanation could be that information on adoption of CSA practices in livestock management were not collected during the survey. Maybe the results could be different if we controlled information on adoption of CSA practices in livestock management. The literature from the developed world reveal that climate-smart options are available for land-based systems depending mainly on grazing, e.g., reductions in methane gas emissions through improved feed digestibility and carbon dioxide removals through soil carbon sequestration (FAO 2013). However, the applicability of these options to low-input systems with infrequent human intervention in the context of communal farmers in developing countries tends to be quite limited because they require a high level of management (FAO 2010). Adoption of CSA practices in livestock management is very common in wetter regions where households own a limited amount of land that should be optimized between crop cultivation and livestock production for sustainability (FAO 2013). Previous studies observed CSA practices associated with livestock management such as grazing and pasture management (i.e., production of fodder crops as part of agroforestry practices and paddock for rotational grazing). There was also significant heterogeneity across gender. The study revealed significant positive impact on food security and household vulnerability for male headed households who owned plots, Hadsell rights and received vulnerable input subsidy.

6 Conclusion

The study sought to determine the drivers of adoption of CSA practices by smallholder farmers in Zimbabwe and the subsequent impact of adoption of CSA practices on food security, household savings, and household vulnerability. The study found that male headed households who own plots, have sell rights received input subsidies, age, slope of land, soil quality, type of soil, tree loss experience, input subsidy programmes, whether a household hired labour, land ownership, experience of soil erosion and climatic variables such as rainfall and temperature were significant determinants of household adoption decisions. However, the study revealed that CSA adoption had positive impact on food security and reduced household vulnerability but a negative impact on household savings as proxied by value of livestock holding on average. In terms of gender, adoption of CSA was found to have a positive impact on household food security and a negative impact on household savings for both male and female headed households. However, adoption of CSA practices was found to reduce household vulnerability for female headed households but increase vulnerability for male headed households. It can therefore be concluded that on average, adoption of CSA practices is economically and socially beneficial for smallholder farmers. It is therefore imperative for the provincial governments to strive to increase resources towards supporting CSA to greatly impact on food security by boosting crop yields in the face of increasing climate uncertainty and extreme weather shocks. The results also confirm the potential role of adoption of climate smart technologies in improving household food security and reducing vulnerability.

In terms of policy recommendations, the study findings point to the need for promotion of CSA practices aimed at livestock management due to increased income because of increased yields from adoption of CSA practices. Most rural households often invest in livestock assets given an option of which they can liquidate to bridge household income gaps on a rainy day. This is a more resilient measure compared to investment in domestic household assets. The positive effects of CSA adoption on food security confirm the essence of increasing capacity enhancing activities in agricultural development projects, and design mechanisms to eliminate barriers to adoption of CSA practices among smallholder farmers. Scaling up of CSA technologies would contribute to farmers' resilience against the adverse effects of climate change through enhancing food security and reduction of household vulnerability. To enhance agricultural productivity, policy and institutional efforts should strike at reducing resource constraints that inhibit farmer capacity to adopt complementary climate smart agricultural packages such as conservation agriculture, drought tolerant maize and improved legume varieties must be gender sensitive and context specific. More extension work in the form of information provisioning particularly to the new farmers, trial or demonstration plots, look and learn tours are needed to demonstrate the benefits of CSA practices.

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Table 1: Summary Statistics

	Whole Sample			Adopters			Non Adopters		
Variable	**N**	**mean**	**Sd**[1]	**N**	**Mean**	**Sd**	**N**	**mean**	**Sd**
Household Dietary Diversity	14,585	8.20	1.45	4,007	8.35	1.40	10,578	8.14	1.46
Vulnerability Index	14,585	4.14	3.75	4,007	4.07	3.69	10,578	4.17	3.77
Amount of Tree Sale	14,585	1.19	15.9	4,007	1.41	21.8	10,578	1.09	13.0
Value of Livestock	14,585	46.7	249.1	4,007	33.6	187.0	10,578	51.7	268.8
Animal Expenses	14585	2.29	32.8	4,007	3.01	44.8	10,578	2.01	26.9
Household head is male	14,585	0.59	0.49	4,007	0.60	0.49	10,578	0.59	0.49
Age of household head	14,585	48.3	14.4	4,007	49.8	14.0	10,578	47.7	14.5
Household Graze Livestock	14,585	0.65	0.48	4,007	0.61	0.49	10,578	0.66	0.47
Pasture Land size	14,585	499.5	4400	4,007	418.2	5287	10,578	530.2	4013
Years plot left fallow	14,585	0.21	0.80	4,007	0.05	0.26	10,578	0.27	0.92
No of household members on plot	14,585	2.15	1.37	4,007	2.09	1.41	10,578	2.18	1.36
Household hired labor	14,585	0.12	0.33	4,007	0.15	0.36	10,578	0.11	0.31
Household planted on time	14,585	0.72	0.45	4,007	0.78	0.42	10,578	0.69	0.46
Household used hybrid seeds	14,585	2.13	0.99	4,007	2.15	0.99	10,578	2.12	0.99
Household used certified seed	14,585	0.41	0.49	4,007	0.41	0.49	10,578	0.42	0.49
Household used free seeds	14,585	0.25	0.43	4,007	0.24	0.43	10,578	0.25	0.43
Distance to seed market	14,585	10.2	35.7	4,007	9.20	31.8	10,578	10.5	37.0
Number of trees	14,585	196.1	838.5	4,007	172.2	639.3	10,578	205.1	902.4
Household lost trees	14,585	0.04	0.19	4,007	0.02	0.15	10,578	0.04	0.20
Household owned animals	14,585	0.14	0.35	4,007	0.13	0.33	10,578	0.15	0.35
Household dipped animals	14,585	0.062	0.24	4,007	0.06	0.24	10,578	0.06	0.24
No of Plots	14,585	2.90	2.50	4,007	2.98	2.77	10,578	2.87	2.40
Household own land document	14,585	0.21	0.41	4,007	0.22	0.41	10,578	0.20	0.40
Household own plot	14,585	0.28	0.45	4,007	0.26	0.44	10,578	0.29	0.45
Household own land	14,585	0.01	0.11	4,007	0.01	0.09	10,578	0.01	0.12
Household have sell rights	14,585	0.005	0.07	4,007	0.01	0.09	10,578	0.003	0.06
Temperature	14,585	21.7	0.91	4,007	21.7	0.94	10,578	21.7	0.90
Rainfall	14,585	55.3	10.2	4,007	56.5	9.44	10,578	54.9	10.5
CV[2] of Rainfall	14,585	126.7	9.85	4,007	127.6	9.52	10,578	126.4	9.95
CV of Temp	14,585	14.0	1.20	4,007	13.8	1.06	10,578	14.0	1.24
Distance to Agric Market	14,585	0.02	0.95	4,007	0.02	0.392	10,578	0.02	1.09
Household received Residential Input	14,585	0.06	0.25	4,007	0.05	0.23	10,578	0.07	0.25
Household received Vulnerable input	14,585	0.03	0.18	4,007	0.03	0.17	10,578	0.03	0.18
Household experienced erosion Problem	14,585	0.32	0.47	4007	0.40	0.49	10,578	0.29	0.45

Table 2: Distribution of CSA practices by Gender

	Total			Female			Male		
Variable	**N**	**mean**	**Sd**	**N**	**mean**	**Sd**	**N**	**mean**	**Sd**
Irrigation	14585	0.047	0.212	5925	0.041	0.198	8660	0.052	0.221
Water Harvesting	14585	0.023	0.151	5925	0.017	0.130	8660	0.028	0.163
Border Trees	14585	0.382	0.486	5925	0.356	0.479	8660	0.400	0.490
Erosion Control	14585	0.389	0.488	5925	0.366	0.482	8660	0.405	0.491
Cover Crop	14585	0.043	0.203	5925	0.037	0.188	8660	0.047	0.212
Organic Manure	14585	0.233	0.507	5925	0.249	0.519	8660	0.222	0.498
Intercropping	14585	0.276	0.447	5925	0.319	0.466	8660	0.246	0.431
Zero Tillage	14585	0.035	0.184	5925	0.037	0.188	8660	0.034	0.182
Fallow Farm	14585	0.099	0.298	5925	0.100	0.299	8660	0.098	0.298

[1] Standard deviation
[2] Coefficient of variation

Table 4: Comparison between adopters and non-adopters of CSA practices

Variable	CSA Adopters		Non-CSA adopters		Mean difference	
	Mean	**s.e**	**Mean**	**s.e**	**Mean**	**s.e**
Household Dietary Diversity	8.348***	0.022	8.143***	0.014	0.205***	0.027
Vulnerability Index	4.065***	0.058	4.171***	0.037	0.105	0.070
Amount of Tree Sale	1.333***	0.086	1.097***	0.126	-0.235	0.202
Value of Livestock	33.614***	2.953	51.680***	2.613	18.066***	4.619
Animal Expenses	3.013***	0.708	2.013***	0.261	-0.999	0.608
Household head is male	0.603***	0.008	0.590***	0.005	-0.013	0.009
Age of household head	49.793***	0.221	47.717***	0.141	-2.075***	0.267
Household Graze Livestock	0.611***	0.008	0.662***	0.005	0.050***	0.009
Pasture Land size	1173.04***	40.72	530.228***	39.01	-642.81***	93.061
Years plot left fallow	0.204***	0.004	0.271***	0.009	0.068***	0.010
No of HH members worked on plot	2.509***	0.006	2.175***	0.013	-0.400***	0.015
Household hired labor	0.153***	0.006	0.110***	0.003	-0.043***	0.006
Household planted on time	0.778***	0.007	0.692***	0.004	-0.086***	0.008
Household used hybrid seeds	0.426***	0.008	0.438***	0.005	0.013	0.009
Household used certified seed	0.410***	0.008	0.415***	0.005	0.005	0.009
Household used free seeds	0.242***	0.007	0.250***	0.004	0.008	0.008
Distance to seed market	9.897***	0.145	10.533***	0.360	0.636*	0.362
Number of trees	188.05***	3.277	205.149***	8.774	17.094**	8.331
Household lost trees	0.023***	0.002	0.040***	0.002	0.018***	0.003
Household owned animals	0.127***	0.005	0.145***	0.003	0.176***	0.006
Household dipped animals	0.059***	0.004	0.062***	0.002	0.003	0.004
No of Plots	3.085***	0.012	2.867***	0.023	-0.218***	0.029
Household own land document	0.218***	0.007	0.204***	0.004	-0.014*	0.008
Household own plot	0.258***	0.007	0.286***	0.004	0.028***	0.008
Household own land	0.009***	0.001	0.015	0.001	0.006***	0.002
Household have sell rights	0.008***	0.001	0.003***	0.001	-0.004***	0.001
Temperature	21.773***	0.004	21.742***	0.009	-0.031***	0.009
Rainfall	54.862***	0.041	54.910***	0.102	0.049	0.102
Distance to Agric Market	0.091***	0.010	0.024***	0.011	-0.067***	0.024
Household received residential input	0.054***	0.004	0.068***	0.002	0.014***	0.005
Household received vulnerable input	0.030***	0.003	0.033***	0.002	0.003	0.003
Household experienced erosion Problem	0.395***	0.008	0.291***	0.004	-0.104***	0.009

Table of mean differences and test of significance. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5: CSA adoption and marginal effects of probit models

VARIABLES	CSA Practice	Marginal Effects
Age of household head	0.0178***	0.00554***
	(0.00640)	(0.00199)
Age of household head squared	-0.000113	-3.51e-05
	(6.85e-05)	(2.13e-05)
Slight Slope land	0.182***	0.0558***
	(0.0259)	(0.00785)
Moderate Slope land	0.336***	0.107***
	(0.0451)	(0.0151)
Steep/Hilly land	0.529***	0.176***
	(0.0836)	(0.0301)
Poor soil Quality	-0.244***	-0.0768***
	(0.0283)	(0.00905)
Fair soil quality	-0.0793**	-0.0261**
	(0.0357)	(0.0117)
Clay soil	-0.294***	-0.0897***
	(0.0377)	(0.0112)
Sand& Clay soil	-0.173***	-0.0547***
	(0.0303)	(0.00958)
Forest soil	0.278***	0.0979***
	(0.0482)	(0.0175)
Loam soil	0.261***	0.0919***
	(0.0408)	(0.0146)
Other soil type	-1.966***	-0.289***
	(0.254)	(0.00869)
Household owned animals	-0.0548	-0.0171
	(0.0342)	(0.0106)
Household lost trees	-0.402***	-0.125***
	(0.0675)	(0.0209)
Household received Residential Input	-0.303***	-0.0944***
	(0.0885)	(0.0275)
Household received Vulnerable input	-0.479***	-0.149***
	(0.111)	(0.0345)
Household used free seeds	0.0335	0.0104
	(0.0330)	(0.0103)
Household hired labor	0.218***	0.0679***
	(0.0352)	(0.0109)
Household own land	-1.220***	-0.380***
	(0.217)	(0.0674)
Household have sell rights	-2.783***	-0.866***
	(0.244)	(0.0770)
Household experienced erosion Problem	0.183***	0.0569***
	(0.0253)	(0.00783)
Household Graze Livestock	-0.170***	-0.0529***
	(0.0251)	(0.00778)
Male # Own Plot	-0.0948***	-0.0295***
	(0.0335)	(0.0104)
Male # Vulnerable Input Subsidy	0.513***	0.160***
	(0.133)	(0.0414)
Male # Residential Input Subsidy	0.181*	0.0563*
	(0.101)	(0.0314)

VARIABLES	CSA Practice	Marginal Effects
Male #Sell rights	4.442***	1.382***
	(0.198)	(0.0626)
CV of Rainfall	0.00296**	0.000922**
	(0.00138)	(0.000428)
CV of Temp	-0.0651***	-0.0202***
	(0.0114)	(0.00354)
No of Plots	0.00588	0.00183
	(0.00492)	(0.00153)
Constant	-0.522	
	(0.324)	
Observations	14,585	14,585

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 6: ATT estimates from IPW regression model results

Variables	Household Dietary Diversity	Vulnerability index	Value of Livestock
CSA Adoption	0.220***	-0.187***	-13.372***
	(0.026)	(0.068)	(3.554)
Constant	8.145***	4.126***	50.309***
	(0.014)	(0.036)	(2.513)

Table 7: ATT estimates from IPW regression model results: male headed Households

Variables	Household Dietary Diversity	Vulnerability index	Value of Livestock
CSA Adoption	0.121***	0.226***	-17.517***
	0.039	0.092	4.495
Constant	8.116***	4.022***	55.083***
	0.018	0.0481	3.667

Table 8: ATT estimates from IPW regression model results: female headed Households

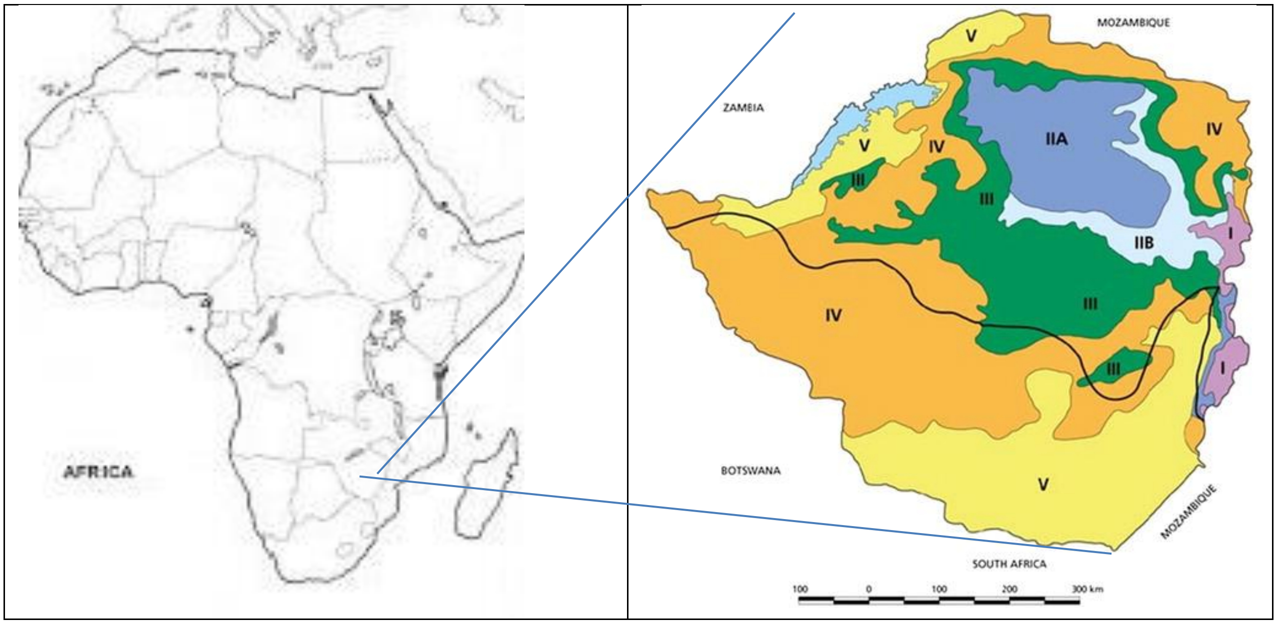
Variables	Household Dietary Diversity	Vulnerability index	Value of Livestock
CSA Adoption	0.313***	-0.673***	-11.419**
	0.042	0.107	5.280
Constant	8.198***	4.267***	43.479***
	0.022	0.055	3.229

Table 9: OLS and Instrumental variable regression model Results

	OLS Model estimates	IV Regression model estimates		
	(1)	(2)	(3)	(4)
VARIABLES	HDD	HDD	Value of Livestock	Vulnerability Index
CSA Practices	0.212***	0.248	-216.4***	-12.43***
	(0.0259)	(0.550)	(80.23)	(2.473)
Animal Expenses	0.000536	0.000381	0.403	0.000644
	(0.000459)	(0.000472)	(0.351)	(0.00147)
Age of household head	0.0135*	0.0127	-0.525	-0.141***
	(0.00733)	(0.00786)	(1.028)	(0.0308)
Age of household head squared	-0.000140*	-0.000135*	0.0117	0.00175***
	(7.71e-05)	(8.01e-05)	(0.0105)	(0.000319)
Years plot left fallow	0.0309**	0.0477	-18.55***	-1.000***
	(0.0133)	(0.0406)	(5.797)	(0.186)
No of HH members worked on plot	0.00648	0.00560	-2.098	-0.0231
	(0.00860)	(0.0111)	(1.759)	(0.0499)
Household hired labor	0.301***	0.264***	28.82**	0.168
	(0.0370)	(0.0612)	(11.24)	(0.287)
Household planted on time	0.163***	0.235***	14.69*	0.266
	(0.0273)	(0.0562)	(8.565)	(0.258)
Distance to seed market	0.000757*	0.000729*	0.00808	-0.00390**
	(0.000421)	(0.000437)	(0.0719)	(0.00165)
Number of trees	5.05e-05***	6.03e-05***	-0.00224	-0.000211***
	(1.16e-05)	(1.45e-05)	(0.00270)	(6.47e-05)
Household lost trees	0.792***	0.785***	-33.90***	-1.703***
	(0.0555)	(0.0799)	(11.71)	(0.348)
Household own land document	0.329***	0.284***	27.81***	0.165
	(0.0298)	(0.0303)	(6.889)	(0.145)
Household owned animals	0.0551	0.0571	322.7***	-0.563***
	(0.0338)	(0.0360)	(12.51)	(0.166)
Household dipped animals	0.0484	0.0491	16.78	-0.686***
	(0.0533)	(0.0542)	(12.64)	(0.234)
No of Plots	0.00982**	0.0291***	-1.442*	-0.164***
	(0.00428)	(0.00471)	(0.808)	(0.0261)
Household own land	0.671***	0.618***	-49.69	-5.756***
	(0.0980)	(0.160)	(37.93)	(0.743)
Household have sell rights	0.567***	0.830***	-143.4**	-0.930*
	(0.102)	(0.122)	(63.04)	(0.499)
Household Graze Livestock	0.304***	0.305***	-7.114	-1.085***
	(0.0257)	(0.0342)	(4.843)	(0.171)
Pasture Land size	-2.81e-06	-2.05e-06	0.00255**	-1.01e-05
	(2.00e-06)	(1.99e-06)	(0.00126)	(2.01e-05)
Male # Own Plot	0.123***	0.158***	-9.324	-1.201***
	(0.0319)	(0.0390)	(5.717)	(0.179)
Male # Vulnerable Input Subsidy	0.319***	0.280***	-8.413	2.579***
	(0.0861)	(0.0958)	(11.48)	(0.454)
Male # Residential Input Subsidy	0.0309	0.0211	-17.99**	0.278
	(0.0476)	(0.0529)	(7.501)	(0.270)
Male #Sell rights	-0.00581	-0.279	237.3***	9.018***
	(0.129)	(0.308)	(80.47)	(1.845)
CV Rainfall	-0.0242***			
	(0.00140)			
CV Temp	-0.194***			
	(0.0113)			
Constant	13.05***	7.197***	55.06**	11.57***
	(0.350)	(0.187)	(22.67)	(0.696)
Observations	14,585	14,585	14,585	14,585

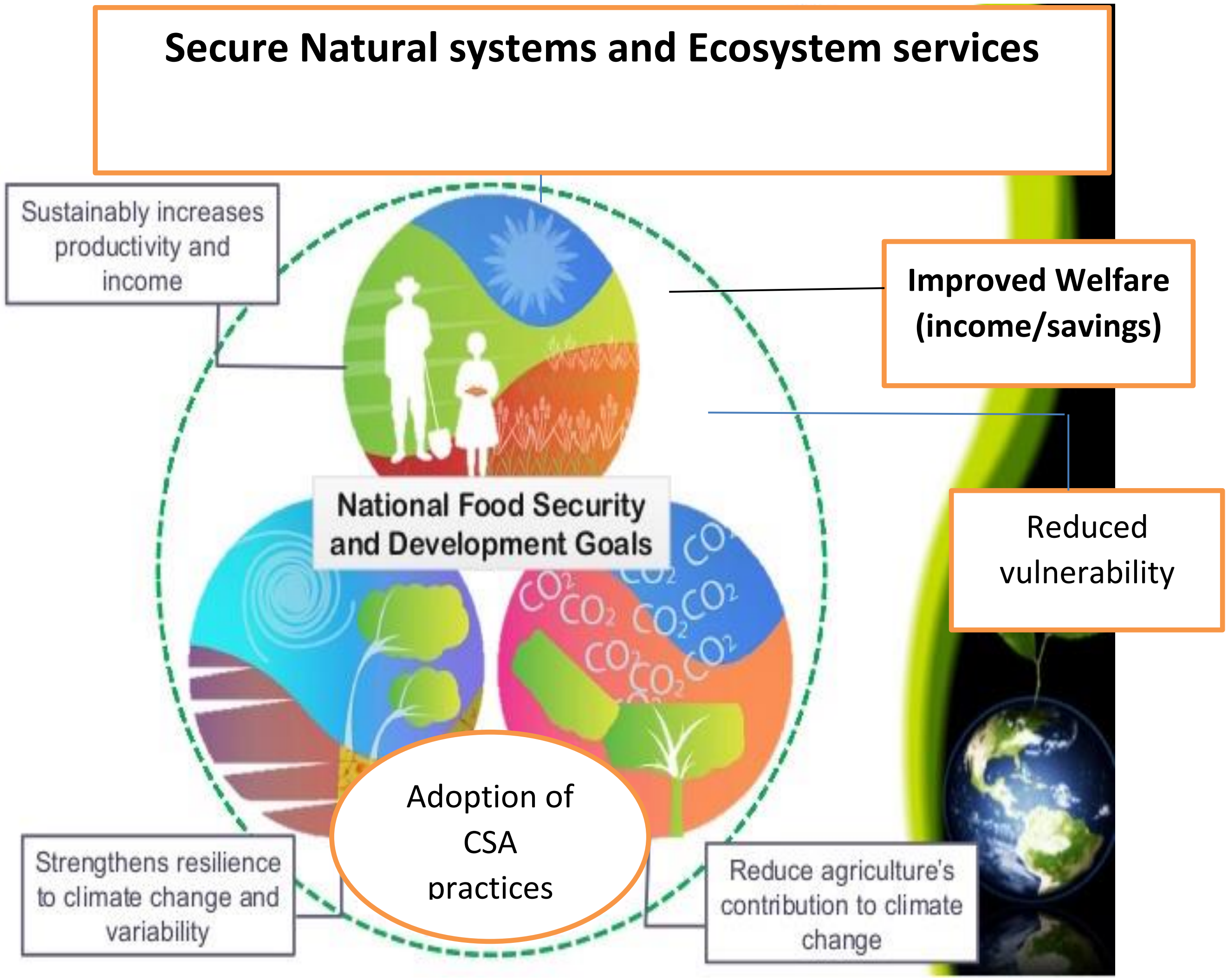
Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Figure 1: Map of Zimbabwe's agro-ecological zones



Source: http://www.fao.org/3/a0395e/a0395e06.htm

Figure 1: Conceptualization of Climate Smart Agriculture



Source: Adapted from FAO (2013)

Annex 1

Table A1. Distribution of CSA practices by region (Province)

	Manicaland			Mashonaland Central			Mashonaland East			Mashonaland West		
variable	**N**	**mean**	**Sd**	**N**	**mean**	**Sd**	**N**	**Mean**	**Sd**	**N**	**mean**	**Sd**
Irrigation	2469	0.0737	0.261	1944	0.0118	0.108	1810	0.189	0.392	1732	0.00577	0.0758
Water Harvesting	2469	0.0162	0.126	1944	0.0108	0.103	1810	0.0271	0.162	1732	0.0370	0.189
Border Trees	2469	0.534	0.499	1944	0.383	0.486	1810	0.387	0.487	1732	0.447	0.497
Erosion Control	2469	0.519	0.500	1944	0.461	0.499	1810	0.403	0.491	1732	0.317	0.465
Cover Crop	2469	0.0186	0.135	1944	0.00977	0.0984	1810	0.0906	0.287	1732	0.0167	0.128
Organic Manure	2469	0.306	0.592	1944	0.270	0.595	1810	0.274	0.485	1732	0.174	0.449
Intercropping	2469	0.154	0.361	1944	0.224	0.417	1810	0.222	0.415	1732	0.0906	0.287
Zero Tillage	2469	0.00648	0.0803	1944	0.107	0.309	1810	0.0442	0.206	1732	0.0779	0.268
Fallow Farm	2469	0.145	0.352	1944	0.120	0.325	1810	0.153	0.360	1732	0.00289	0.0537

	Masvingo			Matabeleland North			Matabeleland South			Midlands		
Variable	**N**	**Mean**	**Sd**	**N**	**Mean**	**Sd**	**N**	**Mean**	**Sd**	**N**	**mean**	**Sd**
Irrigation	1639	0.0189	0.136	1669	0.0330	0.179	1901	0.0252	0.157	1421	0	0
Water Harvesting	1639	0.0122	0.110	1669	0.0569	0.232	1901	0.0147	0.120	1421	0.0162	0.126
Border Trees	1639	0.373	0.484	1669	0.460	0.499	1901	0.0179	0.133	1421	0.440	0.497
Erosion Control	1639	0.605	0.489	1669	0.123	0.329	1901	0.319	0.466	1421	0.294	0.456
Cover Crop	1639	0.0336	0.180	1669	0.0935	0.291	1901	0.0268	0.162	1421	0.0746	0.263
Organic Manure	1639	0.217	0.453	1669	0.191	0.442	1901	0.160	0.462	1421	0.239	0.468
Intercropping	1639	0.455	0.498	1669	0.241	0.428	1901	0.593	0.491	1421	0.263	0.441
Zero Tillage	1639	0.00854	0.0921	1669	0	0	1901	0.0132	0.114	1421	0.0246	0.155
Fallow Farm	1639	0.210	0.407	1669	0.000599	0.0245	1901	0.109	0.312	1421	0.0113	0.106