Investigating Agricultural Innovation Platforms, Soil Moisture Monitoring Tools and Farm Adaptation Behaviour in Irrigation Schemes in Sub-Saharan Africa

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List of Acronyms

ACIAR	Australian Centre for International Agricultural Research
AIC	Akaike information criteria
AIP	Agricultural innovation platforms
AIPW	Augmented inverse probability weighted
AIS	Agricultural innovation systems
ATE	Average treatment effect
AUD	Australian Dollar
BIC	Bayesian information criteria
CLAD	Censored least absolute deviations
CV	Contingent valuation
FAO	Food and Agriculture Organisation of the United Nations
IPW	Inverse probability weighting
IPWRA	Inverse probability weighted regression adjustment
NGO	Non-governmental organisation
OLS	Ordinary least squares
PSM	Propensity score matching
RA	Regression adjustment
SSA	Sub-Saharan Africa
SUR	Seemingly unrelated regression
SUTVA	Stable unit treatment value assumption
TISA	Transforming Irrigation in Southern Africa
TLU	Tropical livestock units
UNDESA	United Nations Department of Economic and Social Affairs
USD	United States Dollar
VIA	Virtual Irrigation Academy
VIF	Variance inflation factor
WFD	Water Front Detector
WTP	Willingness to pay

Dedication

To my family

Abstract

This thesis investigates the impact of various irrigation tools and behavioural interventions in irrigation schemes within three countries of Sub-Saharan Africa (SSA). The thesis consists of three empirical case studies, namely: i) influences on the adoption of, and willingness to pay (WTP) for, monitoring tools; ii) farm-level effects of irrigation development interventions (agricultural innovation platforms (AIP) and monitoring tools); and iii) influences on irrigation farm adaptation behaviour. Data on farm behaviour was collected by an irrigation development project via two rounds of face-to-face irrigation household surveys in a number of schemes in 2014 and 2017 (following the same households wherever possible).

The first study explored irrigation farm households' adoption willingness for a monitoring tool that was introduced for the first time to farmers operating in four of the irrigation schemes (n=234). A contingent valuation method was implemented to elicit farm households' WTP. The findings from the Tobit regression indicated that irrigators were interested in adopting (and paying for) monitoring tools – as reflected by their positive average WTP price. WTP was found to be associated with various socio-demographic and locational variables. Given irrigation water saving innovations – such as the monitoring tool – are knowledge-oriented and that the market does not entirely reflect all social adoption costs and benefits, the findings imply that economic measures may not result in the desired adoption. Instead, policy measures fostering social learning may encourage greater technology adoption – so that adoption would have a broader-scale effect at the scheme or catchment level.

The second study sought to examine the role that irrigation development interventions had on farming households' living conditions, after the first four years of implementation. The interventions studied included AIPs – which acted as an instrument for making a series of market and other changes – and monitoring tools devised to induce individual as well as social learning. There remains inadequate research to date conducted on the practical relevance and impact of AIPs within developing countries. Hence, this study contributes to the literature by employing doubly robust estimation regression techniques, as well as considering the likely spillover effects resulting from the project interventions (n=361 for AIPs and n=241 for monitoring tools). The study found a positive and statistically significant association between engagement in AIPs or monitoring tools and irrigation farm and household outcomes. Specifically, farm households participating in AIP events (as compared to those not directly involved in AIPs) had greater on-farm income; had increased ability to fund child education;

had an increased chance of obtaining off-farm income; and experienced around one month less of food shortages yearly. Similarly, farmers provided monitoring tools obtained higher on-farm income and had a much greater ability to fund child education, compared with those who were not granted monitoring tools. In addition, there was evidence of a substantial positive spillover effect from the implemented interventions on irrigation households that were not actually involved in AIP events or granted monitoring tools – highlighting the benefit of development projects for the irrigation schemes as a whole.

The third study investigated the influences on farm adaptation behaviour in SSA by applying fractional probit and binary probit models. In this study, farm adaption denotes changes in farming practices in reaction to a broad series of uncertainties unique in the farming landscape – such as climate anomalies, market, development projects, health, etc. It investigated two key questions, namely: i) understanding the influences on planned farm adaptation behaviour (i.e., what the farmer planned to do in the next three years from 2014-2017) using the 2014 survey data (n=371); ii) understanding the stability of irrigators taking part in both surveys (n=263) in terms of planned farm adaptation behaviour in 2014 and actual farm implementation three years later in 2017. It was found that a broad array of influences affected various forms of planned farm adaptation behaviour, and that there was not always consistency between the impacts of various influences on the planned and actual adoption of a specific practice. The result also demonstrated that a higher proportion of irrigators actually adopted a particular practice than those who had planned to do so – again indicating strong support for the project implementation within SSA regions. Overall, the findings emphasise the relevance of formulating a diverse range of policy programs to encourage farm adaptation behaviour.

In summary, the findings from this thesis contribute to the literature by highlighting that projects committed to fostering social learning and institutional development (such as markets) can have a significant impact on irrigation household outcomes. To achieve further adoption, understanding the influences on existing farmer adoption and farmers' WTP for new innovations, will help shape future policy programs designed to maximise societal net gains in SSA countries. Another noteworthy implication is that the relevance of appreciating the presence of a strong divergence between irrigation farm practices that irrigators intended to pursue over the coming period and the practical execution of them at a later time. This indicates that policy practitioners should be mindful of this distinction when planning and introducing farm adaptation polices and interventions.

Declaration

I certify that this work contains no material which has been accepted for the award of any other degree or diploma in my name, in any university or other tertiary institution and, to the best of my knowledge and belief, contains no material previously published or written by another person, except where due reference has been made in the text. In addition, I certify that no part of this work will, in the future, be used in a submission in my name, for any other degree or diploma in any university or other tertiary institution without the prior approval of the University of Adelaide and where applicable, any partner institution responsible for the joint-award of this degree.

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Conference paper presentation

Abebe, F., *et al.* (2020). Agricultural innovation platforms and soil moisture monitoring tools in Africa, *64th Australasian Agricultural and Resource Economics Society Conference*, 10th – 14th February, Perth, Australia.

Abebe F., *et al.* (2019). Irrigators' willingness to pay for soil moisture monitoring tools in South-Eastern Africa, *the 9th National Water Forum*, 28th March 2019, Adelaide, Australia.

Current working papers

Abebe F., *et al.* (2022). The effects of agricultural innovation platforms and soil moisture and nutrients monitoring tools on household farming outcomes in Sub-Saharan Africa.

Abebe F., *et al.* (2022). Small-scale irrigation farm households' planned and actual farm adaptation decisions in Sub-Saharan Africa.

Chapter 1 Introduction

1.1 Background

1.1.1 Agriculture and poverty in Sub-Saharan Africa

Among world regions, sub-Saharan Africa (SSA) stands at the bottom in terms of key performance indicator metrics, namely: poverty, hunger, education, income, health, and – importantly – agricultural productivity. Indeed, the SSA region encompasses around 85% of economically deprived countries worldwide (World Bank 2021a). In addition, there is no other place comparable with SSA, given that poor residents make up larger than 40% of the population (World Bank 2021b). When assessing the scale of poverty in terms of location, there is a marked asymmetry – with around eight out of the ten impoverished people in SSA are in rural vicinities (Castañeda et al. 2018), often relying on farming for their overall sustenance. In most circumstances, agriculture in SSA is mostly rain-fed, which makes it susceptible to climate anomalies. Issues are also experienced with obsolete technology and small plot sizes (Di Falco et al. 2011; Lowder et al. 2016; Mignouna et al. 2020). Hence, poverty and food insecurity are common among many of the 53% of inhabitants engaged in the farming sector (World Bank 2021c).

There is also a consensus from the literature that poverty in SSA is likely to be exasperated over the coming time period for the obvious reason of climate change issues (e.g., Sam et al. 2021) and the fact that the region has minimal or no management ability for counteracting its influence. A rapidly increasing population and defective political environment also magnifies the problem (Barbier et al. 2009; Dupas and Robinson 2010). As farming is the powerful ingredients of the economies of SSA countries and a far greater victims of poverty overly spread in rural areas, it is argued that harnessing development to transform agriculture will be a suitable vehicle in combatting poverty (Diao et al. 2010). Accordingly, irrigation development is a routinely touted initiative to boost food production, advance economic development and avert poverty (Bjornlund et al. 2019; Brelle and Dressayre 2014).

1.1.2 Irrigation in Sub-Saharan Africa

Irrigation involves the wide use of various inputs and catalyses intensification and diversification of cultivation (Burney et al. 2010). It can help reduce output price shocks and broaden cultivation choices, and potentially increasing price premiums. At the same time, if designed correctly, irrigation may act as a means for stabilising climate anomalies (Deressa et al. 2009). There is increasing literature on the relevance of irrigation in averting poverty, fostering farming yield, and enabling overall economic and social change – both in Africa and other places (Adeoti et al. 2009; Dillon 2011a, 2011b; Mangisoni 2008; Nonvide 2019; Sellamuttu et al. 2014; Smith 2004). Dillon (2011a), for example, illustrated that irrigated farming households had far greater consumption, crop produce and wealth as opposed to non-irrigators in Malawi. Bacha et al. (2011) discussed the influences of irrigation on poverty and revealed a statistically significant association between poverty outcomes and irrigation in Ethiopia. Conversely, there have also been occasions whereby irrigation has provided no role at all for the poor and may even have resulted in adverse influences (Inthakesone and Syphoxay 2021; Manero et al. 2019; Peter et al. 2008). Ecological and environmental influences from irrigation also need to be taken into consideration for irrigation to accomplish long-lasting economic prosperity.

It is believed that SSA has a strong opportunity to make irrigation more economically useful (FAO 2016a; You et al. 2011). One reason for this is that SSA still has an irrigation coverage far below a tenth of the cultivated farmland (FAO 2016c), although – as described in Namara et al. (2014) – there may be considerable underreporting of irrigation in numerous SSA countries. In the preceding century, several number of irrigation schemes were initiated in a large sets of SSA countries (Kamwamba-Mtethiwa et al. 2016; Mutiro and Lautze 2015). In spite of massive quantity of resources directed for irrigation, a series of questions have been raised over whether the investment have been socially gainful (Dittoh et al. 2013; Kikuchi et al. 2021). It has been conceived that irrigation is an expensive activity in SSA and that many of the schemes have had marginal influence on economic progress (Kikuchi et al. 2021).

The notable causes as to why irrigation has not been successful include: flawed infrastructure; defective design; inadequate markets; input constraints; absence of proficient institutions and policies; ambiguous regulations concerning resource ownership; wrong crop choices; colonial legacy; and dearth of suitable technologies – among many other cofounding factors (Bjornlund, V et al. 2020; Dittoh et al. 2013; García-Bolaños et al. 2011; Inocencio et al. 2007; Muema et al. 2018). All these factors are often related to one another; therefore, any endeavour that sought to uncover answers to each impediment in isolation would likely fail. As such, it is unlikely that a single solution would solve all irrigation issues. In the research carried out in two small irrigation schemes in Tanzania, for instance, paucity of reliable financial resources was shown to be among the list of known influences that deterred irrigation viability – so that farmers were unable to acquire modern inputs, better technologies and other critical inputs (Mdemu et al. 2017). In addition, it was also pointed out that farmers would be encouraged to borrow as soon as the output market functioned very well.

Under this setting, it is imperative to view irrigation far beyond the engineering/technological sphere of influence, and instead understand it as a “complex system” composed of a wide array of actors and elements (technology, institution (e.g., finance, market, land tenure, policy, politics, water distribution), people, water, weather, natural features, etc.) (van Rooyen et al. 2020). For instance, Wheeler et al. (2017) differentiated agricultural technologies as: 1) hard technologies, in irrigation, covering irrigation infrastructure and waterways, canals, and storages – which are somewhat expensive by their very nature; and 2) soft technologies, including changes in management skills and expertise around irrigation timing, frequency, institutions and altering crop combinations. Hence, framing and devising intervention programs in the manner to reflect and consolidate these elements could play a meaningful role for overall economic and social transformation – thereby maintaining the functionality of current infrastructure investments (van Rooyen et al. 2020). As pointed out by Inocencio et al. (2007), the proportion of budget dispersed towards softer elements of irrigation including institutions, project preparation and empowerment, was shown to have a positive influence on irrigation viability.

1.1.3 The six case study irrigation schemes

This thesis centres on six communal irrigation schemes from a case study in three SSA countries (Chilundo et al. 2020; Mdemu et al. 2017; Moyo et al. 2017). These include Khanimambo and 25 de Setembro schemes from Mozambique, Kiwere and Magozi schemes from Tanzania, and Silalatshani and Mkoba schemes from Zimbabwe. As is the case with many other schemes in SSA, these were largely commenced by external partners or governments, often with no or tiny contribution and consultation of local-level farming communities (e.g., Bjornlund et al. 2017; De Sousa et al. 2015). While some of these schemes are old with more than three decades of operation lifetime (e.g., Mkoba and 25 de Setembro), others (e.g., Khanimambo and Kiwere) have been in service for around fifteen years (Table 1.1).

Of all the study schemes, Magozi covers the largest land area, 939 hectares, whereas Khanimambo has the smallest area coverage with only ten hectares (Table 1.1). However, a large proportion of the land area in many of these schemes are no longer used for food production. Most of these schemes did not work very well in terms of bolstering food production and averting poverty. The absence of farmer engagement in management and maintenance processes; inappropriate crop choices; collapsed infrastructure; a shortfall in expertise; a paucity of reliable credit and extension facilities; and reliable market linkage problems have all prevented the progress of these schemes (e.g., Bjornlund et al. 2017; Wheeler et al. 2017). Further details about the studied schemes are provided under Section 1.4.

Keeping these interrelated concerns in mind, an Australian Centre for International Agriculture Research (ACIAR) sponsored project was initiated within the identified schemes from 2013 onwards. The project intended to restore the functionality and boost up the profitability and productivity of these schemes via the application of "agricultural innovation platforms" (van Rooyen et al. 2017) and "monitoring tools" (Stirzaker et al. 2017) – as opposed to initiating new schemes. The underlying idea of the project was that irrigation schemes are multifaceted by their very nature, in relation to the actors involved at different levels, along with expertise requirements, institutions, water management and infrastructural developments, and so many other features. Within this system, any initiatives with the drive to bring enhanced outcomes through an over-simplified technological cure would be less likely to succeed. Rather in such circumstances, interventions that encompass the complexity of irrigation and the full array of stakeholders and set of elements (i.e., infrastructure/engineering, finance, market, management) would be more likely to generate lasting and meaningful outcomes. In this regard, AIPs were formed in each of the studied irrigation schemes encompassing several stakeholders – including the irrigation households within the schemes, which had a strong stake in agriculture – in order to overcome irrigation impediments, and put forward relevant remedies. On the other hand, monitoring tools were distributed free of charge to identified irrigation farmers (with a set of criteria such as gender, location and age) to prompt farmer learning including social "spillover" learning with regards to irrigation management.

Hence, the overall focus of this thesis is to investigate: a) SSA small-scale irrigation farming communities' willingness to adopt monitoring tools (Chameleon Sensor device); b) how these two irrigation development interventions (AIP and tools) are capable of, or effective in, changing the living conditions of irrigation households; and finally, c) farm adaptation behaviour in cross sectional setting and over time. Research questions associated with these three broad objectives are presented in Section 1.3 and subsequently investigated in-depth in the three empirical Chapters (2-4).

1.2 Literature review of irrigation monitoring tools and AIPs

This section delivers an overview of the literature on irrigation monitoring technologies and agricultural innovation systems. It also highlights the farm adaptation literature and the various gaps in the literature.

1.2.1 Irrigation monitoring technologies and gaps in the literature

It is suggested that realising greater productivity through irrigation profoundly depends upon how water resources are sustainably used and managed. Irrigation entails a great deal of specialised expertise and experience compared with rain-fed agricultural activities (Stirzaker et al. 2017). Beyond simple field watering, irrigators are expected to understand the reaction of the plant to applied water, as well as other factors of production. For centuries, producers in developing economies have been implementing irrigation on the basis of their longstanding expertise and skills (Bjornlund, V et al. 2020). Their practices were exclusively carried out through customary and sometimes tenuous ways of scheduling, to control the extent of water applied at a particular moment along with correcting any adverse issues following irrigation actions. Often during this process, irrigation was susceptible to potential mistakes, leading to misuse of water, as farmers often failed to accommodate weather episodes in their watering timeline (Annandale et al. 2011; Barnard et al. 2017). In this regard, alternative and enhanced irrigation application methods (such as irrigation scheduling innovations) are desirable to produce the optimum amount of food to humanity with less water and fewer ecological externalities (Stirzaker et al. 2017).

"Irrigation scheduling" is a procedure of regulating water consumption during the course of food production (Seidel et al. 2016). The use of irrigation scheduling innovations increases the decision-making ability of farmers to carry out their irrigation in the most desirable manner – and simultaneously raise yield, conserve water, cut input spending and maintain ecological health (Barnard et al. 2017). To date, a great deal of effort has been made by research, industry and other stakeholders in creating more systematic and robust irrigation management procedures (Annandale et al. 2011; Gu et al. 2020). As a consequence, a large array of scheduling systems have been designed and introduced to potential buyers to enhance their irrigation business (Jones 2004; Pardossi and Incrocci 2011). Gu et al. (2020) provided four comprehensive profiles of several scheduling technologies that have emerged in previous decades, based on: a) "evapotranspiration and water balance", b) "soil moisture status", c) “plant water status”, and d) “models”. A lot more individual innovations/applications are encompassed under each of the four groups, with unique benefits and flaws.

The fact is that the overwhelming share of these technologies were designed and tested in the northern hemisphere, and principally confined to meet the needs of large commercial producers prevalent in these regions (Ganjegunte et al. 2012; Gu et al. 2020; Pardossi and Incrocci 2011). Hence, innovations were found to be sophisticated, often demanded vast resources – including high costs and advanced operating skills – demonstrating that these technologies were beyond the reach of most smallholders in developing countries. As a result, many of these devices failed to engage subsistence producers in developing countries and ultimately irrigators remained averse to use them (Pardossi and Incrocci 2011; Stirzaker et al. 2014).

These issues steered exploratory works towards alternative ways of scheduling more suited to subsistence farming. Consequently, several innovative products were put forward. Amongst others, the “Wetting Front Detector” (WFD) and “Chameleon Sensor”’ are prominent examples of these (Stirzaker 2003; Stirzaker et al. 2017). In contrast to previous systems, the WFD and the Chameleon Sensor are easy to implement, reasonably priced and robust (Stirzaker et al. 2017) (the details of these technologies are discussed in Chapter 2).

As noted above, plenty sets of innovations believed to assist irrigation practices have been created and introduced into the market to potential buyers, however are yet to be adopted by the majority of farmers (Bjornlund et al. 2009; Ibragimov et al. 2021; Montagu and Stirzaker 2008; Nicol et al. 2010). This is especially the situation in Africa (Annandale et al. 2011). The potential explanations behind for the observed small adoption may be linked with the intrinsic nature of these technologies. By their very nature, water management innovations are knowledge oriented with a sizeable public good component (Stirzaker et al. 2017; Wheeler et al. 2017). For this reason, there would be spillover externality effects from their introduction – on top of the private benefits for adopting irrigators. In such settings, the private sector (e.g., irrigation farmers) might reluctant to invest on these technologies since the market could not fully pay for adoption – adoption may be sub-optimal. In addition, as indicated in Stirzaker et al. (2017), the other major issue in Africa is that in many occasions the delivery of these technologies to intended adopters is principally carried out through external bodies such as research projects and government departments – at discounted prices or free of charge (e.g., Stirzaker et al. 2010). The knock-on effect of such actions may encourage increased dependence – thereby eroding autonomous adoption and seriously impeding agricultural change. For example, the two monitoring tools (WFD and Chameleon Sensor) studied in this thesis were made known to the study irrigation schemes via the project and granted for use by local irrigation farmers free of charge along with other related supports. However, in general, it is highly doubtful to warrant the ongoing adoption of such kind of technologies with a sole reliance on external bodies.

A closer observation of the available research works indicated that there is the absence of proper research that carefully studied farming communities' preferences expressed in terms of willingness to pay (WTP) towards the adoption of irrigation scheduling technologies including Chameleon sensors. Instead, the literature has disproportionally concentrated on testing their real-world applicability such as: gauging their success (e.g., raising produce), overall adoption progress, application procedures and potential gains out of their adoption (Nicol et al. 2010; Parry et al. 2020; Stirzaker and Hutchinson 2005; Stirzaker et al. 2017). Hence, exploring the WTP for adoption could be one pathway for getting greater information on the views and preferences of intended adopters. This is particularly of interest for our study context. More specifically, as the Chameleon Sensor device is: 1) previously unknown to general irrigation communities in the study schemes; 2) provided free of charge to farmers via the project; and 3) in pre-commercial stages of production – evaluating farmers' preference would offer valuable information for policy mechanisms to ensure greater and continued adoption in the future.

Overall, understanding small-scale irrigators stated WTP for the Chameleon Sensor device is vital for two reasons. Firstly, given cost is one of the serious impediments for greater adoption (Pardossi and Incrocci 2011), WTP information could serve as a first step for innovation makers to better understand their market prospects, and to develop products accordingly. Secondly, since farmers within given schemes are working in a shared environment – such as sharing of surface-water and waterways – the adoption of the Chameleon Sensor device by one farmer may have a significant implication on the water availability for other farmers and overall ecological sustainability. As such, understanding the demand for moisture monitoring tools could enable the formulation of various policies and institutional facilities to best manage the adoption of technologies, as well as other improvements in market access. Hence, an in-depth analysis of small-scale irrigators' WTP for the adoption of chameleon sensor device is provided in Chapter 2.

1.2.2 Agriculture innovation platforms and gaps in the literature

As discussed previously, in many circumstances across SSA, the adoption of irrigated agriculture and other modern factors of production has been shown to be fall short of the optimal level. Although there are numerous causes for this, one particularly apt is aligned with the *technology transfer model,* which has been believed to be the root cause for the recorded adoption failure in the region (Biggs 2007; Röling 2009). This model is considered to be blind in relation to the relevance of institutions and to be overly reliant on technical cures from scientific communities to address agricultural concerns (Hounkonnou et al. 2012). In response, a series of alternative methods have been devised (Biggs 2007; Röling 2009). "Agricultural innovation system" is amongst such methods (World Bank 2006). The special qualities of this approach is that it places institutions as highly imperative in inducing innovation production (Hounkonnou et al. 2012). Under this approach, "innovation platforms" are crucial – as they help ensure practical changes on the ground (Sanyang et al. 2016; Schut et al. 2018; Schut et al. 2019). Despite numerous other terminologies are present in the literature to denote *innovation platforms,* we use the term *agricultural innovation platforms* throughout this study in order to be consistent with the project design.

During the past fifteen years or more so, agricultural interventions adhering to the notion of AIS have been increasingly adopted throughout Africa to induce agricultural change (Hounkonnou et al. 2012; Quarmine et al. 2012; van Rooyen and Tui 2009). Following this, the literature has greatly concerned on studying how platforms should be formed; which stakeholders should take part in the platforms; outlining working guidelines and templates; and many other related issues (van Rooyen et al. 2017). However, the present state of knowledge in quantitatively studying the progress of such interventions using sound econometric methodologies has been far less evident (Pamuk and Van Rijn 2019). Some of the attempts in Africa so far, include Kaaria et al. (2008); Mapila et al. (2012); Mdemu et al. (2020); Moyo et al. (2020); Ogunniyi et al. (2017); Pamuk et al. (2015); Pamuk et al. (2014); Parry et al. (2020) and Siziba et al. (2013). Many of these findings were shown to be inconclusive, and only a small number of them have explicitly looked at the potential spillover effects or selection bias related with the implemented interventions.

In addition, a great deal of the present literature has studied the influences of various development projects. For example, research works such as Pamuk et al. (2014), Pamuk et al. (2015), Pamuk and Van Rijn (2019) and Siziba et al. (2013), which were perhaps the most eminent works in terms of the depth of methodology applied, discussed the influnces associated with a mega-project titled the *"Sub-Saharan African Challenge Program"*. Overall, a large proportion of the current innovation platform literature was drawn from the data and lessons of this single project. As indicated by Pamuk and Van Rijn (2019), the results of a particular program in terms of delivering its stated purpose could closely align with the activities and working customs of the entity who initiated the intervention, along with other factors. As such, it is unknown whether programs that function well in one setting will work with definite certainty under other conditions. Hence, understanding AIS under diverse circumstances across SSA is paramount. Given AIS is still a relatively fresh concept, with less than two decades of familiarity in the African agricultural landscape, testing and experimenting the viability of this approach with appropriate refinement under a broad array of settings is also imperative. With such knowledge, decision-makers can better define the necessary policy instruments to harness AIS in furthering rural development.

Given the issues above, of particular interest for this thesis - the focus of Chapter 3 – is attempting to answer the causality question of whether there is evidence that irrigation intervention executed according to AIS guidelines improves living standards (in terms of improving on-farm income, off-farm income, reducing food shortages and funding child education). Specifically, this thesis: 1) assesses the influence of AIPs and monitoring tools implemented in small-scale irrigation schemes on irrigation household outcomes; and 2) attempts to quantify the likely spillover effects from the implemented project on intervention non-participating irrigation households. Chapter 3 provides the full analysis of these findings.

1.2.3 Farm adaptation behaviour and gaps in the literature

A volatile climate is among the list of leading risk factors influencing farming in SSA (Di Falco et al. 2011; Sarr 2012). Knox et al. (2012) elaborated that due to climate risks, African farmers will most likely incur a reduction of nearly a tenth of their agricultural production by the middle of the twenty-first century. In addition to climate anomalies, the farming landscape is also influenced by government policies (e.g., tax, subsidies); politics (e.g., war); demographic shifts; and market forces (Ouédraogo et al. 2017; Wheeler et al. 2014; Yarong and Minpeng 2021). The outcomes of these factors might not be uniform when it comes to food production and welfare, as some have a positive influence (e.g., input subsidy, project intervention) whereas others might have an unfavourable consequence (e.g., political insecurity). It is for this very reason that adaptation for a varying climate besides to other uncertainties becomes vital, through a series of choices made by SSA farmers.

The decision to adapt is closely aligned with adaptive capacity, which in turn is linked with numerous sets of influences such as personal and demographic characteristics, availability of resources and institutional variables (Ellis 1999). Note that since irrigation communities have a greater opportunity of using the same farm practices to curb both climate and other external shocks – and that our survey did not specifically ask farmers to describe their adaptation attitudes – in this thesis, agricultural adaptation refers to irrigation farming communities reactions to a bundle of uncertainties surrounding the farming environment. This signifies that adaptation is a far greater idea than purely aligned to climate risks. On the other hand, adoption is far broader than adaptation, and referred to as "a change in practice or technology used by economic agents or a community" (Zilberman et al. 2012; pp.28). It is noted that studying farm adaptation behaviour pertaining to a series of uncertainties is presumed as the very basic initial point for fostering adaptation, through the formulation of relevant policy programs to improve rural development.

Given the insights gained from earlier research works (Wheeler et al. 2013; Yarong and Minpeng 2021); our overall premise in this thesis (a focus of Chapter 4) is that small-scale farming is subject to many interconnected uncertainties. In such circumstances, it is the interplay between climate risks and other uncertainties – in conjunction with farmers' adaptive ability – that most likely dictates the boundless of adaptation practices adopted. Therefore, framing the question in this fashion offers a full overview of farm adaptation behaviour, which could deliver decision-makers more information on adaptive capacity and adaptation overall. In other words, policy initiatives that are based upon the appreciation of numerous uncertainties are more likely to succeed in effectively and efficiently creating improved agricultural processes. Generally, outlining intervention programs in this way better facilitates adaptation (and adoption), because of which resources would be used in their most beneficial way.

In several farm household survey studies, it has been argued that the risk arising from an unstable climate was is shown to be secondary for farming households compared to risk stemming from other uncertainties (e.g., McCubbin et al. 2015). For instance, Nyantakyi-Frimpong and Bezner-Kerr (2015) pointed out that climate anomalies were not the leading obstacles for farming communities in Ghana. In contrast, farmers named increased food prices and other factors as the major difficulties confronting farming practices and their overall livelihoods. Likewise, research undertaken across five African countries concluded that farming adjustment in reaction to land, market and climate risks constituted the first three motivating influences for altering farming practices, with a substantial level of asymmetry seen between countries (Ouédraogo et al. 2017). In other parts of the world, such as Tuvalu, McCubbin et al. (2015) presented similar findings in their study of obstacles influencing societies' overall welfare.

When looking at the spectrum of research works across SSA and other parts of the world, the very great majority of them have explored farm behaviour in regards to climate risk (Ouédraogo et al. 2017; Roesch-McNally et al. 2017; Tessema et al. 2019). Conversely, research works that have sought to consolidate climate and other uncertainties altogether in the investigation are less in number (Kogo et al. 2021; Ouédraogo et al. 2017). Tessema et al. (2019) critique the literature on the grounds that much of it was disproportionately concerned on adaptation behaviour towards climate anomalies. In addition, much of the literature is strongly centred on previous farm adaptation behaviour (e.g., de Jalón et al. 2018; Deressa et al. 2009; Roesch-McNally et al. 2017) – as opposed to planned behaviour (Wheeler et al. 2013). One major difference is that there has been a shortage of study on how farm adaptation behaviour has evolved over time – following the same farmers – in reaction to a series of shocks prevalent to farming. Earlier studies were merely reliant upon cross-sectional datasets, with the notable exception of Wheeler et al. (2021) who studied adjustment patterns over time utilising a panel dataset.

This thesis (namely Chapter 4) contributes to the literature by investigating planned farm adaptation behaviour in response to diverse classes of uncertainties – including but not limited to climate variability – and traced planned and actual adaptation behaviours over a three-year timeframe, using two waves of survey data collected in 2014 and 2017. Generally, it is strongly believed that studying planned farm adaptation behaviour delivers policy makers with meaningful information on the actions farm households would likely undertake in the future, and the potential influences of such behavioural decisions (Niles et al. 2016; Wheeler et al. 2013). This information is critical to develop robust policy programs that align with the realities of farming households, empower adaptive ability, and maximise investment net returns (Below et al. 2012; Niles et al. 2016). Chapter 4 explores this issue in more depth.

1.3 Research objectives and questions

The overall aim of this thesis is to examine irrigators' stated behaviour in relation to irrigation monitoring tools adoption; the actual impact of project irrigation interventions (namely AIPs and monitoring tools); and irrigation farm household farm adaptation behaviour in SSA. In order to attain these objectives, this research sought to offer answers to the following research questions:

1. What are the socio-economic, demographic and location variables influencing irrigators' WTP for access to monitoring tools?
2. How much are farm households willing to pay to access monitoring tools?
3. Are AIPs and monitoring tools successful in enhancing irrigation farm household outcomes? Is the success (or otherwise) of these interventions heterogeneous among male-headed vs female-headed farming households?
4. Is there any spillover evidence on household outcomes linked with the project interventions?
5. What are the main factors influencing farmers' decisions to adopt various planned farm adaptation practices? Are farmers' climate perceptions associated with various planned farm adaptation practices?
6. How different/similar are irrigation farm practices that were planned in 2014 from actual farm practices implemented three years later in 2017?

By investigating the above questions, this thesis offers significant insight for policy-makers to promote the adoption of irrigation monitoring technologies, improve farm adaptation and improve the success rates of development interventions largely intended to curb poverty.

1.4 Study area and irrigation interventions

This thesis employed the data stemming from three SSA countries including Mozambique, Tanzania and Zimbabwe (Figure 1.1). As previously mentioned, the thesis is based on an ACIAR-financed project implemented in these countries from 2013 to 2017. The selection of study countries was not arbitrary, rather determined objectively by the evidence produced by exploratory research (Pittock et al. 2013). This study encompassed a review of published and unpublished materials, discussion with subject matter professionals and government bodies, and evaluation of similar interventions previously implemented in the region – to offer the Australian Government information on targeted and possible agricultural development interventions in Africa. Consequently, the study countries of Mozambique, Tanzania and Zimbabwe were nominated as the primary countries of Australian development interventions in Africa. Some of these factors behind this choice included the close relationship of these countries with Australia, production potential from irrigation, proportion of communities that could potentially be reached by development initiatives, and the presence of enabling working situations.

Hence, an ACIAR supported development project titled "*Increasing irrigation water productivity in Mozambique, Tanzania and Zimbabwe through on-farm monitoring, adaptive management and agricultural innovation platforms"* was launched in 2013. This project applied two interventions, "agricultural innovation platforms" and "monitoring tools", with an overall purpose of enhancing the viability of small-scale irrigation schemes.

Figure 1.1 Study schemes map

Source: Mwamakamba et al. (2017, p. 827)

Two irrigation schemes from each country were identified as case studies for the project, including: 25 de Setembro and Khanimambo schemes from Mozambique; Kiwere and Magozi schemes from Tanzania; and lastly, Mkoba and Silalatshani schemes from Zimbabwe (Table 1.1). Likewise, numerous factors were considered when identifying each scheme, including variety of crops grown; presence of local actors with greater passion to work hand in hand with the project; pertinence of schemes to execute the proposed intervention; and presence of active supporting facilities, such as availability transport services and logistics.

Table 1.1 highlights some of the features of the studied schemes. For instance, while Khanimambo scheme contained a small number of farming households, Magozi scheme was the largest in terms of farming households. In regard to farming land size, Khanimambo and Magozi schemes encompassed the smallest and largest farming area respectively. Agriculture entailing both crop and livestock, along with off-farm activities, were practiced across the studied schemes. Finally, various methods of gravity irrigation were used in all schemes.

Table 1.1 Summary of study area characteristics

	Schemes					
Characteristics	***Kiwere***	***Magozi***	***25 de Setembro***	***Khanimambo***	***Mkoba***	***Silalatshani***
District	Iringa	Iringa	Boane	Magude	Gweru	Insiza
Altitude (metre above sea level)	740	700	12	150	–	950
Annual rainfall (mm)	700	600	650-900	454-593	650-900	450-650
Major soil types	Sand clay	Fertile clay	Fertile soils	Fertile soils	Infertile sandy	Fertile clay
Water source	River	River	River	River	Dam	Dam
All year road access to schemes	Available	Available	–	Available	–	–
Distance from nearest city in km	20	60	30	–	40	150
Total irrigating households	168	512	38	27	75	212
Sampled households (2014)	100	100	25	9	68	100
Sampled households (2017)	100	100	28	–	54	84
Households interviewed in both survey (2017)	60	77	19	–	54	72
Currently irrigated land (ha)	194.47	939.4	38	10	10.1	109.7
Land ownership	Inheritance	Inheritance	Cooperative hold land title	Cooperative hold land title	Government	Government
Irrigation water delivery	Gravity	Gravity	Motor pump	Motor pump	Gravity	Gravity
Irrigation method	Flooding	Flooding	Flooding	Flooding	Flooding	Flooding
Canal type	Lined and earthed	Lined and earthed	Concrete and earthed	Lined concrete and PVC pipeline	Predominantly lined	Concrete lined
Water payment method	Payment per irrigated land area (fixed)	Payment per irrigated land area (fixed)	No water payment, but farmers covers fuel expenses for pumping and pump maintenance	No water payment, but farmers covers fuel expenses for pumping and pump maintenance	Payment per irrigated land area (fixed)	Payment per irrigated land area (fixed)
Cropping decision	–	–	Individual irrigators	Individual irrigators	Irrigation management committees	Irrigation management committees
Establishment year	1969	2007	1981	2004	1969	1969

Sources: Adapted from De Sousa et al. (2015, p. 7); Moyo et al. (2014, p. 11) and Mziray et al. (2015, p. 5); Bjornlund, H et al. (2020); irrigation survey data and various project documents

The starting point of the project was that irrigation barriers in SSA are many-faceted including institutional, environmental, governance and economic – implying that efforts centred merely on one of these impediments would be unlikely to succeed. In other words, there would be no straightforward answers to irrigation issues; instead, they would be resolved through a constant iterative effort by a broad spectrum of interested parties within the farming industry. On this basis, the project was activated following an "agricultural innovation system" approach using AIP as an avenue for its application. As such, AIP in conjunction with monitoring tools (WFD and Chameleon Sensor devices) interventions were implemented. As a whole, AIPs encompass an association of a variety of actors with expertise and resources, who work together under the shared goal of removing agricultural barriers (van Rooyen et al. 2017); while WFD is a method of tracking and handling soil water and nutrient levels underground. It is a meaningful procedure tailored for irrigation activities around the world and has been in use over the last 15 years. The technology provides producers with live data in order to make proactive decisions around watering (Stirzaker 2003; Stirzaker et al. 2017). Alternatively, the Chameleon Sensor is a more recent solution to moisture management, still in the pre-commercialisation stage – and at the time of this study had not been officially introduced into the market. It was designed principally to meet the needs of smallholders by tracking the volume of water under the soil and adjusting irrigation watering episodes accordingly (Stirzaker et al. 2017). Additional explanations on how these two interventions applied in the sampled schemes are provided in both Chapters 2 and 3.

Upon the completion of the first phase of the project in 2017 (investigated in this thesis), another ACIAR-supported project *"Transforming smallholder irrigation into profitable and self-sustaining systems in southern Africa" (TISA)* was started in July 2017 and was anticipated to be implemented for another four years, with a particular focus in southern Africa. This project was formulated in accordance with the first phase project with an overreaching target of finding ways to "out-scale" and "up-scale" the TISA approach.

This thesis uses irrigation household survey data gathered from six irrigation schemes across SSA. Two surveys were carried out within a three-year timeframe. The first survey was undertaken in early 2014 as a baseline survey to capture the initial conditions of farming, livelihoods and other related activities within the scheme, prior to the actual project implementation. The survey gathered relevant information from 402 farm households on aspects of agricultural production, irrigation practices, socio-economic profiles, information access on market and extension facilities, household assets, views on water distribution and many other issues.

The second survey (end of first project survey) was performed during the completion of the project in 2017 with the intention of quantifying changes that happened over the lifespan of the project (2013-2017), in relation to living conditions of irrigation communities, and irrigation practises including farm input uses and institutional service accesses. Chapters 2 and 3 use the end of project survey data, while Chapter 4 uses both the baseline and the end of project surveys to explore farm adaptation behaviour both in a cross-sectional setting and from changes overtime.

1.5 Research methodology

Diverse research methodologies have been applied to study each research question outlined above. A contingent valuation framework and simple statistical analysis were employed to address research questions one and two. Contingent valuation is a methodology that explores the potential value of an item that does not have a price within a commonplace market. This technique is also worthwhile for calculating the prices of commodities with market values – including pre-testing of newly introduced commodities (such as those being studied in this thesis). A Tobit regression model was employed to measure the WTP of irrigation farm households for the adoption of monitoring tools.

Research questions three and four were addressed through the application of appropriate treatment effect regression methodology. In addition, the potential spillover effects were also analysed. For the last two research questions, we applied fractional probit model regression combined with the control function approach (research question five) and binary probit model regression for comparing planned and actual farm adaptation behaviour from 2014-2017 (research question six).

Table 1.2 illustrates a brief overview of the three analytical chapters of this thesis, including the data used and empirical approaches applied to analyse the six research questions.

Table 1.2 Sample, data sources and estimation methodologies of empirical chapters

Chapters	*Chapter focus*	*Number of Schemes*	*Sample size[a] (number of households)*	*Data source*	*Estimation methodology*
Chapter 2	Irrigators' WTP for monitoring tools adoption	4	234	ACIAR project baseline survey data (2014)	Tobit model, censored least absolute deviations (CLAD) and OLS
Chapter 3	AIP impact assessment	5	361	ACIAR end of project survey data (2017)	OLS, probit model, Poisson regression and treatment effects models
	Spillover effects from AIP intervention	5	361	ACIAR end of project survey data (2017)	Treatment effects models in the presence of neighbourhood interactions
	Monitoring tools impact assessment	4	241	ACIAR end of project survey data (2017)	OLS, probit model, Poisson regression and treatment effects models
	Spillover effects from monitoring tools intervention	4	241	ACIAR end of project survey data (2017)	Treatment effects models in the presence of neighbourhood interactions
Chapter 4	Irrigation farm households' planned farm adaptation behaviour	6	371	ACIAR project baseline survey data (2017)	Fractional probit, Poisson regression, OLS, SUR, Recursive bivariate probit model, Binary probit model
	Comparison of irrigation farm households' planned and actual farm adaptation behaviour	4	263	ACIAR project baseline (2014) and end of project survey (2017) data	Binary probit model

Note: [a] The full description of sample sizes and missing observations is provided in each analytical Chapter.

1.6 Thesis outline

This thesis is organised into five main chapters. Chapter 1 provides an overview of SSA agricultural development issues with irrigation in the region; an introduction of the study area and project interventions; gaps in the literature; and research objectives, questions and methodology. Chapter 2 presents a research work published in a high-quality peer-reviewed journal:

> Abebe F., *et al.* (2020). Irrigators' willingness to pay for the adoption of soil moisture monitoring tools in South-Eastern Africa, *International Journal of Water Resources Development, 36 (sup1), pp. S246-S267.*

Chapter 2 examines the first two research questions of the thesis. It provides results regarding the price that farming households are willing to pay for chameleon sensor adoption, along with the influences driving irrigators' specified WTP, using baseline 2017 survey information gathered from four irrigation schemes in SSA.

Chapter 3 presents soon to be submitted research work prepared in manuscript format. This chapter investigates the role of development interventions that were applied within the small-scale irrigation schemes in three SSA countries. Specifically, the chapter explores whether AIPs and monitoring tools, using the 2017 survey data drawn from five irrigation schemes, meaningfully enhanced farmer welfare (measured through on-farm income, off-farm income, food shortage reduction and education outcomes). A doubly robust treatment effects model encompassing "inverse probability weighting regression adjustment" (IPWRA) and "augmented inverse probability weighting" (AIPW), which overcomes specification concerns, was applied for the analysis. In addition, Chapter 3 provides insights for policymakers regarding the influences of the implemented interventions, taking into consideration of potential spillover effects on non-participant irrigation households (and does so by applying the approach of Cerulli (2017)). Furthermore, Chapter 3 provides evidence on the extent female-headed irrigation households benefited from interventions, as compared to male-headed households.

Chapter 4 also presents yet to be submitted research work prepared in manuscript format. It analyses farm adaptation practices planned to be implemented by smallholder farmers over the coming three years, from 2014. This chapter applies fractional probit and recursive bivariate probit modellings and uses the control function approach to mitigate the potential endogeneity of climate perception regarding adaptation. The binary probit modelling presents results on how similar/different planned farm adaptation practices stated in 2014 compared to their actual implementation after three years in 2017 – using two waves of the same farm household data collected in 2014 and 2017.

Chapter 5 offers a summary of the thesis, policy implications, limitations of the work and future research directions.

Chapter 2 Irrigators' Willingness to Pay for the Adoption of Soil Moisture Monitoring Tools in South-Eastern Africa

This chapter is published in **International Journal of Water Resources Development** *as:*

Abebe F., *et al.* (2020). Irrigators' willingness to pay for the adoption of soil moisture monitoring tools in South-Eastern Africa, *International Journal of Water Resources Development, 36 (sup1), pp. S246-S267.*

Given the same database from six irrigation schemes were employed for this thesis, there is some repetition among chapters, especially in the data and study area description sections.

Abstract

Contingent valuation is used to elicit irrigators' willingness to pay for soil moisture tools in irrigation schemes in Africa, with various econometric methods employed to mitigate potential bias. Key results include that there is a neighbourhood effect influencing adoption, and that being located downstream and spending more on irrigation water positively and statistically significantly influenced willingness to pay for tools. The result suggests that although focusing on economic incentives and promoting farmer learning by those using the tools may promote greater adoption, there is likely to still be a need for co-investment by other bodies.

Keywords

Tanzania; Zimbabwe; Mozambique; irrigation; contingent valuation method; hypothetical bias

Statement of Authorship

Title of Paper	Irrigators' willingness to pay for the adoption of soil moisture monitoring tools in South-Eastern Africa
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Principal Author

Name of Principal Author (Candidate)	Fentahun Abebe		
Contribution to the Paper	Conducted literature review, organised the data for analysis, planned the econometric methodology, undertake data analysis, interpreted the results, and wrote the majority of the manuscript and acted as a corresponding author.		
Overall percentage (%)	70%		
Certification:	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.		
Signature		Date	13/10/21

Co-Author Contributions

By signing the Statement of Authorship, each author certifies that:

i. the candidate's stated contribution to the publication is accurate (as detailed above);
ii. permission is granted for the candidate in include the publication in the thesis; and
iii. the sum of all co-author contributions is equal to 100% less the candidate's stated contribution.

Name of Co-Author	Sarah Ann Wheeler		
Contribution to the Paper	Supervised development of the work, suggested econometric methodologies, edited and wrote parts of the manuscript.		
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Name of Co-Author	Henning Bjornlund		
Contribution to the Paper	Supervised development of the work, provided the data, assisted with interpreting the results and edited the manuscript.		
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2.1 Introduction

Agriculture is the highest fresh-water-extracting sector in sub-Saharan Africa (SSA), accounting for 79% of the region's fresh water withdrawal, with most of this used for irrigation (FAO 2016a), with the industrial and municipal sectors consuming only 5% and 16%, respectively. SSA's population is predicted to increase from about 13% of the world's population in 2015 to nearly 22% by the mid twenty-first century (UNDESA 2017), and thus agricultural crop production demand will increase (Van Ittersum et al. 2016). However, the availability of water resources has deteriorated over time (FAO 2016b), mainly driven by climate change along with the growing population (Besada and Werner 2015).

The potential productivity increase of irrigated over rain-fed agriculture is one of the reasons it is expected to play a fundamental role in producing food for the growing population (Faurès et al. 2007). Many argue that irrigation is not used fully enough across SSA (You 2008) and that there is considerable scope for improving the efficiency of irrigation management. SSA has a low share of irrigated agriculture in total crop production, with 3.4% of its cultivated area irrigated (FAO 2016c). Many small-scale irrigation schemes in SSA perform well below expectations (Bjornlund et al. 2018; Stirzaker and Pittock 2014; Sullivan and Pittock 2014) mainly because of poor operation and maintenance (Moyo et al. 2017). Also contributing to the failure of irrigation in the region are the lack of appropriate extension services, technical support, institutions, stakeholder empowerment, training and education (for stakeholders such as farmers, communities, extension agents and water user associations), credit and market access (Bjornlund et al. 2017; Mwamakamba et al. 2017; Pittock et al. 2017; Wheeler et al. 2017). One current technique to improve irrigation management includes soil moisture monitoring technology, to manage irrigation water losses and provide farmers with data to make better-informed decisions about when to irrigate and for how long (Bjornlund et al. 2018; Pittock et al. 2018; Stirzaker et al. 2017).

This study investigates which farmers are willing to pay for soil moisture monitoring technologies in south-eastern Africa, and how this willingness to pay (WTP) relates to current market prices, to help determine the economic feasibility of broader uptake of monitoring tools in developing countries. The potential for bias in irrigators' answers is also investigated. The research questions include: What are the socio-economic, demographic and location variables influencing irrigators' WTP for access to soil water monitoring tools?; And, how much are farm households willing to pay to access these tools? The present research uses cross-sectional data collected across four irrigation schemes in three countries: Kiwere in Tanzania, Mkoba and Silalatshani in Zimbabwe and 25 de Setembro in Mozambique (see Chilundo et al. 2020; Mdemu et al. 2020; Moyo et al. 2020 for details of each scheme). This study uses contingent valuation (CV) to elicit irrigators' WTP for the tools and uses insights from the agricultural innovation adoption literature (e.g., Akrofi et al. 2019; Bennett and Balcombe 2012; Hill et al. 2013; Wanyoike et al. 2019). CV is a well-known technique used to value resources that are not traded in markets, but, it is susceptible to a multitude of issues (Carson and Groves 2007). Partly this is because of the inability of a constructed imaginary market to represent practical/real exchange between buyers and sellers of goods and services. In this study, we attempted to reduce the inherent defects with the CV method by using ex post remedying techniques – econometric methods: logarithmic transformation and censored least absolute deviations models.

The rest of the article is arranged in the following way. The next section provides an overview of water scarcity and policies, technology adoption decision, monitoring technologies and issues associated with valuation techniques. In the third section, we describe the data and methodology. Key findings and discussions are presented in the fourth section. In the final section, we offer concluding remarks.

2.2 Literature review

2.2.1 Water scarcity and policies

Water management policy alternatives to deal with water scarcity are categorised as "supply-side" or "demand-side" instruments (FAO 2012). Supply-side management polices focus on building or upgrading water infrastructure, such as desalination plants and dams, to collect and transfer water resources (Bates et al. 2008; Gleick 2003). However, structural management approaches to water scarcity are subject to growing challenges, as many countries have physical limits on surface and groundwater resources but face large increases in water demand in all sectors (Gleick 2000; Koundouri et al. 2006). For this reason, since the end of the twentieth century there has been increasing attention to demand-side management to address water scarcity (Gleick 2000).

Demand-side water management policy tries to optimise the utilisation of water resources through modernizing water management and governance, adjusting water use timing, encouraging the uptake of water saving innovations and water use productivity. It focuses on institutional, regulatory, research, educational and economic strategies to deal with the challenges of scarcity (Gleick 2003; Grafton and Wheeler 2015).

2.2.2 Agricultural technology adoption theory

New agricultural innovations are key for improving productivity and profitability and achieving sustainable development (Channa et al. 2019), especially in developing countries (Doss 2006; Feder et al. 1985). Studies suggest that the uptake of innovation is a dynamic process through which individuals gradually learn about an innovation and adopt it (Baumüller 2012). A wide range of empirical literature has studied what drives or constrains agricultural innovation adoption (Dinar and Yaron 1992; Koundouri et al. 2006). The adoption behaviour of farmers is conditioned by economic factors, such as credit access, technology costs, input and output prices, wealth, income, labour availability and information access (Dinar et al. 1992; Feder et al. 1985; Foster and Rosenzweig 2010; Wheeler et al. 2017). Studies have considered farmers' characteristics, such as education, training, gender and farming experience, and farm-specific features like plot size, soil (quality, type and slope) and distance to market centre, to explain technology adoption decisions (Abdulai and Huffman 2014; Abdulai and Huffman 2005; Haensch et al. 2019). These decisions are also constrained by climatic and geographical factors like water access and weather (Baumüller 2012). Adoption choice is also significantly influenced by geographical proximity (the neighbourhood effect), which accelerates information flow through interpersonal dialogue and communication within the farming society (Case 1992; Haensch et al. 2019).

The features of an innovation, such as its comparative benefit, suitability to the prevailing system, simplicity to learn, use and operate, and visibility of outcomes are also important in facilitating adoption (Pannell et al. 2006; Rogers 1983). There have also been a growing number of studies on the influence of social capital in stimulating the uptake of an innovation (Bandiera and Rasul 2006; Haensch et al. 2019). Social capital is usually associated with tradition, beliefs and values, which assist communal decision making within a social system (Woolcock and Narayan 2000).

In understanding the adoption of agricultural innovations, careful consideration must be given to the type of innovation itself. Wheeler et al. (2017) distinguish between the adoption of "hard"' innovations (e.g., improved seed varieties) and "soft" ones (e.g., farm management) and show that various attributes have differing influences. Innovations that are predominantly knowledge based, and those that have a public-good element (either in their provision or in the externalities associated with their use) are significantly different from innovations that have more private farm benefits. Water-management-based farm innovations such as the one we are investigating here in this study are knowledge-based (soft) technologies with a considerable public-good element. It is known that for such types of innovations, strong institutional arrangements and networks can be essential for sustainable agricultural adoption (Hounkonnou et al. 2012; Wheeler et al. 2017). Ostrom (1990) outlined key lessons for common governance innovations, which are useful for insights for this study. Part of the reason water-saving technology may be under-adopted in Africa is a complex combination of institutions, public-good issues and governance.

2.2.3 Soil moisture monitoring technologies: the Chameleon

Understanding soil water content is essential for efficient irrigation practice, as over-irrigation wastes private farm agricultural inputs and micro- and macronutrients and hence, potentially reduces agricultural output (Barton and Colmer 2006; Fiebig and Dodd 2016; Lizarraga et al. 2003; Vories et al. 2017). Under-irrigation, on the other hand, increases crop stress and thus can reduce agricultural return (Lizarraga et al. 2003). However, it is also critical to note the difference between water consumption and water extraction, and the consequences for private-public water resource availability (Grafton et al. 2018).

A variety of soil moisture monitoring technologies, including tensiometers, gravimetric, psychro meters and neutron probes, can help farmers decide when to irrigate and for how long (Jones 2004). However, the adoption of these techniques is low in Africa (Annandale et al. 2011; Myeni et al. 2019). One reason for this may be inadequate extension services and information dissemination (Stevens 2006). In response to this low rate of adoption, the Commonwealth Scientific and Industrial Research Organization developed a moisture monitoring tool which is easy to use, provides critical data for farmer learning and is less expensive, to help resource-poor farmers make optimal and efficient watering decisions in the field (Stirzaker et al. 2014; Stirzaker et al. 2017). It represents both a "hard" and a "soft" innovation, as it involves both technology adoption and management expertise (Wheeler et al. 2017).

The Chameleon measures soil water suction at the root zone. It includes a reader and a sensor array, with three moisture sensors, which are buried in the soil at varying depths. Each array can be connected to a reader, which depicts the outcome visually, in a way that is easy for small-scale farmers to understand and that facilitates learning about "soil-water and nutrient dynamics" to improve irrigation management decisions. The Chameleon does this by measuring the stress intensity at the specified soil depth of each sensor array and revealing the reading outcome as blue if soil is wet, green if it is moist and red if it is dry. This provides helpful information to farmers to decide when and how much to irrigate; if used correctly, it minimises both under-irrigation and over-irrigation. It also helps farmers plan fertiliser application and agronomic practices (see Stirzaker et al. 2017; Virtual Irrigation Academy 2019, for more details).

This study aims to understand African irrigators' WTP for Chameleon soil moisture monitoring tools. Given that monitoring tools were introduced for the first time in the study area by the project, we used CV to estimate irrigators' WTP for these technologies. The next section provides an overview of the method.

2.2.4 Valuation techniques

In resource valuation studies, there are two main valuation methods, namely *"revealed preference"* and *"stated preference"* techniques, that practitioners and scholars frequently use to collect crucial information regarding the approximate value of commodities or services that do not have monetary prices in conventional markets (Adamowicz et al. 1994). Revealed preference methods (e.g., travel cost, hedonic method, averting behaviour) tries to measure the prices of non-tradable goods and services by directly assessing the behavioural responses of an economic agent in a practical context (Willis 2014). They can be used to quantify direct use values and have the advantage that people's responses are not susceptible to a constructed scenario. However, they do not estimate non-use or indirect values. Stated preference approaches (e.g., CV, contingent behaviour, choice modelling, conjoint analysis) attempt to estimate the monetary value of non-tradable items by presenting a simulation-based imaginary market with survey questionnaires. Their ability to capture some non-use and indirect values of public resources (Arrow et al. 1993) is the main benefit of these approaches, but their estimates are highly vulnerable to bias (Gregg and Wheeler 2018; Willis 2014).

In particular, CV is one of the most common valuation approaches, often used as a 'pre-test' of commodities that would have prices in the conventional system (Cameron et al. 2002). CV uses survey questions, in either a close-ended or open-ended format (Arrow et al. 1993) to elicit the maximum amount of money targeted respondents are willing to pay to improve the provision/establishment of communal resources, or the minimum amount of money respondents are willing to accept for a decline in the provision/availability of goods and services (Arrow et al. 1993). In the CV approach, individual respondents are asked to reveal their preference for a specific commodity contingent on the hypothetically established market/ scenario. The method has been used around the world to estimate farmers' WTP for a variety of services and products (e.g., Akrofi et al. 2019; Bennett and Balcombe 2012; Masud et al. 2015; Poudel and Johnsen 2009; Wanyoike et al. 2019).

In this study, a payment card CV format was adopted to elicit irrigators' WTP for access to Chameleon soil moisture monitoring technology. In payment card elicitation (Mitchell and Carson 1981), an interviewer gives study participants a card showing alternative bid values arranged in ascending order and asks them to tick the amount they would be willing to pay for provision of or access to goods or services. The bids start with 0 and would change sequentially at constant intervals. The payment card technique is a standard format whereby respondents consider the listed prices of the good in question and say whether they would buy it at those prices (Kerr 2001).

Although CV is a well-known valuation technique and has been used for decades, it is subject to a growing number of shortcomings (Champ and Bishop 2001; Mitchell and Carson 1981). Among others, hypothetical, strategic and instrumental bias have been extensively discussed in the literature (Gregg and Wheeler 2018; Mitchell and Carson 1981). Hypothetical bias occurs when the stated WTP in hypothetical markets does not match WTP values in regular markets, which involve practical transactions between market players (Champ and Bishop 2001). Strategic bias is related to "non-excludability" aspects associated with communal resources, and is where participants purposefully distort their valuation answers with the notion to affect the availability of a good or service (Mitchell and Carson 1981), either overstating or understating WTP. Instrumental bias occurs where WTP data collection instruments are not properly designed and so do not reflect the full picture of the commodity being valued. It is related to the applicability of the proposed payment method (e.g., tax, fee or donation), the clarity of the preference question, and the question's placement in the survey (Mitchell and Carson 1981).

Certainty scale, inferred valuation, consequential design and cheap talk are some approaches widely employed to deal with hypothetical bias (Carson and Groves 2007; Cummings and Taylor 1999; Gregg and Wheeler 2018; Li and Mattsson 1995; Lusk and Norwood 2009). The certainty scale is a post-preference question used to alleviate potential bias in resource valuation (Li and Mattsson 1995). In this method, study participants are asked to endorse their level of assurance that they would pay the bid value they have already mentioned in a simulation-based theoretical market. Inferred valuation is a new method used to minimise parts of the CV method's potential defect by inviting an economic agent for interview to estimate others' preferences (Lusk and Norwood 2009). A valuation design is said to be consequential if targeted respondents have understood that their answers determine the intended aims of the proposed policy change and that the policy outcome would influence their utility. Under such a valuation design, respondents are assumed to make a rational decision, with little or no incentive to provide biased responses for valuation questions (Carson and Groves 2007). "Cheap talk" design refers to a pre-survey interaction between the investigator and the respondents with the aim of reducing the bias associated with the constructed imaginary market (Cummings and Taylor 1999). Median estimation and logarithmic transformation have also been used to reduce hypothetical bias (Gregg and Wheeler 2018).

In the context of this study, it is important to understand that while there were no market prices for the monitoring tools in local shops, farmers had used the tools for four years and seemed to understand their value in the form of greater yields and less labour (Chilundo et al. 2020; Mdemu et al. 2020; Moyo et al. 2020). When the project originally started, farmers were unwilling to express a WTP. Even midway through the project, when they recognised how much their yield had improved and how much time they had saved, they still did not want to state a WTP. However, after four years of use (monitoring technologies were given to farmers freely by the project), farmers started to be willing to express an amount. This WTP has been further confirmed in recent focus groups during phase two of the project. Hence, we suggest that there is potential for both hypothetical and strategic bias in the answers. Strategic bias could be present in either an understatement or overstatement of WTP by irrigators, depending on their views on subsidised prices, future provision and neighbour's responses. Hence, we report WTP estimated by two different methods, as explained next.

2.3 Data and methodology

2.3.1 Data collection

This research uses data from an *Australian Centre for International Agricultural Research* project *"Increasing Irrigation Water Productivity in Mozambique, Tanzania and Zimbabwe through On-Farm Monitoring, Adaptive Management and Agricultural Innovation Platforms"*. The project, started in 2013, aims to "improve the productivity and profitability" of SSA small-scale irrigation through soil water management, "agricultural innovation platforms" and policy reforms (Pittock et al. 2017; van Rooyen et al. 2017). In 2014 and 2015, the project introduced Chameleon soil moisture monitoring tools across five schemes: Kiwere in Tanzania, Mkoba and Silalatshani in Zimbabwe, and 25 de Setembro (Boane) and Khanimambo in Mozambique (Bjornlund et al. 2018). In each sample irrigation site, the project selected 20 irrigators to use the soil moisture monitoring tool in their field to learn about irrigation water and micronutrient management for efficient irrigation practice. Each farmer received a sensor array, which was installed in their plot for free (Stirzaker et al. 2017). The project also deployed two Chameleon readers in each scheme, as well as a wetting front detector (Bjornlund et al. 2018). The project employed field personnel and trained them to monitor tool installation, measurement, data recording and reporting. Soil moisture readings were initially taken weekly, and recorded in farmers' field books, so the farmers could see changes over time and adjust their irrigation practice accordingly (Stirzaker et al. 2017). At the beginning of the project, the irrigation infrastructure in Khanimambo was damaged by flooding, and irrigation largely ceased, so that scheme was excluded from this analysis.

This study uses face-to-face farm survey data collected from four irrigation schemes in Mozambique, Zimbabwe and Tanzania. A pilot survey was conducted to ensure the validity and consistency of survey instruments across schemes, and questionnaires were refined before the actual fieldwork. In total, 266 households were surveyed in March – May 2017, with complete responses available from 234 respondents across the four schemes, which were used for modelling for this study.

Data were collected on socio-economic and demographic characteristics, agricultural input and output prices, marketing and institutional variables, monitoring tools, irrigation practices, perception of changes that have taken place during the project, decision making, and irrigators' WTP for access to monitoring tools. Interviews were conducted with either the household head or other key decision-making household members. A payment card was used to elicit irrigators' WTP for the monitoring tools. Respondents were shown bids ranging from 0 to USD75 for the sensor array, and from 0 to USD50 for permanent access to a sensor reader on a weekly basis.

2.3.2 Econometric methodology

Given the nature of our survey data, a Tobit model was chosen as the best method to estimate the determinants of farmers' WTP for the sensor array and for weekly access to the reader. Zero-WTP responses are common in CV studies, and the Tobit model is one of the regression methods most suitable for analysing data with censored responses (Tobin 1958). The unique feature of the Tobit model is that it attempts to incorporate each piece of information (censoring values as well as values greater than censoring point) into the investigation (Tobin 1958). In our survey, there are farmers with WTP responses clustered at 0 (bottom limit) for both sensor array and reader, and WTP values of USD75 and USD50 as an upper censoring response for sensor array and reader, respectively, so the Tobit method was appropriate.

For individual irrigation farm households, the latent willingness to pay variable, WTP_i^*, which is a linear function of independent variables X_i and normally distributed stochastic term, is given as:

$$WTP_i^* = X_i'\beta + \varepsilon_i, \qquad \varepsilon_i \sim iid(0, \sigma^2) \qquad [2.1]$$

Then, observed WTP_i, is defined as:

$$WTP_i = \begin{cases} \mathrm{WTP}_i^*, & if\ \mathrm{WTP}_i^* > 0 \\ 0\,, & if\ \mathrm{WTP}_i^* \leq 0 \\ 75(50), & if\ \mathrm{WTP}_i^* \geq 75(50) \end{cases} \qquad [2.2]$$

where WTP_i^* is the latent (unobserved) WTP for the access to soil monitoring tools (both sensor array and reader); WTP is the observed maximum WTP with a censoring point at zero for the lower limit and 75 and 50 for upper limits for sensor array and reader respectively; X_i represents a set of covariates that influence WTP; β is unknown coefficients; and ε_i represents the stochastic term.

As a form of sensitivity analysis, we also tested other methodologies and compared their results against the Tobit results. For example, as well as employing ordinary least squares (OLS), we also tested censored least absolute deviations (CLAD) and natural logarithmic transformation methods to minimise the potential hypothetical bias related to the CV approach. The CLAD model is an estimation approach that uses median values instead of mean values. Estimates based on CLAD are robust to non-homoscedastic error terms (Powell 1984) and outliers (Gregg and Wheeler 2018). Given the performance (coefficients) and test statistics (e.g., based on Akaike and Bayesian information criteria , AIC and BIC) of the models, only Tobit and natural logarithmic transformation results are reported here, as these models provided the best fit compared to the OLS and CLAD models (both in level and natural logarithmic transformation) estimates. For the CLAD model in particular, most of the estimated coefficients of independent variables (e.g., gender, plot location within the scheme, knowledge of monitoring tools) had a statistically insignificant influence on WTP for both the sensor array and reader. In contrast, most of the significant covariates in the Tobit model had similar effects on irrigators' WTP in the OLS model. However, given that the OLS method fails to recognise the inherent clustering and censoring nature of our data, a limitation the Tobit method overcomes (Amemiya 1973), then the OLS method may provide biased outcomes. Thus, the AIC and BIC tests suggest that the Tobit model is more suitable for our data than OLS. The Tobit model (natural logarithmic transformed) also provides conservative estimates of average WTP values for both the sensor array and the reader, which the resource valuation literature (Arrow et al. 1993; Gregg and Wheeler 2018) suggests should be a criterion for method choice.

Based on the literature (e.g., Akrofi et al. 2019; Bennett and Balcombe 2012; Masud et al. 2015; Poudel and Johnsen 2009; Qaim and De Janvry 2003; Wanyoike et al. 2019), socio-economic, demographic and location variables were hypothesised to influence WTP and hence were included in our models. We conducted multicollinearity diagnostics using variance inflation factors and correlation coefficients. These tests found that gender and marital status of head were highly collinear (0.8), so marital status was excluded. We added 0.1 to the value of all observations in order to allow natural log transformation estimation for zero-WTP responses. Finally, we used robust standard errors to account for potential heteroscedasticity (Table 2.2).

2.4 Results and discussion

2.4.1 Descriptive results

Summary statistics are provided in Table 2.1. Approximately 75% of respondents were male, and the mean age of household head was about 56. The mean family size is approximately six, and 29% of heads had attended secondary school or above. The median irrigated land size was 0.8 hectare. On average, farmers' annual gross farm income (crop and livestock) was USD1230 per year, and they spent USD40 per year on irrigation water (including water fee, maintenance and pump fuel). Nearly three-quarters of respondents knew what the monitoring tools measure and the benefits of adopting them.

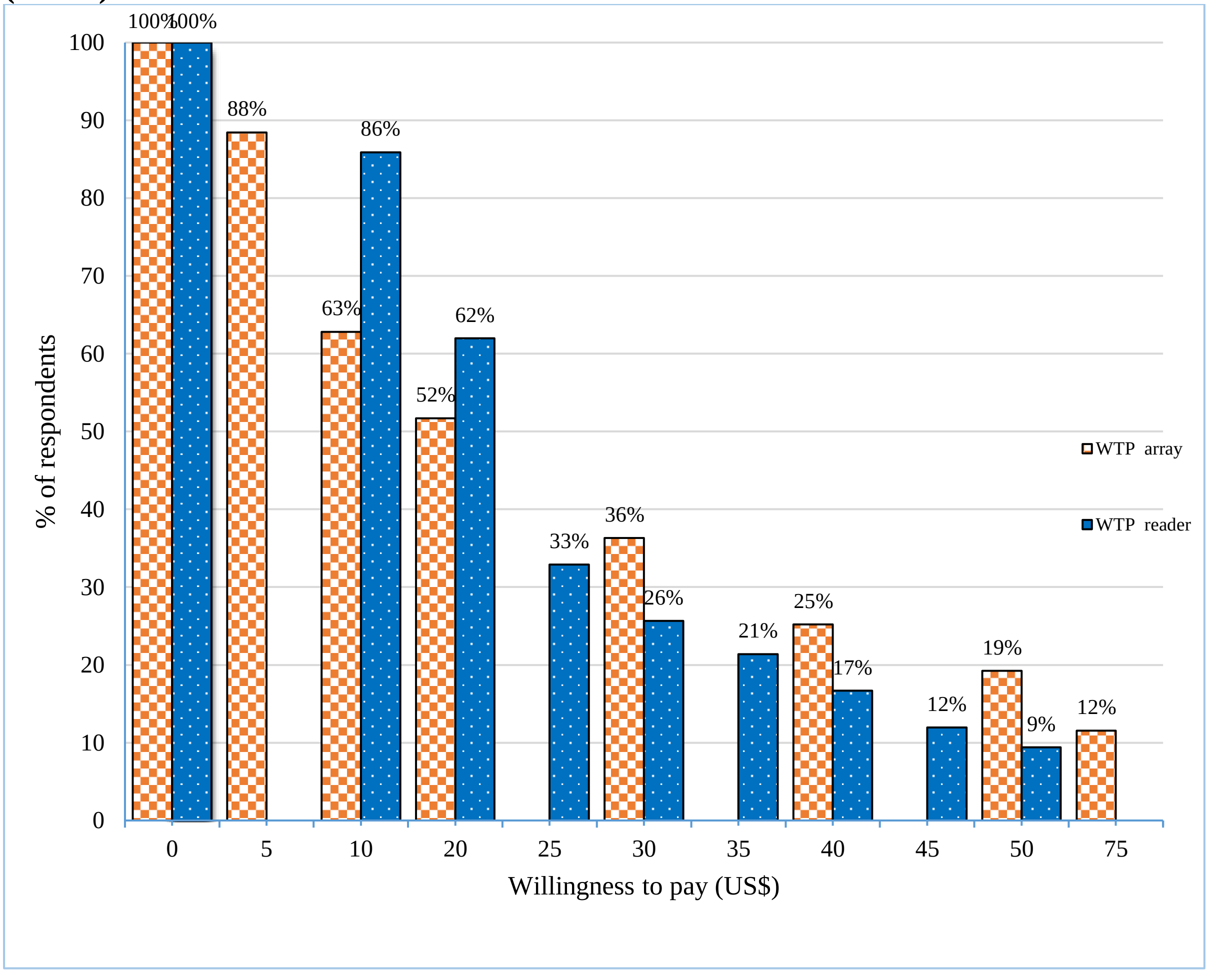
Table 2.1 Descriptive statistics (n=234)

Variables	*Definition*	*Measurement*	*Mean*	*Std. Dev.*	*Min*	*Max*
Dependent variable						
WTP array	WTP for access to chameleon sensor array	US$ (in 2017 prices)	23.70	23.60	0	75
WTP reader	WTP for weekly access to chameleon sensor reader	US$ (in 2017 prices)	20.68	14.73	0	50
Covariates						
Male	Household head gender	1=male; 0=otherwise	0.75	0.44	0	1
Age	Household head age	Years	55.50	16.15	20	92
Household size	Number of household members	Person	5.72	2.43	1	12
Education: Secondary or above	Household head education level	1=attended secondary school or above; 0=otherwise	0.29	0.46	0	1
Irrigated land	Irrigated land area	Hectare	0.8	1.09	0	11
Water costs	Annual irrigation water cost, including water fee, maintenance and pumping fuel in thousands	1,000US$ (in 2017 prices)	0.04	0.10	0	1.32
Farm income	Gross farm household income from crop and animal product sale in thousands	1,000US$ (in 2017 prices)	1.23	1.61	0	10.65
Tool knowledge	Knowledge on tools benefit and use	1=irrigators stated that they know what the tools measure and what they are used for; 0=otherwise	0.78	0.42	0	1
Tool location to farmer	Location of nearest installed tools	1=own tools; 2=on the neighbour plot; 3=two plots away; 4=three plots away; 5=on the same canal; 6=on different canal	2.47	1.64	1	6
Field days	Access to information services	1=any household member access information service from farm field days; 0=otherwise	0.94	0.23	0	1
Upstream	Plot location within the scheme	1=upstream; 0=otherwise	0.28	0.45	0	1
Middle (base)	Plot location within the scheme	1=midstream; 0=otherwise	0.41	0.49	0	1
Downstream	Plot location within the scheme	1=downstream; 0=otherwise	0.31	0.46	0	1
Mkoba	Irrigation scheme	1=Mkoba; 0=otherwise	0.22	0.42	0	1
Kiwere	Irrigation scheme	1=Kiwere; 0=otherwise	0.35	0.48	0	1
25 de Setembro	Irrigation scheme	1=25 de Setembro; 0=otherwise	0.11	0.32	0	1
Silalatshani (base)	Irrigation scheme	1=Silalatshani; 0=otherwise	0.32	0.47	0	1

Summary statistics of the WTP answers on access to monitoring technologies are shown in Table A.1 in Appendix A. About 89% and 86% of the irrigators have positive WTP responses for the Chameleon sensor array and access to the reader, respectively. Scheme-level responses indicate that 100% and 96% of 25 de Setembro farmers have non-zero WTP for sensor array and reader, respectively, compared to 81% and 79% for Silalatshani farmers. This might be because irrigators in 25 de Setembro are charged for pump fuel proportional to water use and so may be more financially motivated and willing to pay for the uptake of moisture monitoring technology. The percentage of irrigators willing to pay for access to a sensor reader is slightly smaller than that for buying a sensor array, for both pooled and disaggregated scheme-level data (Table A.1, Appendix A). However, a sensor array has no value without access to a reader. This difference probably reflects that farmers are willing to pay for the sensor array, which they need to have installed in their own field, but hope the irrigation association or somebody else will pay for the reader.

Figure 2.1 shows the cumulative distribution of WTP for a sensor array and weekly access to a reader. WTP response is a decreasing function of price, consistent with the theory of demand. Around 63% of respondents were willing to pay USD10 for a sensor array, compared to 86% for weekly access to the reader. More than half were willing to pay USD20 for a sensor array and nearly two-thirds for weekly access to the sensor reader at this price. About 12% and 9% of farmers were willing to pay the maximum listed bid for access to a sensor array and reader, respectively.

Figure 2.1 Commutative distribution of irrigators' WTP for a sensor array and reader (n=234)

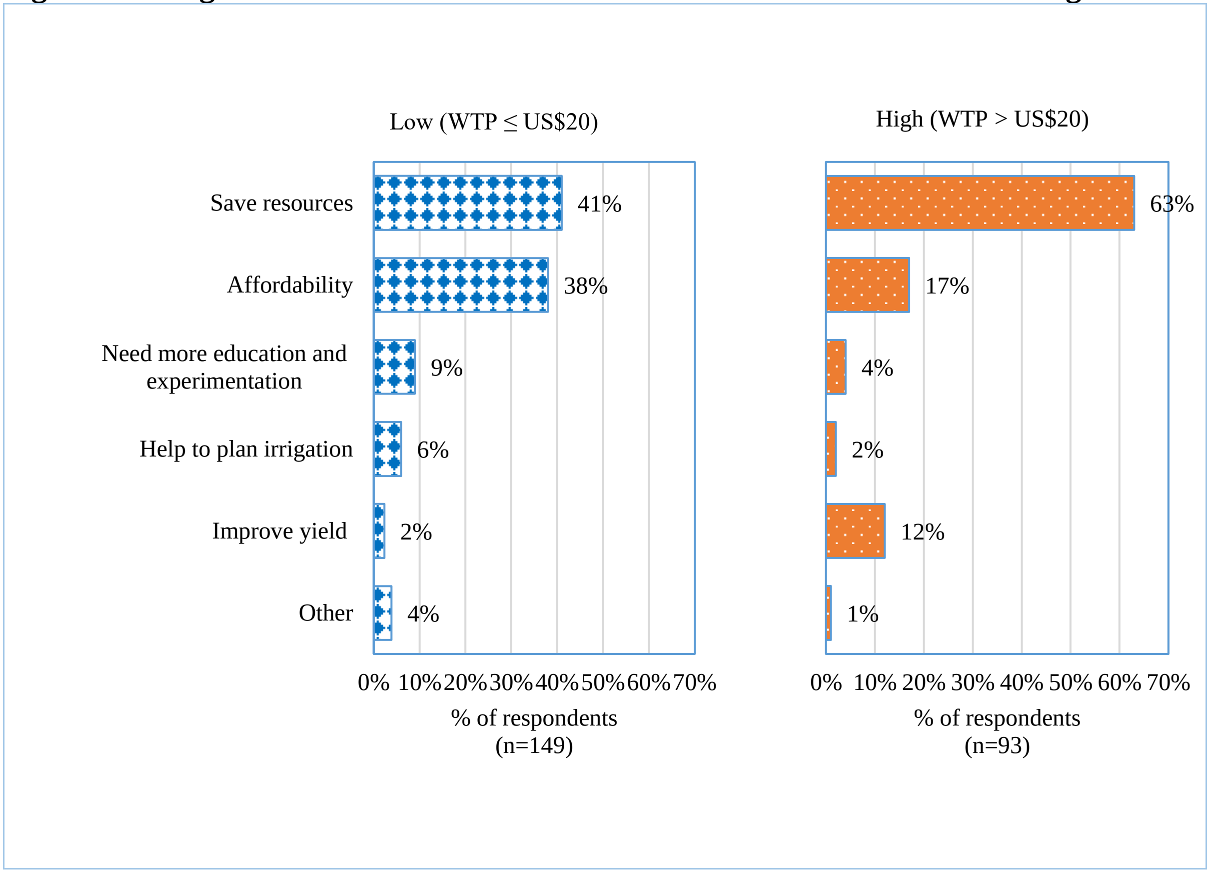


Note: There are variations in WTP bid prices offered to irrigators for sensor array and reader. For example, WTP bid values $US25, $US35 and $US45 were not asked to farmers for the adoption of sensor array and $US5 and $US75 were not asked to farmers for the adoption of sensor reader.

2.4.2 Irrigators' stated reasons for their WTP for monitoring tools

Farmers were asked why they would be willing to pay for monitoring tools (Figure 2.2). For comparison, respondents who answered this question were categorised into two groups: low WTP (bids of USD20 or less) and high WTP (bids over USD20). The reason for splitting irrigation farm households into these distinct set of clusters was to see whether respondents indicated reasons for monitoring tools access that deviated with their stated WTP. Saving resources, such as water, fertiliser and labour, was the most frequently mentioned reason, in both the low-WTP group (41%) and the high-WTP group (63%). Affordability was cited by 38% of the low-WTP group and 17% of the high-WTP group. About 12% of the high-WTP group cited better yield, compared to 2% of the low-WTP group. Irrigation-planning benefits were cited by 6% of the low-WTP irrigators and 2% of high-WTP irrigators.

Figure 2.2 Irrigators stated reasons for their WTP for soil moisture monitoring tools



Note: Figure 2.2 is based on the sum of total answers of reasons for irrigators' WTP for access to monitoring tools. From those irrigators who answered the question, about 85% (n=180) of them provided only one reason while 15% (n=31) provided two reasons.

2.4.3 Determinants of WTP for access to monitoring tools

The regression results of farmers' WTP for the adoption of the monitoring tools are presented in Table 2.2. Along with the Tobit regression, we used natural log transformed WTP to mitigate hypothetical bias, as suggested by Gregg and Wheeler (2018). The AIC and BIC for Tobit models showed that the model with natural log transformation better fit the survey data, so coefficient interpretation in this study is based on the transformed Tobit model (Table 2.2).

For clearer presentation of the key findings, we categorise them under subheadings, such as household and scheme/location characteristics.

2.4.3.1 Household characteristics

Gender of the household head was associated with WTP for access to the sensor reader at the 10% significance level, with a male household head having a lower WTP. This could be because women do most of the irrigation work, and perhaps that female-headed households have less access to man-power, and an inequitable share of water resources, and thus benefit more from access to a sensor reader, as it reduces the labour needed for irrigation and makes the water supply more reliable. This finding could also partly be attributed to the unequal productive resource distribution between male-headed and female-headed farm households. The research of Hite et al. (2002) in Mississippi documented similar effects of gender on WTP for technology adoption, although Hill et al. (2013) found that female heads have a lower WTP for the adoption of insurance innovation.

Table 2.2 Tobit model WTP estimated results for tools adoption across four irrigation schemes in SSA

	Sensor Array		*Sensor Reader*	
Variables	***Tobit (linear)***	***Tobit (ln)***	***Tobit (linear)***	***Tobit (ln)***
Male	-0.15	-0.09	-4.36	-0.81*
	(5.73)	(0.47)	(3.75)	(0.47)
Age	-0.30	-0.01	-0.84*	-0.07
	(0.69)	(0.06)	(0.45)	(0.06)
Age squared (divided by 100)	0.18	0.00	0.62	0.05
	(0.63)	(0.06)	(0.41)	(0.06)
Household size	0.80	0.01	0.40	0.05
	(0.87)	(0.07)	(0.55)	(0.07)
Secondary education or above	-4.74	-0.82	-7.09	-1.29
	(10.40)	(0.88)	(6.37)	(0.89)
Male*secondary education or above	7.52	1.28	12.22*	2.25**
	(11.31)	(0.96)	(7.26)	(1.00)
Irrigated land	-0.96	-0.05	0.23	0.03
	(1.09)	(0.10)	(0.82)	(0.15)
Water costs	122.53***	8.16**	19.59*	1.47
	(43.58)	(3.28)	(9.95)	(1.12)
Farm income	-0.69	-0.01	-0.51	-0.04
	(0.88)	(0.08)	(0.65)	(0.09)
Tool knowledge	2.20	0.36	5.60*	0.80*
	(4.42)	(0.42)	(2.98)	(0.45)
Field days	12.14	0.97	8.85*	0.99
	(7.42)	(0.83)	(4.95)	(0.80)
Tool location to farmer	-4.32***	-0.29***	-2.96***	-0.28***
	(1.17)	(0.10)	(0.71)	(0.10)
Upstream	5.61	0.51	2.81	0.50
	(4.80)	(0.41)	(3.08)	(0.42)
Downstream	7.42*	0.68*	3.97	0.65*
	(4.40)	(0.39)	(2.85)	(0.39)
Mkoba	7.79	0.52	-3.37	-0.35
	(7.32)	(0.62)	(4.42)	(0.57)
Kiwere	-6.51	0.25	-3.54	0.59
	(6.04)	(0.56)	(3.72)	(0.52)
25 de Setembro	5.53	1.21**	-0.24	0.38
	(7.25)	(0.54)	(4.17)	(0.49)
Intercept	19.96	1.26	40.35***	3.10
	(19.44)	(1.89)	(13.17)	(1.98)
Log likelihood	-914.42	-471.67	-832.17	-472.88
AIC	1843.56	957.61	1680.78	962.60
BIC	1909.21	1023.26	1746.43	1028.25
Pseudo R^2	0.03	0.03	0.02	0.04
N	234	234	234	234

Notes: Robust standard errors are in parenthesis
*p < 0.1; **p < 0.05; ***p < 0.01

Knowledge of the uses of the tools was another statistically significant (10% level) influence on irrigator WTP for weekly access to a sensor reader, suggesting that respondents with better knowledge of the function and use of tools were willing to pay more for access to them. It seems that innovation adoption decisions are strongly influenced by farmers' exposure to and awareness of the benefits of the technology (Rogers 1983). Our finding is consistent with Channa et al. (2019) and Qaim and De Janvry (2003). For the sensor arrays, however, the estimated coefficients for tool knowledge were insignificant. This may mean that the knowledge of how to use the tool was associated with how to interpret and respond to the display on the reader.

Findings from the linear Tobit model (although not the preferred model) showed that age and access to information influenced WTP for the sensor reader. Older farmers had a lower WTP for a sensor reader, maybe because they are more risk averse and thus reluctant to pay for new technologies. This is consistent with the findings of Hill et al. (2013). Farmers who accessed information by attending farm/field days had a higher WTP for monitoring tools than those who did not, presumably because it improved their practical knowledge of agronomic issues and/or their understanding of the tools' benefits. This is consistent with the findings of Toma et al. (2018).

The regression results also showed that male household heads with secondary or greater education have a significant (5%) positive influence on WTP for the sensor reader. This might be because education improves farmers' understanding of the overall benefits of the tools. This is consistent with the findings of both Abdulai and Huffman (2014) and Koundouri et al. (2006).

2.4.3.2 Irrigation scheme and location

The cost of water, which includes a water fee, maintenance, pump fuel, and other related costs, was a key influence on WTP for the monitoring tools. The price a farmer paid for water positively and significantly influenced WTP. In Mozambique (25 de Setembro) this makes intuitive sense because farmers' payments are related to water volume via the cost of diesel pumping. In the other schemes, it is less obvious, as they pay a fixed cost per area, and farmers have much the same area under irrigation. The results could reflect that, particularly at the beginning of the project, many did not pay for water or contribute labour for maintenance. This could suggest that those who did pay and contribute were willing to pay more, as they are likely to be more productive and more profitable, and thus see the benefits more clearly. This shows a clear link between economic incentives and tool adoption. Irrigators have experienced that monitoring tools reduce the cost of fertiliser, labour (money and time), pump fuel, maintenance and other input costs (Chilundo et al. 2020; Mdemu et al. 2020; Moyo et al. 2020), and they may also have perceived that access to the tools reduced production loss from either under- or over irrigation. These results are consistent with Frisvold and Bai (2016) and Moreno and Sunding (2005), who showed that high water costs and pricing drove adoption of water-saving irrigation innovations.

Distance to the nearest installed sensor array had a strong negative influence on farmers' WTP; the further the respondent's plot was from the nearest tool, the less they were willing to pay for the sensor array and reader. This could be because nearness to the installed tool increases farmer-to-farmer learning and the understanding of the benefits. This finding is consistent with Schmidtner et al. (2011) regarding the contribution of proximity in technology adoption, and Haensch et al. (2019) regarding the influence of neighbours for selling permanent water in Australia.

The farmer's plot location within the scheme also influenced WTP. Having a downstream plot raised farmers' WTP for a sensor array and reader, significant at the 10% level. This may reflect inequitable water distribution due to poor infrastructure, unsatisfactory maintenance and obsolete canal design (ACET 2017). Another reason might be that farmers at the head end of canals use too much water through ignorance. In such irrigation systems, water access and distribution are uneven, with downstream irrigators regularly denied access to reliable and fair irrigation water supply, which is clearly illustrated in all the schemes included in this study (Chilundo et al. 2020; Mdemu et al. 2020; Moyo et al. 2020). Water inequality is often worse during the dry period, resulting in water use competition, conflict, yield loss and many plots remaining fallow (Mdemu et al. 2017; Ostrom 1990). Consequently, downstream farmers might have a higher WTP for the access to tools because it enables better management of their less reliable water supply. These farmers have also experienced substantial improvements to their water supply since the project intervention, and a significant reduction in conflicts over water access (Chilundo et al. 2020; Mdemu et al. 2020; Moyo et al. 2020), because of upstream farmers irrigating less due to learning from the tools. Thus, these farmers see greater benefits from the overall adoption of the tools, as they ensure more equitable and reliable water distribution throughout the irrigation season. This is consistent with findings in the Indus Basin, Pakistan, where Hussain et al. (2004) found a significant difference between upstream and downstream farmers in terms of water access and wheat productivity. Manero et al. (2019) also found that both upstream and downstream farmers had low agricultural output, compared to midstream farmers, in Tanzania. It is also possible that this finding that downstream irrigators have higher WTP for the tools reflects an element of strategic bias, where irrigators deliberately overstate their WTP in order to encourage the use of the tools across the whole irrigation scheme, particularly by upstream irrigators. Finally, irrigators in 25 de Setembro were willing to pay more for sensor arrays than irrigators in Silalatshani (significant at 5%). This might be because farmers in the former scheme pay for pump fuel (i.e., they have an incentive for efficient water application because it will save fuel).

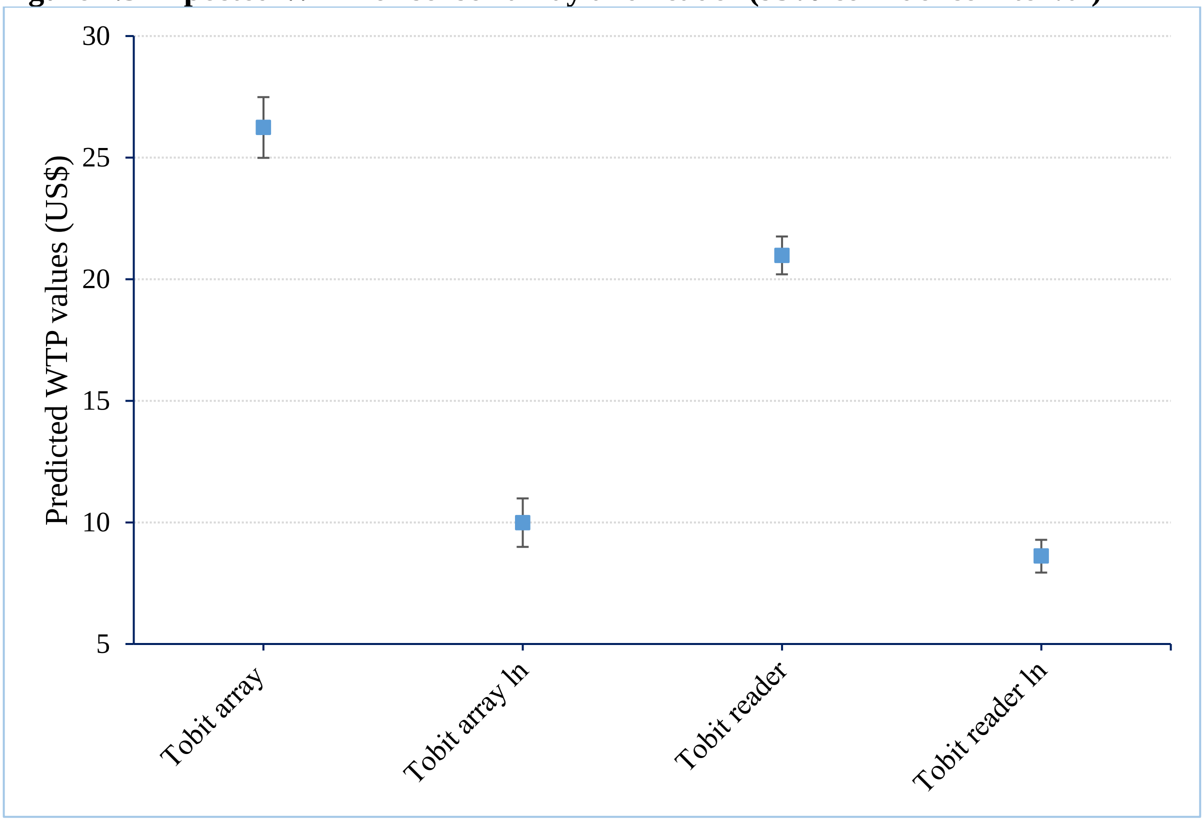
Table 2.3 presents the estimated mean WTP for access to monitoring tools for irrigated farming households, derived from the regressions. Per our Tobit model (linear), expected WTP for sensor array and weekly access to sensor reader in the sample households was USD26 and USD21, respectively. The Tobit model with transformation (employed to reduce hypothetical bias) produced estimates of only USD10 for a sensor array and USD9 for a reader, less than half of the estimates from the linear Tobit model (Table 2.3 and Figure 2.3). This comparison suggests that the application of natural log transformation to CV estimation is an efficient and alternative way to remedy the problem of hypothetical bias, as Gregg and Wheeler (2018) found. There are also questions regarding strategic bias in our results, which could lead to both either under- or over-statement of WTP. Further comparison of the adoption of soil moisture monitoring tools in the African situation over time will provide more insights into the robustness of our WTP findings.

Table 2.3 Expected WTP for soil moisture monitoring tools (95% confidence interval)

		Sensor Array (US$)			***Sensor Reader (US$)***		
Models	***Sample (n)***	***Lower***	***Expected***	***Upper***	***Lower***	***Expected***	***Upper***
Tobit (linear)	234	24.98	26.24	27.49	20.20	20.98	21.76
Tobit (ln)	234	8.98	9.99	10.99	7.94	8.61	9.29

Currently, the Chameleon moisture monitoring tool is in its prototype manufacturing stage; it is produced in Australia and South Africa and supplied to the market through the Virtual Irrigation Academy (2019). A Chameleon sensor array (three sensors) and one card reader currently can be bought for USD68.35 (exchange rate: AUD1=USD0.6904 (Reserve Bank of Australia 2019), excluding taxes, duties and transportation. However, commercial production and wholesaling could add costs. Note that this is not the reader farmers in the project used, though it has the same functionality, so this was the most appropriate price for comparison. Around 25% of our survey respondents were willing to pay the online price to get the full set of moisture monitoring tools (a combination of reader and array; see Figure A.1 in Appendix A). This finding implies that the adoption of this technology by small-scale farmers could be significant in the future and that farmers are willing to at least co-contribute within schemes. Our study also suggests a significant spread of learning among farmers with the adoption of the tools. Twice as many farmers reported changing their farming practices, and benefitting thereby, as had access to the tools (Chilundo et al. 2020; Mdemu et al. 2020; Moyo et al. 2020).

Figure 2.3 Expected WTP for sensor array and reader (95% confidence interval)



However, there are several reasons why adoption over time might be different from the preferences expressed by farmers in this study. There is a broader question of why, after more than 50 years of trying and billions of dollars of donor funding, is almost no water saving technology evident in small-scale schemes in Africa? That water management tools are a knowledge-based innovation with public-good elements is part of the reason, while the other part is the failure of institutions and governance. This suggests that the tools need to be part of a wider learning system. Parry et al. (2020) emphasised farmer-to-farmer learning and the broader uptake of the lessons from the tools. Other issues include tool warranty, longevity and maintenance, a learning system for extension officers, and the involvement of public-sector stakeholders. Further investigation is warranted of farmers' adoption of tools, its public-good benefits, and the institutional conditions of schemes that promote adoption.

2.5 Conclusion

Agriculture is the largest water-extracting sector in SSA, and agricultural water productivity is low. Adoption of soil moisture monitoring tools could play an instrumental role to improve on-farm water use productivity. Understanding the willingness of irrigators to pay for soil moisture monitoring tools to reduce water use and increase farm profitability is important for decision making when planning new schemes or refurbishing old schemes. This will help decision makers design appropriate policy instruments for wider uptake of monitoring tools by resource-poor small-scale farmers.

This study examined the factors influencing WTP and farm households' mean WTP for monitoring tools using CV methodology and various econometric techniques (e.g., CLAD and log transformation) to reduce hypothetical bias.

We find that being closer to installed tools (the "neighbourhood effect"), being located downstream, and paying more for irrigation water positively and significantly affected the willingness of irrigators to pay for a sensor array. For the sensor reader, WTP was positively and significantly influenced by farmers' knowledge of the use and benefits of the tools, geographical proximity to installed tools (the "neighbourhood effect"), being located downstream, having a female household head, and male heads with higher education. Most farmers stated a non-zero WTP for the sensor array and access to a reader, although there is probably still a need for co-investment by public bodies. Our results suggest that there is a demand for monitoring tools, and focusing on economic incentives and encouraging farmer learning may promote greater tool adoption by small-scale irrigators, though there are still considerable issues to investigate further regarding the link between institutional scheme characteristics and farmer adoption.

Although the findings of this research offer essential insights for decision making regarding the uptake of water use productivity enhancing innovations, care must be taken in making certain inferences from this study. Because sample size is too small for country/scheme–level analysis, the results are dependent on pooled data across three SSA countries with diverse institutional structures, farmer education levels and behaviours, and working environments, so additional investigations with country/scheme level data are necessary to check for country/scheme level heterogeneity. It is also well known that respondents in CV studies often overstate their WTP, as compared to prices in a real market context, mainly due to hypothetical bias. This highlights the need for future research in this area, especially in the context of agriculture in the SSA.

Chapter 3 The Effects of Agricultural Innovation Platforms and Soil Moisture and Nutrients Monitoring Tools on Household Farming Outcomes in Sub-Saharan Africa[1]

Given the same database drawn from six irrigation schemes were employed for this thesis, there is some repetition among chapters, especially in the data and study area description sections.

Abstract

Utilising 2017 survey information obtained from five sub-Saharan Africa irrigation schemes, the influence of agricultural innovation platforms (AIPs) and monitoring tools was investigated on a range of farm and household outcome indicators. Doubly robust estimation was used to measure the effects of these interventions, with a variety of other methods used for robustness checks. Involvement in AIP activities or monitoring tools was found to be statistically associated with increased on-farm income together with an increased capacity to fund for child education. Participation in AIP activities also had a significant positive influence on off-farm income and reduced food shortages. Moreover, spillover effects were accounted for in the estimations and statistically significant effects were found regarding on-farm income for non-participants. These findings suggest that interventions with strong agricultural innovation system approaches in SSA could provide significant irrigation societal beneficial outcomes.

Key words:

Agricultural innovation platforms; irrigation, monitoring tools; spillovers; treatment effect; doubly robust estimation

[1] We are grateful to the team members of ACIAR project for providing the data employed in this study.

Statement of Authorship

Title of Paper	The effects of agricultural innovation platforms and soil moisture and nutrients monitoring tools on household farming outcomes in Sub-Saharan Africa
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Principal Author

Name of Principal Author (Candidate)	Fentahun Abebe		
Contribution to the Paper	Conducted literature review, organised the data for analysis, planned the econometric methodology, undertake data analysis, interpreted the results, and wrote the majority of the manuscript and acted as a corresponding author.		
Overall percentage (%)	80%		
Certification:	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.		
Signature		Date	13/10/21

Co-Author Contributions

By signing the Statement of Authorship, each author certifies that:

i. the candidate's stated contribution to the publication is accurate (as detailed above);
ii. permission is granted for the candidate in include the publication in the thesis; and
iii. the sum of all co-author contributions is equal to 100% less the candidate's stated contribution.

Name of Co-Author	Sarah Ann Wheeler		
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Contribution to the Paper	Supervised development of the work, provided the data, assisted with interpreting the results and edited the manuscript.		
Signature		Date	13/10/21

3.1 Introduction

At the international level, sub-Saharan Africa (SSA) recorded the smallest score with respect to farming productivity (Ariga et al. 2019; World Bank 2021d), with an immense discrepancy between actual and potential levels of agricultural produce (e.g., Ragasa and Chapoto 2017). Irrigation is customarily put forward as a favourable policy mechanism in dealing with this kind of challenge, speed up agricultural change and ultimately curbing poverty (Manero and Wheeler 2022; Speelman et al. 2011).

Many suggest that SSA has an extensive opportunity to carry out valuable irrigation that could have a lasting and powerful influence on economic prosperity (e.g., You et al. 2011) – given their current water resources (FAO 2016a); land availability (The Land Matrix 2021); and bourgeoning marketplaces as a result of the rising population (UNDESA 2017). However, the propensity of irrigation success was shown to be exceptionally small in SSA (Kikuchi et al. 2021). For instance, Mutiro and Lautze (2015) completed an historical in-depth investigation of irrigation covering small, medium and large schemes within Southern Africa. The authors illustrated that only around six in ten schemes fulfilled minimal performance yardsticks. Regarding small-scale irrigation, in a systematic review of pump irrigation, Kamwamba-Mtethiwa et al. (2016) revealed positive irrigation impact in less than 60% of the studies. García-Bolaños et al. (2011) examined the status of 22 irrigation schemes in Mauritania and concluded that many of these schemes were shown to be defective, with little irrigation production. Muema et al. (2018) also found suboptimal performance in a sample of Kenyan irrigation schemes. Reasons for this include market problems, concerns about resource ownership, static cropping and irrigation arrangements, governance and the absence of local support (Bjornlund et al. 2017; Hounkonnou et al. 2012; Röling 2009; Wheeler et al. 2017). In addition, legacy issues from colonialism exist that may hamper further development (Bjornlund, V et al. 2020; Jew et al. 2020).

The predominance of the traditional linear school of agricultural extension proposed that technical advances are meant to trickle down and be adopted on-mass by farmers. Such an approach has not always been successful in SSA, nor in many other countries (Hounkonnou et al. 2012; Pamuk et al. 2014; Wheeler et al. 2017). As a result of criticisms of this traditional approach, there has been increasing focus on other methods of agricultural extension such as "Agricultural Innovation Systems" (World Bank 2006). In general, for an agricultural investment to be meaningful and viable, AIS attempts to ensure the needs of everyone within the sector are met and that they work in cooperation – from the initial concept to the broadcasting of improved methods (Sumberg 2005).

To date, a number of interventions compatible with AIS working guidelines (such as agricultural innovation platforms (AIP)) have been introduced across many African countries to improve agriculture's productivity and profitability (Hounkonnou et al. 2012; Schut et al. 2018). For example, a cocoa innovation platform was initiated in Ghana with the targets of overcoming information related challenges of farm households (Quarmine et al. 2012). Similarly, a goat (livestock) innovation platform was formed in Zimbabwe, which intended to improve the productivity of goat keepers with remunerative market links (van Rooyen and Tui 2009). The "enabling rural innovation" was another intervention introduced within several African countries from around 2001 and was designed to change the living conditions of farming households through market connections and resource conservations (Kaaria et al. 2008).

Given that a series of programs embedded with AIS principles have been operational for over a decade in Africa (Hounkonnou et al. 2012; Kaaria et al. 2008; Quarmine et al. 2012), there is increasing attention on evaluating the success of these programs (e.g., Pamuk and Van Rijn 2019). The vast majority of studies have concerned exclusively on the implementation and development of AIP working procedures and guidelines (van Rooyen et al. 2017), and have had limited success in addressing the issue of causality (in other words, is it the presence of the AIP that improves outcomes, or is it because the farmers that participate in such programs are more likely to be better off anyway?). The existing literature that has examined the effects of AIPs on farm household outcomes are often statistically inconclusive, or have not implemented robust statistical methods to assess causality questions, although most of them argued that innovation platforms have resulted in positive effects (Bjornlund, H et al. 2020; Kaaria et al. 2008).

Since the relationship between AIPs and associated farm outcomes is still questioned, this paper seeks to offer a deeper understanding of the casual links of AIPs on various farm and household outcome indicators in SSA. The overall goals of this study was to quantify the causal influences of AIPs and soil moisture and nutrients monitoring tools, implemented as part of a large-scale project, on various farm and household outcome indicators in five irrigation schemes in SSA in 2017. In this study, soil moisture and nutrients monitoring tools includes "Wetting Front Detector" and "Chameleon sensor" technologies. Hereafter, they are referred to as "monitoring tools". A "doubly robust" estimation technique is employed to investigate the contribution of these interventions on on-farm income, off-farm income, the ability to pay for child education and household food shortages in SSA. In addition, likely spillover impacts of AIP participation and monitoring tool use on non-participants and non-users are accounted for, to estimate the potential treatment effects of AIP participation and monitoring tools, respectively.

3.2 Agricultural innovation systems literature

As mentioned previously, the *technology supply push* approach has customarily been the main focus of agricultural extension (Wheeler et al. 2017). This approach postulates that key value-adding processes are made by scientific or technical personnel, and passed on for practical utilisation by end customers via a diverse set of outlets/mechanisms (e.g., extension personnel) in the system (Biggs 2007). Agrarian societies were provided with no role in decision-making, they were instead left to consume the by-products of the research (Röling 2009), and it has routinely been claimed that the "green revolution" was the solid result from this "linear" style of agricultural change (Biggs 2007). However, there has been massive critics of this approach, with the suggestion that it ignores access to services and other factors that drive productivity and change (Biggs 2007; Hounkonnou et al. 2012; Röling 2009; Wheeler et al. 2017).

The limited and sparse take up of novel agricultural technologies in SSA has led to the need to further understand agricultural barriers, and to find practical solutions, while considering local resources, customs and services. Hence, from around the last decade of the second millennia, there has been more focus on AIS models (World Bank 2006). The AIS model recognises that improved technologies are the result of coordinated and iterative work by various agricultural entities. Overall, AIS strives to accommodate every component within the agriculture jurisdiction, as opposed to other methods (Hounkonnou et al. 2012; World Bank 2006).

Under AIS guidelines, "innovation platforms" are crucial – to help ensure practical changes on the ground (Sanyang et al. 2016; Schut et al. 2018; Schut et al. 2019). Typically, an AIP involves an association of entities, with expertise and resources, who work together to reduce agricultural barriers. Within an AIP, local farmers can take part in discussions, and raise concerns to influence decision-making. Practices and exercises of AIPs are routinely adjusted, using voluntary and flexible processes to reflect the general consensus. Facilitators play a vital role in the success of AIPs, their role is to progress negotiations between a diverse set of parties and harness resources (van Rooyen et al. 2017). Building trust among key agents, representation, and embracing diversity are critical parts of the effectiveness, serviceability and practicality of AIPs (Schut et al. 2018; van Rooyen et al. 2017). For instance, the meta-analysis of Schut et al. (2018) depicted that AIPs that engaged all stakeholders and acted in accordance with their needs were shown to be more effective.

The literature evaluating AIPs is growing steadily, although the existing work to date has relied primarily on simple descriptive statistics to assess impacts. Focus has also primarily been on the impact of the intervention on participating farmers only (Ahimbisibwe et al. 2020; Mapila et al. 2012; Siziba et al. 2013). For instance, Bisseleua et al. (2018) examined the influences of "multi-stakeholder processes" on a range of household outcomes and showed evidence that taking part in these programs had positively enhanced the efficiency of farm production and capital availability – utilising descriptive analysis, and Tobit and stochastic frontier models. In the same way, Chilundo et al. (2020), Mdemu et al. (2020), and Parry et al. (2020) used descriptive statistics and qualitative data to examine the potential benefits of AIPs and monitoring tools. While these investigations found evidence that AIP and monitoring tools resulted in a positive impact on participants' productivity, income and water use, they did not address causality and did not account for selection bias. In a recent study, using descriptive statistics, Osorio-García et al. (2020) measured the influence of AIPs on various outcome variables in Colombia. They observed positive effects of the AIP in increasing farming use practices and disseminating climate change information.

On the other hand, in Malawi, Mapila et al. (2012) examined the casual links between "enabling rural innovations" and a number of key welfare indicators. They employed "propensity score matching" (PSM) and revealed that innovation programs enabled cultivating households to attain more income, production and better farming methods. Ogunniyi et al. (2017) also used PSM techniques to analyse the roles of a "growth enhancement support scheme" in Nigeria, an intervention formulated with AIS protocols to bolster the profitability and productivity of farming households by suppling subsidised farming inputs. They depicted that the intervention had a statistically significant positive income and production impact on intervention households. However, despite the fact that PSM is one of the classic intervention assessment toolkits used traditionally (Rosenbaum and Rubin 1983), it is an imperfect method to manage biases connected with unobserved influencing variables and specification errors (Imbens and Wooldridge 2009).

Another investigation by Siziba et al. (2013) concluded that innovation platforms had positively and statistically significantly boosted agricultural production in three countries of Africa, using instrumental variable techniques. In Uganda, Ahimbisibwe et al. (2020) used an endogenous switching regression and illustrated that AIPs enhanced the consumption level of farmers. Pamuk et al. (2014) studied the roles of innovation platforms, initiated from around 2008 in a number of African countries, using a rigorous panel data assessment technique. While they found that AIP interventions had positive payoffs in terms of the use of some agricultural practices, AIP had no observed significant benefits for other practices. The same study also demonstrated that individual and context specific platforms could have inconclusive results: AIP positively boosted the use of some practices; whilst it reduced the use of other practices or had no impact at all. Using panel data, a similar study carried out by Pamuk et al. (2015) measured the poverty curtailing contribution of AIPs in three countries of Africa and found inconclusive AIP results.

This study seeks to offer twofold contribution to the limited literature. First, we seek to compute the causal influence of AIPs and monitoring tools implemented from a large-scale project on farm and household outcomes in five irrigation regions in SSA. The studied outcomes include: on-farm income, child education, household food shortages and off-farm income in small-scale irrigation households. Second, we estimate the impact of the interventions on those who did not engage (in other words – identifying whether a positive spillover effects of AIP events or monitoring tools on non-participants exists).

3.3 Data and research methodology

3.3.1 Survey overview and area

Farm-level information obtained from a face-to-face survey in 2017 from an ACIAR-sponsored project, dedicated to enhance irrigation outcomes in five schemes from Mozambique, Tanzania and Zimbabwe, was employed for this investigation. The project designed and then applied two interventions within the targeted irrigation schemes: AIPs together with monitoring tools. The underlying consideration was that barriers to the performance of irrigation schemes in SSA are multi-faceted, implying that efforts concentrating solely on one aspect to resolve them would be unlikely to succeed. On this basis, the project was originally activated in 2013 and applying two interventions, AIPs and monitoring tools concurrently (Bjornlund, H et al. 2020).

The monitoring tools include the "Wetting Front Detector", which tracks soil water to look at the extents of nitrates at different depths to foster watering decisions. The other monitoring tool was the "Chameleon sensor" device, which was designed essentially to fulfil the demands of smallholders by tracking the magnitude of soil moisture at different depths and facilitate enhanced irrigation decisions. The method was designed to rate soil moisture in a clear and easy way: a red, green and blue light represent dry, moist and wet soil respectively – rather than building in too much complexity. Subsequently, farmers are able to easily gauge soil moisture and take appropriate action – making better use of production factors, in particular water and fertiliser (Stirzaker et al. 2017).

3.3.1.1 AIP details

AIPs were deployed in each scheme from 2013 onwards to identify productivity barriers and practical solutions. AIPs were established to comprise all stakeholders involved with the schemes such as, farmers and their organizations, government departments, civic leaders, development agencies, transport, input suppliers, output buyers, technocrats and advisory services (van Rooyen et al. 2017). The AIP members were nominated on the basis of: 1) experience in identifying productivity barriers; 2) expertise to put forward relevant ideas to overcome impediments; 3) willingness and expertise to play a part in overcoming the barriers; and 4) ability to distribute ideas, information and experiences over the course of time (Bjornlund, H et al. 2020).

The strategies adopted by the project regarding AIP participants varied across the three countries, according to each study area's existing situation. The scheme in Mozambique had a small number of farmers; hence, the entire farmers attended AIP meetings and became involved in AIP deliberations (Table 3.1). The schemes in Tanzania and Zimbabwe had much larger farming households. In these countries, only a small fraction of farmers participated in the AIP meetings while all farmers were invited to attend and benefit from the AIP initiatives/interventions. These included workshops, focus group discussions, field visits, demonstration programs, study and market visits, visits to input suppliers, among many others (Bjornlund, H et al. 2020).

In Tanzania, irrigation scheme leaders invited farmers to take part in the AIP meetings based on their location within the schemes, gender and age. These farmers were expected to represent all farmers within their scheme and communicate meeting outcomes to other farmers. Meeting frequency depended on the issues that needed to be addressed, with field days often scheduled. In Zimbabwe, farmers were invited to nominate their representatives at the AIP meetings. The AIP initiated diverse forms of activities and interventions to overcome the identified barriers and all irrigators were invited to participate. Examples of barriers raised during the meetings and the solutions suggested with the AIP deliberations are outlined in Table B.1 in Appendix B.

Different approaches were exercised to facilitate the AIP meetings. In Zimbabwe, project staff facilitated the meeting. In Tanzania, an independent facilitator was first engaged; however, this did not work, and the role was taken over by project staff. In Mozambique, public extension experts were assigned to guide the facilitation process. Before the first AIP meeting, training programs on AIP facilitation and implementation was provided by an AIP expert from the Zimbabwe team and continued as a principal consultant on AIP related issues during the project. AIP facilitators were required to record, and track all processes taken place under the AIP and share the outcomes with the project leader and key change agents.

3.3.1.2 Monitoring tools details

Working in conjunction with AIPs, the "Wetting Front Detector" and "Chameleon sensor" devices were granted at no charge to a group of irrigators (Stirzaker et al. 2017). The tools were used in four schemes (they were not applicable in Magozi as the prime crop was rice). Once again, tools were provided to irrigators based on the following factors: 1) location within the scheme; 2) perceived capability to operate monitoring tools; 3) ability to communicate the ideas, learnings and new practices from using the tools to other irrigators; and 4) reputation in the community (Bjornlund, H et al. 2020). Subject to meeting these conditions, the tools were granted to around 20 irrigators[2] in each of the four schemes. Consequently, each farmer was given two Wetting Front Detectors and sensor arrays and two Chameleon sensor readers were provided to each scheme for joint use (Stirzaker et al. 2017).

3.3.1.3 Survey data

The 2017 farm household survey data did not allow separate econometric analysis of those directly involved in the AIP meeting. However, information on AIP initiated activities participation were gathered and hence, AIP participation in this analysis is comprised of farmers who participated in an AIP activity or event (hereinafter named "AIP events" - 270 respondents had participated while 91 had not).

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[2] It should be noted that, in addition to this study, another project named *"Virtual Irrigation Academy"*, was also carried out in the Kiwere site of Tanzania from 2016. Therefore, the number of surveyed irrigators with monitoring tools in Kiwere within this study was 39, rather than the intended 20. We included these observations in the analysis on the basis that some of the project team members were involved in the two projects and that both of these projects were sponsored by the same institution (ACIAR).

Table 3.1 Respondents, AIP events participation and access to monitoring tools across five SSA irrigation schemes in 2017

	AIP			***Monitoring tools***		
Schemes	***Participated (AIP=1)***	***Did not participate (AIP=0)***	***Sample (n)***	***Received (Tools=1)***	***Did not receive (Tools=0)***	***Sample (n)***
Mkoba	45	9	54	18	34	52
Silalatshani	42	41	83	19	56	75
Kiwere	79	19	98	39	47	86
Magozi	76	22	98	–	–	–
25 de Setembro	28	0	28	19	9	28
Total	270	91	361	95	146	241

Note: '–' represents not applicable

In the face-to-face survey data collection process, taking into consideration of each study site conditions, different sampling methods were followed to draw sample farm households. For example, irrigators from Kiwere and Magozi schemes were drawn using stratified sampling techniques, whilst purposive methods were applied in the Silalatshani scheme. At the same time, considering the overall small size of total irrigation households in Mkoba and 25 de Setembro schemes, efforts were made to survey all irrigators, although this was not always possible. About 366 irrigation farm households in total participated in the 2017 survey. However, due to missing observations for some variables, five surveys were not included. Hence, a total of 361 responses from irrigation households over the five schemes (two schemes from Zimbabwe, two from Tanzania and one from Mozambique) were utilised for this study to examine the influence of AIP interventions (Table 3.1). As stated previously, monitoring tools were not offered to those irrigation households working in the Magozi scheme, hence could not be contained in the monitoring tools analysis (hence n=241 for the four schemes). The survey gathered detailed information on vast range of themes including farm household profiles, consumption, information access, resource use (including time and money), decision-making role in the household over a number of issues and involvements in various activities. Changes in irrigation practices, revenues from various activities, food security, education and the change in marketing conditions were also gathered with the survey. Furthermore, data on farming activities such as irrigate and dryland area in hectares, livestock holdings, and types of crops grown in both dryland and irrigated agriculture were also captured. The survey also gathered information with respect to the implemented interventions such as whether or not a farm household granted monitoring tools and involvements in AIPs. The information was gathered via face-to-face interviews of irrigation household' heads or another household member actively involved in the household decision making.

3.3.2 Dependent and independent variables

This study used objective as well as perception-based dependent variables to investigate the influences of agricultural innovation platforms and monitoring tools (Table B.2, Appendix B). The household outcomes analysed included on-farm income, food insecurity, capacity to pay for child education and off-farm income.

The *on-farm income* variable was constructed by adding income from three different activities (irrigated crop sales, rain-fed crops sales and livestock sales) over the past year. Information was also used on the total production from different crops, the percentage of production sold for each crop, their respective market prices, rain-fed (i.e., dryland) crop income and the type and quantity of livestock owned, consumed and sold. All income figures in the survey were collected in local currencies for Tanzania and Mozambique, whereas, in Zimbabwe, USD was the local currency at the time. We converted the on-farm income of Mozambique and Tanzania into USD using the respective country official exchange rates.[3]

Food insecurity was another dependent variable considered in this study. It was computed as the number of months a given household experienced *food shortage* over the last one-year period before the survey.

Furthermore, we analysed two perception-based variables, *child education* and *off-farm income* to measure the impacts of project interventions. In the survey, irrigators were asked to describe their current ability to fund child education and their off-farm earnings since the inception of the project in 2013. Farmers were asked to provide their answers in "Likert scales" with five potential values including "1=much worse"; "2=worse"; "3=same"; "4=better" and "5=much better", which were turned into two dummy variables. An irrigator's capacity to pay for child education and their off-farm income, were assumed to be improved if the irrigator stated that his/her capacity/income were getting better or much better, and not improved if it remained the same, worse or much worse in the previous four years (Table B.2 of Appendix B offers greater information).

[3] Exchange rate in 2017: 1USD=2228.86 Tanzanian Shilling; 1USD=63.58 Mozambique Metical (World Bank 2019).

We included all independent variables that past literature (e.g., Abebe et al. 2020; Ogunniyi et al. 2017; Wheeler et al. 2017) has suggested may influence the outcomes and the interventions/participation. The variables considered included: age, gender, family size, education, health status, cultivated land area, livestock holdings, media access, information access, affiliations to farmer groups or any community-based organisations, scheme/country dummies and plot locations from the irrigation canal (Table B.2, Appendix B).

Except for scheme/country dummies, identical covariates were incorporated to investigate the roles of AIP and monitoring tools interventions on the dependent variables. Given that the independent variables within an investigation should not be influenced by the investigated intervention (Wooldridge 2005), agricultural inputs (fertiliser, non-family labour employment, seed, water spending) were not included in the on-farm income regressions as inputs were presumed to be influenced through AIP events and monitoring tools use. Furthermore, on-farm income would also influence child education and food shortage, and therefore on-farm income was not included as a covariate in the capacity to pay for child education and food shortage regressions.

Collinearity checks suggested there were no strong relationships among independent variables (i.e., no VIFs>10) (Table B.6, Appendix B, and Table B.7 also reported the correlation analysis). Outlier issues were managed using the "Winsorizing" method. This technique helps to manage the issue through the substitution of the identified outlier observations with particular threshold percentiles. We changed the upper as well as lower-end 1% of those outlier observations with 99 percentile and 1 percentile values respectively to alleviate any potential bias. Robust standard errors were also used to reduce potential heteroscedasticity issues (Table B.8 of Appendix B).

3.3.3 Descriptive statistics

The variable definition and summary statistics are illustrated under Table B.2 of Appendix B. As previously discussed, the number of observations for AIP events (n=361) and monitoring tools (n=241) in the modelling are different. This section discusses the summary statistics of the AIP database. The result shows that about three-quarters of sampled irrigator's took part in the survey were male, and the average age was just above 52 years. Households, on average, contain about six members. More than two-thirds of irrigators attended primary school, while 23% attended secondary school or above. The mean cultivated area was slightly greater than two hectares. Almost a third of farmers possessed a plot placed at the tail end of the scheme. It outlines that close to eight in ten irrigators had the option to obtain information from shows or trade fairs and that nearly nine out of the ten farmers gained information from media outlets. Furthermore, 75% and 27% of farmers participated in AIP events and received monitoring tools, respectively.

Table B.2 in Appendix B highlights that irrigators earned an average income of USD1132 from crop and animal product sales, but faced a food shortage for nearly 7 months a year. Finally, 50% and 39% of sampled respondents specified that their ability to pay for their child education and off-farm revenue earnings respectively increased over the past four years (since the beginning of the project).

Table 3.2 shows the comparison between irrigators who participated in AIP events (or tools receivers) compared with those who did not. AIP participants had more household heads with good health, accessing more media and information, higher monitoring tool use and higher membership of farmer group/community-based organisations. All these proportional divergences were found to be statistically significant. Conversely, the fraction of farmers having farm areas situated in the tail-end of the schemes[4] was smaller in AIP participants compared with non-participants, statistically significant at the 10% level.

For monitoring tools, users had a higher percentage of household heads with good health, and larger household sizes and higher membership of farmer groups/community-based organisations, compared to those who did not. The proportion of irrigators who accessed monitoring tools were statistically significantly higher in 25 de Setembro than the reference scheme (Silalatshani). This difference is for the fact that the overall irrigation population working in 25 de Setembro were very small and hence much of them received monitoring tools. The proportion of irrigators engaged in AIP events was higher in Tanzania compared to the reference countries (Zimbabwe and Mozambique) at the 5% significance level. Lastly, there seemed to be no discernible deviations across groups pertaining to the remaining variables.

[4] In this study context, “tail-end/downstream” of the scheme refers to those farmers whose plots were located in the downstream/lower parts of the irrigation canal.

Table 3.2 Difference in independent variables by intervention across five SSA irrigation schemes in 2017

	AIP			***Monitoring tools***		
	Participated (n=270)	***Did not participate (n=91)***	***T/χ^2 test***	***Received (n=95)***	***Did not receive (n=146)***	***T/χ^2 test***
Variables	***Mean***	***Mean***		***Mean***	***Mean***	
Age	51.88	52.88	-1.00	53.67	56.24	-2.57
Male	0.78	0.73	0.05	0.79	0.72	0.07
Primary school	0.69	0.70	-0.01	0.64	0.64	0.00
Secondary school or above	0.24	0.21	0.03	0.32	0.27	0.05
Household size	5.69	5.93	-0.24	6.22	5.66	0.56*
Better health	0.81	0.70	0.11**	0.84	0.68	0.16***
Livestock	4.25	4.63	-0.38	4.76	4.30	0.46
Crop land	2.18	2.06	0.12	2.39	2.19	0.20
Media access	0.93	0.84	0.09***	0.92	0.86	0.06
Information access	0.85	0.66	0.19***	0.78	0.71	0.07
AIP	–	–	–	0.84	0.68	0.16***
Tools use[a]	0.30	0.18	0.12**	–	–	–
Membership	0.95	0.87	0.08**	0.96	0.88	0.08**
Downstream location	0.30	0.41	-0.11*	0.26	0.34	-0.08
Mkoba	–	–	–	0.19	0.23	-0.04
Kiwere	–	–	–	0.41	0.32	0.09
25 de Setembro[b]	–	–	–	0.20	0.06	0.14***
Country: Tanzania	0.57	0.45	0.12**	–	–	–

Notes: ***p≤0.01; **p≤0.05; *p≤0.1

'–' represents not applicable

[a] In Magozi site, monitoring tools were not granted to any farmers, yet the AIP was introduced. In the AIP analysis, we have assigned a zero value for irrigators from this site for the monitoring tools variable and included them in the analysis to increase the observation size.

[b] All *25 de Setembro* scheme farmers participated in AIP events, so we were not able to include scheme dummies to control cross-scheme heterogeneity in AIP intervention, as we did for monitoring tools. For this reason, we considered country dummy instead of scheme dummy in AIP events investigation.

Similarly, the differences among dependent variables, by irrigator participation, are reported in Table 3.3. For AIP events, a significant mean variation in on-farm income and food insecurity outcomes was revealed. For instance, on average, households involved in AIP events obtained USD441 more on-farm revenue and faced almost one month less food shortages during a year than irrigators who did not take part in AIP events. In addition, irrigators using tools obtained – on average – a USD621 greater level of income than those who did not, along with increased capacity to pay for child education.

Table 3.3 Differences in dependent variables by intervention across five SSA irrigation schemes in 2017

	AIP			***Monitoring tools***		
	Participated (n=270)	***Did not participate (n=91)***	***T/χ^2 test***	***Received (n=95)***	***Did not receive (n=146)***	***T/χ^2 test***
Variables	***Mean***	***Mean***		***Mean***	***Mean***	
On-farm income	1243.51	802.79	440.72^{**}	1576.97	955.93	621.04^{***}
Child education	0.54	0.37	0.17^{***}	0.65	0.36	0.29^{***}
Food insecurity	6.24	7.31	-1.07^{**}	5.84	6.37	-0.53
Off-farm income	0.43	0.29	0.14^{**}	0.41	0.37	0.04

Note: $^{***}p\leq0.01$; $^{**}p\leq0.05$; $^{*}p\leq0.1$

As a whole, these descriptive findings signal that interventions may have brought benefits to participating irrigators. However, one potential explanation for these results may be directly associated with the selection bias caused by the project intervention design. During the project implementation, those irrigators who were provided monitoring tools and participated in AIP events were nominated in accordance with a set of pre-determined criterions. In view of this, irrigators with greater social, cultural or economic positions may be identified to take part in these interventions, which may lead to "selection bias". The next section describes the econometric techniques applied to mitigate selection bias connected with the observed heterogeneity between project intervention participants and non-participant irrigators and the intervention outcomes.

3.3.4 Econometric methodologies

An overarching aim of impact evaluation of agricultural technologies is to establish the "counterfactual" of the technology/skill participants. "Randomised experimental" methods endeavour to overcome the counterfactual matter by equally inviting every single entities to take part in an intervention, minimising the incidence of "selection bias" (Imbens and Wooldridge 2009).

The use of the randomised experimental methods was not suitable in the present study given the fact that AIP meeting participant and monitoring tools recipient irrigators were purposefully selected based on a set of criteria. Moreover, some irrigators decided to take part in the AIP initiated events, while others did not, which could also lead to selection bias. In a non-randomised controlled setting, the desire to sign up to an intervention may be influenced by either "observed" or "unobserved" factors. In this respect, any descriptive analysis comparing the outcomes of the technologies might be compromised, given it may be liable to selection bias. A range of approaches are suggested in Imbens and Wooldridge (2009) to overcome this, with the choice of an approach broadly determined by data access and the type of intervention. In conditions such as this study, the treatment-effect estimators using observational data were considered to be the only available options to evaluate the causal effects of AIP events and monitoring tools use. Treatment-effect estimator methods search to reveal data patterns of recipients (e.g., those who used monitoring tools) compared to the counterfactual position of non-participants.

3.3.4.1 Doubly robust estimators

We analysed the influence of AIP events[5] and monitoring tools use on various irrigation farm and household outcome of change by applying inverse probability weighted regression adjustment (IPWRA) (Imbens and Wooldridge 2009; Wooldridge 2007) and augmented inverse probability weighted (AIPW) (Bang and Robins 2005) methods. These two methods were implemented by integrating the components of regression based and propensity score based (such as "inverse probability weighting (IPW)") techniques, which are customarily called "doubly robust" estimators, as they are less vulnerable than regression based and IPW techniques to model specification issues (Bang and Robins 2005; Imbens and Wooldridge 2009).

The use of IPWRA and AIPW relies on three key assumptions. The first is the "stable unit treatment value assumption (SUTVA)" (Rubin 1980), posits that the outcomes of those

[5] It is essential to note that due to insufficient observations, it was difficult to examine the joint influences of AIPs coupled with monitoring tools on farm household outcomes. Hence, our analysis was restricted to examine the impacts of each interventions separately, whilst incorporating the other intervention in the analysis as an independent variable.

irrigators who did not receive monitoring tools were not influenced by monitoring tools presence or use, implying the absence of spillover effects from users to non-users on the outcome variables. The "conditional independence assumption" is the second binding requirement (Rosenbaum and Rubin 1983), which assumes that an irrigator's decision to participate in an AIP event and use monitoring tools is only influenced by their measured profiles, ensuring that the unobserved heterogeneity between users' and non-users' adjusted outcomes are unrelated to the intervention. The third prerequisite is the "common support" assumption (Rosenbaum and Rubin 1983), where every irrigator suitable for a proposed intervention with comparable profiles has comparable odds of participating.

For an intervention, $D_i = [0, 1]$, it is purported that an individual irrigator i would have two conceivable but mutually exclusive outcomes. Noting the distinct aspects, z_i, which are unique to every irrigator, the mutually exclusive irrigation outcome equations[6] are given as:

$$q_{1i} = \pi_1 + z_i\alpha_1 + \rho_{1i} \qquad [3.1]$$

$$q_{0i} = \pi_0 + z_i\alpha_0 + \rho_{0i} \qquad [3.2]$$

where q_{1i} and q_{0i} are the outcomes (i.e., on-farm income; child education; food insecurity and off-farm income) of the same irrigator i if assigned and not assigned an intervention, respectively and z_i designates a vector of individual irrigator demographics and farm profiles that are anticipated to influence outcomes. π_0 and π_1 are intercepts; α_0 and α_1 are coefficients of z_i; and ρ_{1i} and ρ_{0i} are error terms.

The project intervention (AIP or monitoring tools) assignment model (Rosenbaum and Rubin 1983) was quantified as:

$$Pr\ (D = 1) = x_i\beta + \varepsilon_i \qquad [3.3]$$

where $Pr\ (D = 1)$ is irrigators' probability of being assigned or not assigned into AIPs or monitoring tools; x_i is individual irrigator features that are anticipated to influence their

[6] For simplicity, the outcome equations are illustrated using linear functional forms. However, we run linear regression for a continuous outcome variable (i.e., on-farm income); probit regression for binary outcome variables (i.e., child education and off-farm income); and Poisson regression for a count outcome variable (i.e., food insecurity).

placement in the interventions; β and ε_i are vectors of coefficients; and the error terms in the assignment model, respectively. As per the conditional independence assumption, z_i and x_i are assumed to be the identical vectors of influence.

Considering both the "conditional independence" and "stable unit treatment value assumptions", the effects of AIPs or monitoring tools uses are therefore, premeditated as:

$$\left.\begin{aligned} ATE &= E(q_{1i} - q_{0i}) \\ &= E(q_{1i}) - E(q_{0i}) \end{aligned}\right\} \qquad [3.4]$$

where ATE signifies the average treatment effect; $E(q_{1i})$ is the mean outcomes of those irrigator assigned in the interventions and $E(q_{0i})$ is the mean outcomes if not assigned in the interventions.

Given the difficulty in obtaining outcomes for a single irrigator i under both intervention and non-intervention at any one time (Holland 1986); doubly robust estimators were used to overcome this issue (Imbens and Wooldridge 2009). Firstly, the propensity scores of being allocated in these interventions were quantified utilising the intervention assignment model (Equation 3.3). Rosenbaum and Rubin (1983) described propensity scores as irrigators' likelihoods of being allocated to receive monitoring tools or participate in AIP events given their measured profiles. We estimated the propensity scores of participating in AIP events or monitoring tools using binary probit regression and incorporating a diverse set of independent variables in the model. Estimated results from this procedure are provided in Table B.8, Appendix B. Then, each irrigator was weighted by the inverse of their unique propensity scores in order to generate an imaginary population such that intervention assignment is unrelated with the household outcomes. Secondly, using the weights generated, the effects of AIP participation or monitoring tool use was estimated by the outcome models (Equations 3.1 and 3.2).

There is considerable evidence that significant gender disparity between men and women exist in a myriad of indicators such as wage, resource ownership, and political participation and many other aspects (e.g., Jayachandran 2015). This is particularly true in developing countries (e.g., Bako and Syed 2018). For a variety of reasons including culture, religion, and socially established values and norms, practices and policies regularly inclined to assist males compared to females (Jayachandran 2015). In rural communities, partiality against female-headed households routinely manifests in terms of access to education, health and resources like land

and credit facilities, which in turn curbs their productivity potentials and finally may jeopardise their welfare and livelihood outcomes (Bako and Syed 2018; Bjornlund et al. 2019; Manero et al. 2020). Bearing in mind this fact, this study also seeks to examine whether there is a gender level differential influence of AIP or monitoring tools. As such, the causal influences of AIP or monitoring tools were estimated separately for both male and female headed household sub-samples employing equation (3.4).

As a robustness check, we also implemented regression based (such as “regression adjustment” (RA)); “propensity score matching” (PSM) (Rosenbaum and Rubin 1983); and “inverse probability weighting” (IPW) (Imbens and Wooldridge 2009) techniques to evaluate the causal effects of an intervention. RA was designed to gauge the influences of an intervention using an outcome model alone, whilst PSM and IPW estimated the effects of these interventions employing the intervention assignment model. In principle, all these techniques are presumed to offer comparable findings and arrive in similar conclusions when the underlining models in question are desirably specified. If findings obtained across these methods lacks stability, it may be an indicative sign that models were wrongly specified and thus need respecifying. Mungsunti and Parton (2017) and Wheeler et al. (2020) are among the recent case studies using these procedures in the field of irrigation.

3.3.4.2 Spillover effects identification

As a general principle, it is imperative to understand the overall construct of an intervention and any likely spillovers that may exist from its execution. The assessed project was designed and applied based on the ethos that granting monitoring tools to a small number of farmers in each individual study region prompts self as well as inter-farmer learnings among all irrigators operating in the respective schemes.

In addition, given that AIPs were formed at the scheme level and that most of the irrigation constraints, such as infrastructure, market and transport were common to the general irrigation scheme community, any solutions devised with the support of AIP interventions may bring extensive public community benefits. For example, AIP non-participants may take advantage of better market links created with the help of AIPs to sell their production and access productive inputs, which may enable them to secure higher income and decrease production costs (Bjornlund, H et al. 2020; Parry et al. 2020).

Furthermore, regarding tools use, the project sought a spillover effect where non-tool user irrigators adjust their behaviour through learning from users, through either proximity or social links. By design, AIP events were also expected to serve as a supplementary conduit to encourage learning and sharing of experiences among farming communities. As a result, monitoring tools use may not only influence the response of participants, but potentially that of non-users – the "stable unit treatment value assumptions" of the estimators employed in the previous section may therefore not be valid. Given the above, it was hypothesised that AIP events or monitoring tools could have a positive spillover on non-participant farmers.

Following the procedure devised by Cerulli (2017), we intended to capture for potential AIP events or monitoring tool use spillovers through redefining equations 3.1 and 3.2:

$$q_{1i} = \pi_1 + z_i\alpha_1 + \rho_{1i} \qquad [3.5]$$

$$q_{0i} = \pi_0 + z_i\alpha_0 + \phi\sum_{j=1}^{N_1} \psi_{ij}q_{1j} + \rho_{0i} \qquad [3.6]$$

where $\sum_{j=1}^{N_1} \psi_{ij}q_{1j}$ designates the spillover benefit received by irrigator i (AIP non-participant or monitoring tools non-user), which could emerge as a result of irrigator's j intervention participation. ϕ is the sensitivity coefficient; and ψ_{ij} is a index denoting the distance between intervention participants and non-participants. After some simplification, this was specified as:

$$\left.\begin{aligned} ATE &= E(q_{1i} - q_{0i}) \\ &= \sigma + \bar{z}\theta - \bar{z}'\tau \end{aligned}\right\} \qquad [3.7]$$

where $\bar{z} = E\ (z_i)$, $\bar{z}' = \sum_{j=1}^{N_1} \psi_{ij}z_j$, $\tau = \phi\alpha_1$, $\sigma = (1 - \phi)\pi_1 - \pi_0$ and $\theta = \pi_1 - \pi_0$.

As the exact geographic location of each irrigator was unknown, an index was composed from individual irrigator profiles to measure the extent of proximity between participators (users) and non-participators (non-users). Following Cerulli (2017), this is labelled as a "correlation matrix". Dryland farming experience in years and education calculated the similarity of AIP participants and non-participants. On the other hand, dryland farming experience, installed tools location[7] with values "1=on different canal"; "2=on the same canal"; "3=three plots away"; "4=two plots away"; "5=in the neighbour's plot" and "6=own tools", and irrigation communities WTP in relation to monitoring tools adoption was used to assess the similarity of monitoring tools users and non-users. Finally, the influences of AIPs or monitoring tools given likely spillovers were predicted through the Stata command *"ntreatreg"* as per Cerulli (2017).

3.4 Regression results

The econometric results are reported in the following sub-sections. We first estimated the drivers associated with individual irrigators' placement (propensity scores) into interventions using probit regressions (Table B.8, Appendix B). The sign of statistically significant variables was in line with expectations. In Table 3.4, the impact of interventions on dependent variables estimated via several treatment-effects estimators, and Table 3.5 reports the treatment effects after accounting for potential spillovers.

Tables B.9–B.11 and Figures B.1–B.3 in Appendix B provide various diagnostic analysis of the treatment-effect estimators. For example, Figure B.1 displays the overlap diagrams of AIP events (panel A) and monitoring tools (panel B). The charts revealed that there were similar patterns in the likelihood values of intervention participation. Distribution evenness tests of influences of AIP participation or monitoring tools were also carried out. The "over identification" test (applied for IPWRA, AIPW and IPW procedures), revealed that the distribution of independent variables – for participant and non-participant irrigators – were analogous for both interventions (Tables B.9-B.10 also illustrated similar findings with other methods). Nonetheless, it is worth noting that the above test was not available for one method – the PSM method. For this reason, diagrammatic and descriptive methods were relied upon to analyse whether the distribution of independent variables contained in the regression was balanced among groups (Table B.11, and Figures B.2-B.3 of Appendix B). The results from these procedures also highlighted that the distribution was similar for participant and non-participant irrigators across both interventions, hence increasing our confidence in the overall results.

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[7] Cerulli (2017) advised that variables utilised to quantify the similarity of irrigation intervention participants and non-participants needs to be numeric. Given that granting monitoring tools to a group of farmers in each study schemes may lead to self as well as inter-farmer learnings, we incorporated tools location and other variables that were expected to trigger learning to produce the correlation matrix. As such, we considered semi-continuous variables along with numeric variables to calculate the matrix, and conducted extensive sensitivity testing.

3.4.1 Treatment effect results

The casual links of intervention participation on a series of outcome dependent variables (using IPWRA and AIPW estimators) are provided in Table 3.4. Generally, both estimators offered very similar results for outcome indicators for both interventions.

Table 3.4 showed that AIP participation statistically significantly increased irrigation on-farm income – an additional on-farm income of USD370-375 under IPWRA and AIPW ($p \leq 0.01$). In addition, there was a positive impact of AIP events on irrigators' ability to fund child education – an 11 percentage points greater ability ($p \leq 0.05$ in IPWRA and $p \leq 0.1$ in AIPW estimators). Participating in AIP events also had a statistically significant effect on food insecurity ($p \leq 0.01$ under IPWRA and $p \leq 0.05$ in AIPW) and off-farm income ($p \leq 0.05$ and $p \leq 0.1$ under IPWRA and AIPW estimators, respectively). To be more specific, irrigators' taking part in AIP events experienced 1.1 fewer months of food shortage annually and earned around 11 percentage points higher off-farm income.

Similarly, monitoring tools use positively and statistically significantly increased irrigation on-farm income by USD419 and 430, under the AIPW and IPWRA estimator, respectively ($p \leq 0.05$). Furthermore, a strong and significant positive child education influence was also observed from the uses of monitoring tools – boosted chances of irrigators' improved ability to pay for child education by about 24 percentage points ($p \leq 0.01$).

Table 3.4 Impacts of monitoring tools and AIP interventions across five SSA irrigation schemes in 2017: average treatment effects (ATE)

	On-farm income		*Child education*		*Food insecurity*		*Off-farm income*	
Estimation strategies	***AIP***	***Monitoring tools***	***AIP***	***Monitoring tools***	***AIP***	***Monitoring tools***	***AIP***	***Monitoring tools***
IPWRA	370.02***	430.44**	0.11**	0.24***	-1.10***	0.41	0.11**	-0.01
	(131.13)	(190.93)	(0.06)	(0.06)	(0.42)	(0.52)	(0.05)	(0.06)
AIPW	375.36***	419.49**	0.11*	0.24***	-1.10**	0.34	0.11*	-0.01
	(131.32)	(194.05)	(0.06)	(0.06)	(0.44)	(0.53)	(0.06)	(0.06)
RA	371.77***	436.14**	0.12**	0.24***	-0.93**	0.25	0.13**	0.00
	(129.12)	(191.71)	(0.06)	(0.06)	(0.44)	(0.54)	(0.06)	(0.06)
PSM	348.57**	436.93***	0.12**	0.25***	-1.04**	-0.06	0.13**	0.02
	(134.97)	(159.52)	(0.06)	(0.06)	(0.41)	(0.41)	(0.06)	(0.07)
IPW	393.96***	392.89**	0.10*	0.23***	-1.12**	0.10	0.11*	-0.02
	(129.34)	(186.14)	(0.06)	(0.06)	(0.45)	(0.48)	(0.6)	(0.06)
OLS	347.96**	393.55*	–	–	–	–	–	–
	(137.21)	(199.69)						
Binary probit	–	–	0.11*	0.26***	–	–	0.12*	0.00
			(0.07)	(0.07)			(0.06)	(0.07)
Poisson	–	–	–	–	-0.12*	0.05	–	–
					(0.07)	(0.08)		

Notes: Robust standard errors in parentheses

***p≤0.01; **p≤0.05; *p≤0.1

'–' represents not applicable

Marginal effects are reported in the binary probit model for the dummy dependent variables

As shown in Table 3.4, RA, PSM and IPW findings reasonably compared to the doubly robust techniques for both interventions. Additional sensitivity analysis using traditional regression methods (OLS, binary Probit and Poisson models) also found comparable evidence with our IPWRA and AIPW findings. Finally, it seems there is strong statistically significant and stable evidence that AIP or monitoring tools interventions improved various household outcomes for SSA irrigation communities.

Appendix B (Tables B.4 and B.5) depicts the gender specific heterogeneous influences of AIPs and monitoring tools, respectively.[8] In summary, the investigation portrayed that there is extensive heterogeneity among households headed by male and female. For male-headed households, engagement in AIPs or monitoring tools was shown to have a positive and significant on-farm income and child education influence. Likewise, AIP intervention significantly reduced food shortage and boosted off-farm revenues. For female-headed households, estimated results highlighted that involvement in AIPs or monitoring tools only significantly influenced food insecurity – female-headed households who participated in these interventions comparatively experienced fewer months of food shortage in a year than those who did not participate.

3.4.2 The spillover estimation results

Table 3.5 reported the influences of project interventions on several outcome variables when likely spillovers were accounted for. The findings in Table 3.4 were built on the SUTVA assumption, reflecting that the outcomes of non-participants were assumed not to be influenced by interventions. However, this assumption was shown to be violated for the on-farm income outcome in the AIP intervention model (Table 3.5), since a positive and significant ($p \leq 0.05$ for F-test) spillover effect was evident whose magnitude, however, was estimated to be small (around 3%) ($p \leq 0.05$). The influences of AIP intervention on other outcomes were not statistically significantly varied between the models accounting for spillovers or not, as evident by statistically insignificant F-test.

[8] Note, as the number of observations available for the sub-sample investigation was very small, estimation results for IPWRA and AIPW did not converge (see Tables B.4 and B.5 of Appendix B). Consequently, the discussion here only relied on converged results. As such, the statistical insignificant impacts of AIPs or monitoring tools for female-headed households for many outcome variables may be to some extent explained because of small sample sizes.

Table 3.5 Spillovers from AIP events and monitoring tools across five SSA irrigation schemes in 2017

	AIP				***Monitoring tools***			
Dependent variables	*ATE without spillovers: IPWRA*	*ATE with spillovers: ntreatreg*	*Spillover effect test (F-test)[a]*	*Bias[b]*	*ATE without spillovers: IPWRA*	*ATE with spillovers: ntreatreg*	*Spillover effect test (F-test)[a]*	*Bias[b]*
On-farm income	370.02***	382.36***	4.45**	-3.33	430.44**	516.37**	3.35***	-19.96
	(131.13)	(141.72)			(190.93)	(211.83)		
Child education	0.11**	0.12**	0.01	-1	0.24***	0.26***	1.32	-0.02
	(0.06)	(0.06)			(0.06)	(0.07)		
Food insecurity	-1.09***	-0.76*	0.00	29.70	0.41	-0.02	0.87	104.10
	(0.42)	(0.44)			(0.52)	(0.52)		
Off-farm income	0.11**	0.12**	0.00	-0.01	-0.01	-0.01	1.25	0.00
	(0.05)	(0.06)			(0.06)	(0.07)		

Notes: Robust standard errors in parentheses.
***p≤0.01; **p≤0.05; *p≤0.1.
[a] F-test examines the null hypothesis that spillover effect coefficients in the *"ntreatreg"* regression are jointly shown to be statistically insignificant in contrast to the alternative hypothesis that coefficients are significant. A significant F-test signifies spillover effect existence and consequently the bias estimate is significantly different from zero.
[b] Bias estimate is reported as percentages for continuous dependent variables (on-farm income and food insecurity), and percentage points for dummy dependent variables (child education and off-farm income).

Table 3.5 also revealed a statistically significant spillover effect for the on-farm income outcome in the monitoring tools model, while no statistically significant spillover effects was found for other outcomes. When spillovers are accounted for, the impact of monitoring tools on on-farm income increased by around 20% (p≤0.01), in contrast to the impact estimated in the IPWRA model. In other words, these technologies increased not only the on-farm income[9] of irrigators who used them but also the on-farm income of nearby non-users of monitoring tools. This result supported the initial project hypothesis that monitoring tools should encourage learning at individual, farm, and societal levels and ultimately help to generate positive spillovers to non-participants. The next section discusses possible reasons for this further.

3.5 Discussion

This study employed a range of econometric methods to model how participation in AIP events and using monitoring tools in five irrigation schemes across SSA improved a range of irrigation

[9] Although these estimates offer an indication of the spillover effects of AIP events or monitoring tools, caution is advised, as our index may not properly reflect the extents of the similarity of intervention participant and non-participant irrigators. Our results could be under or over-estimated.

household outcomes. AIP event participation boost up both on-farm and off-farm income, ability to fund child education and reduced the number of months a household faced food shortage. This supports other qualitative findings by studies such as Bjornlund, H et al. (2020) Chilundo et al. (2020); Mdemu et al. (2020) and Parry et al. (2020) whom explored the mechanisms by which AIPs were successful in identifying irrigation impediments and developing contextual and practical remedies to such problems. It has been suggested that AIP processes helped transform "subsistence" schemes to "business" oriented systems. In Zimbabwe, for example, the AIPs listed all problems (including disputes on water bill, inflexible irrigation programs and market problems) that negatively hampered irrigation and sought to help resolve all these issues through the participation and interaction of key stakeholders (Parry et al. 2020). With these enabling incentives, irrigators were encouraged to expand their production, invested in productivity enhancing activities and thus, obtained greater output, income as well as invested in welfare improving activities.

Similarly, in Tanzania, through the AIP initiated activities and discussions, interrelated productivity and profitability barriers (such as knowledge gaps, low input quality and undersupply of inputs, market problems, disputes over plot borders) were addressed. A range of AIP initiated events, such as focus group discussions, workshops, field visits, and demonstration programs were organised and held with the aims of prompting learning, discussion, experience sharing and information flows. Training programs on gross margin analysis and farming were prepared by the AIPs, which supported farmers to cultivate varieties with high economic returns (Mdemu et al. 2020). Consequently, farmers were more easily linked to input and output markets and thus, able to sell their produce with better prices, which increased income and accessed quality inputs with reasonable prices. Farmers also adjusted their farming practice from producing staple crop varieties to the production of commercial crops and voluntarily engaged in scheme maintenance. In Mozambique, the AIP events also positively contributed in addressing the most critical irrigation challenges (see Chilundo et al. 2020 for the detail) and as a result, better household outcomes, such as higher income and food security were gained. Broadly, the AIP results presented here corresponds with the meta-analysis findings of Schut et al. (2018). This meta-analysis suggested that for an AIP to be functional and have meaningful benefit, it should be representative and suited to the interests and contexts of those actors operating in the sector – the crucial ingredients that the project tried to follow from inception (see van Rooyen et al. (2017), for more on how AIP was applied in the project).

The second intervention, monitoring tools, has also shown a strong positive and significant influence on irrigators' ability to pay for child education and on-farm income. The likely justification for this is that the tools[10] enabled farmers to better utilise resources, including water and family labour, to maximise production and subsequently may be able to sell part of this to obtain some cash revenue. Money was also saved on reduced inputs, as the tools allow them to use a more efficient combination of resources. Abdulai and Huffman (2014) reported similar findings regarding the use of conservation innovations on farm revenue. The income gain due to tools use may be directed into other welfare enhancing activities, such as child education.

In addition to exploring the impacts of AIP events or monitoring tools on aggregate level, the current study also investigated a sub-sample gender specific influence. The analysis offered evidence that male-headed households tend to obtain far greater outcomes out of the interventions than female-headed households. The interventions only benefited female-headed households by reducing food shortages. The question is why? In trying to understand this further, it is worth reflecting on the descriptive statistics (see Table B.3 in Appendix B). It illustrates that female-headed households have statistically significant smaller households, less land, lower on-farm income, household size (and male household members size), and less livestock holdings. In the monitoring tools descriptive analysis, it was also shown that the proportion of female-headed households who mentioned an improvement in off-farm income earning over the past four years were relatively smaller than male-headed households (although this was not statistically significant). This suggests that these female-headed households have less family labour, often the absence of an adult male, and lower ability to buy inputs and implement new cropping methods etc. and their production may be more heavily loaded toward home consumption. Hence, a critical outcome for these households was the reduction in food insecurity. Because of cultural norms and habits, female-headed households face greater challenges in getting desirable resources, and other facilities. Such outcomes are particularly useful finding for the project in general, although female-headed households did end up benefiting somewhat from the interventions, it was not as much as male-headed households, and as a result, inequality within the scheme may magnified even though economic

[10] Utilising the same data, Abebe et al. (2020) illustrated that more than eight out of ten surveyed irrigators described a non-zero adoption willingness for chameleon sensor arrays and readers. On average, farm households specified a WTP magnitude of around USD10 for arrays and USD9 for readers.

development is improving in general (Manero et al. 2020). Future AIPs may need a greater consideration of how to include and improve outcomes for female-headed households.

In summary, AIPs and monitoring tools have transformed the irrigation schemes into more resilient systems and positively changed the living standards of irrigation communities in the study area. In addition, AIP had a 3% spillover effect on non-users on-farm income –indicating the interventions generated external benefits for the scheme as a whole. Monitoring tools assessment also highlighted that the intervention generated about 20% on-farm income spillover for non-participants. Indeed, it was a specific purpose of the project to inspire learning and experience sharing (Mdemu et al. 2020; Moyo et al. 2020; Parry et al. 2020). For example, previous simple descriptive analysis of AIPs and tools use by Moyo et al. (2020) and Parry et al. (2020) suggested that granting tools for about 20% of Mkoba scheme farmers helped approximately up to 50% of non-users to adjust their irrigation behaviour as they learned from those having the tools. The pathways on how monitoring tools use altered the "mindsets" of farmers and created "incentives for change" were studied qualitatively further in Chilundo et al. (2020), Moyo et al. (2020) and Parry et al. (2020). These studies argued that monitoring tools reduced labour needs, input use and rates, disputes and magnitude of irrigation. Accordingly, irrigators raised their production and decreased costs.

Overall, we suggest that the positive and statistically significant AIP intervention results may be explained by the following reasons: 1) increased networking, market and information flows; 2) increased opportunities that arise from networking; 3) increased dispute resolution and scheme participation; and 4) additional capital, on-farm income and reduced labour spent irrigating allows for further investment and business/social opportunities (Mdemu et al. 2020; Parry et al. 2020). This follows other research works such as Ahimbisibwe et al. (2020), Ogunniyi et al. (2017) and Siziba et al. (2013) whom outlined that AIPs led to positive consumption, income and production effects, in Uganda, Nigeria and Malawi respectively.

It is imperative to note the limitations of our study. One particular concern is that, due to the limited number of observations, we were confined to aggregate information gathered from three countries, and could not conduct individual scheme/country analyses. Consequently, a greater volume of observations – specific to each study region and with broad range of information – would help confirm the stability of the reported results from a country/regional perspective. For this sample size reason, some of the female-headed household regressions did not converge. Another limitation of the small amount of observations is that our survey data did not allow us to identify the combined impacts of both AIPs and monitoring tools on irrigation household outcomes. As well, it was not possible to investigate the values of the interventions on different groups of farm households (e.g., the poor vs better-off farmers), as the interventions may not have similar effect across different irrigators. As a final concern, the results are very reliant on the assumption that participation in the interventions were guided only with observed factors, meaning that there may be unobserved influences affecting involvement in the project and thus may nullify those estimated impacts. Addressing these issues could help improve future research in this field.

3.6 Conclusion

Agriculture in SSA remains largely undeveloped compared with other countries around the world, and there is pronounced opportunity for irrigation management to be improved to curb poverty. Issues with traditional methods of extension and knowledge have led to the development of new governance structures and extension forms such as agricultural innovation systems from around the last decade of the second millennia.

This paper examined the impact of an ACIAR-led project on irrigation household livelihood measures in five irrigation schemes across three SSA countries. Project applications included the development of AIPs and the distribution of monitoring tools, with treatment effect regression applied to evaluate household outcomes. Our results demonstrated that involvement in AIP events or monitoring tools use enhanced both on-farm income and the ability to fund child education. In addition, participating in AIP events reduced the number of months a household experienced food shortage during the year and increased off-farm income. The implemented interventions also provided a heterogeneous gender specific effect – male-headed households tended to benefit more from the interventions compared to female-headed households. It was also shown that there was a learning effect that occurred from AIP events (small) and monitoring tool use on non-users. A significant positive spillover benefit influence in relation to the on-farm income of AIP non-participants (albeit this was relatively small at 3%) and nearby tools non-users (much larger impact at around 20%) were also revealed.

These results emphasise the importance of assimilating both scientific knowledge together with local expertise. This could be achieved through greater scale and allowing every entity – including poorer households and female-headed households in the agriculture jurisdiction – to be actively involved in the exercise. For this to happen, a regional level of experience, ideas and institutions should be incorporated.

Chapter 4 Small-Scale Irrigation Farm Households' Planned and Actual Farm Adaptation Decisions in Sub-Saharan Africa[11]

Given the same database drawn from six irrigation schemes were employed for this thesis, there is some repetition among chapters, especially in the data and study area description sections.

Abstract

This study investigates planned and actual farm adaptation behaviour, using survey data collected in 2014 and 2017 from six irrigation schemes in sub-Saharan Africa. Four planned farm adaptation indexes including *expansive, accommodating, contractive and total* indexes were created from 16 potential individual farm practices, and analysed using fractional probit and control function approaches. The results revealed that future planned expansive, accommodating and total farm indexes in 2014 were influenced by similar variables. Education and wealth were shown to be significantly and positively linked with expansive, accommodating and total practices; while their correlations with age, off-farm income and perception of climate were negative. In addition, land holding size, previous farm adaptation experience and credit access were commonly shown to be statistically significantly and positively associated with all farm adaptation indexes. Two waves of survey data (n=263) were utilised to compare planned farm practices in 2014 and actual farm practices adopted by the same farm households in 2017. Results indicated a statistically significant difference between planned and actual farm practices – whereby the proportion of farmers actually undertaking one practice was found to be far greater than those that planned to undertake it. This result might be related to the implementation of projects within the study schemes, where numerous factors previously hampering irrigation activities were resolved increasing farmers ability to adopt more practices.

Key words:

Climate change; farm adoption; fractional probit model; irrigation; climate perceptions

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[11] We are grateful to the team members of ACIAR project for providing the data employed in this study.

Statement of Authorship

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Contribution to the Paper	Conducted literature review, organised the data for analysis, planned the econometric methodology, undertake data analysis, interpreted the results, and wrote the majority of the manuscript and acted as a corresponding author.		
Overall percentage (%)	80%		
Certification:	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.		
Signature		Date	13/10/21

Co-Author Contributions

By signing the Statement of Authorship, each author certifies that:

i. the candidate's stated contribution to the publication is accurate (as detailed above);
ii. permission is granted for the candidate in include the publication in the thesis; and
iii. the sum of all co-author contributions is equal to 100% less the candidate's stated contribution.

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4.1 Introduction

The changing climate situation is a global issue with long-term implications for the sustainable development of all countries (Knox et al. 2012; Palermo and Hernandez 2020); and it is suggested changes will be exceptionally acute in sub-Saharan Africa (SSA) (Codjoe et al. 2012; Comoé and Siegrist 2015). Reasons for this include: a) the region's reliance on farming activities (Barbier et al. 2009; Diallo et al. 2020) and the very small coverage of irrigation (3.4%) (FAO 2016c); and b) the region's lack of functional institutions, technical expertise and skills to offset and adapt to climate shocks (Codjoe et al. 2012).

Farm adaptation to a changing climate therefore is very imperative for SSA farmers (Codjoe et al. 2012; Pauline et al. 2016; Urama et al. 2019). Some of these farm actions encompass intercropping, diversification, irrigation, growing drought resilient and less water-intensive crop varieties, adopting greater water efficient practices, altering sowing timelines, mulching, off-farm activities and migration (Barbier et al. 2009; Comoé and Siegrist 2015; Deressa et al. 2009; Pauline et al. 2016; Wheeler et al. 2013). However, the need to increasingly adapt and to improve both profitability and farm livelihoods in SSA is also very essential (Tessema et al. 2019). Farm adaptation is influenced by many factors such as: government regulations (e.g., land redistribution); changes in population; farm input and output prices; project interventions; changes in personal circumstances/needs (e.g., health); and market expansion/contraction (Dinh et al. 2017; Ouédraogo et al. 2017; Wheeler et al. 2014; Wilk et al. 2013). This signifies that aside from adjusting to climate risks, farmers are also expected to adapt their ways of doing business to a host of other changes for maintaining/rising the viability of their farm and eventually support their livelihoods. Hence, other forms of adaptation also include increasing/decreasing the plot under both dryland and irrigation systems; adjusting working hours (both own farm and other paid activities); changing livestock herds; altering consumption habits (consuming more/less and selling/storing production); reducing expenditure; establishing non-farm enterprises; and adoption of innovations such as modern agricultural inputs (Pauline et al. 2016; Wheeler et al. 2013; Wilk et al. 2013). It is also known that many types of practices could serve as an adaptation means to both climate related risks and other form of external shocks.

The relevance of farm adaptation techniques in stabilising climate-induced risks and subsequently in supporting the living conditions of the rural poor has been clearly articulated in many research works (Abid et al. 2016; Di Falco et al. 2011). However, it has also been argued that farm adaptation in the SSA is far from its optimal level (Deressa et al. 2009; Mulwa et al. 2017). In the broader literature, there is also still much to be learnt about what influences planned and actual farm adaptation practices – both in a cross-sectional setting and over time via the use of panel data (Niles et al. 2016; Wheeler et al. 2021; Wheeler et al. 2013).

Employing farm survey data gathered from three SSA countries (Mozambique, Tanzania and Zimbabwe); this study extends the literature by examining the influences behind planned farm adaptation decisions and testing the dynamics of planned and actual farm practices over a three-year period. In particular, this study intends to offer answers to the following research questions using farm household datasets collected in 2014 and 2017 within different irrigation schemes: 1) What are the main factors influencing farmers' decisions to adopt various planned farm adaptation behaviour? 2) Are farmers' climate perceptions associated with various planned farm adaptation behaviour? 3) How different/similar are irrigation farm adaptation practices planned in 2014 from the actual farm adaptation practices implemented three years later? This study undertakes both cross-sectional analysis and two-wave survey data analysis of the same households over time, allowing us to ascertain whether the drivers of planned and actual farm adaptation practices differ.

4.2 Farm adaptation literature

The SSA region is steadily becoming warmer and drier ever than before (Sarr 2012), which is predicted to compromise the overall performance of agriculture and living standards (Knox et al. 2012). This issue makes farm adaptation a much-needed outcome for agricultural development programs.

Many researchers have noted that useful farm adaptation policies require clear and comprehensive knowledge on the states of adaptation, along with the overall behavioural influences on farmers' decisions and choices (Azadi et al. 2019; Below et al. 2012; Niles et al. 2016; Seidl et al. 2021; Wheeler et al. 2013). Over the past few decades, the "rural livelihood framework" has appeared as a leading methodology in examining the decision-making behaviour of farming communities (Ellis 1999). This framework has five different but interrelated class of capital resources, namely: human, financial, social, physical and natural capital and that farmer decision-making (e.g., ability to alter farming practices to combat uncertainties) is strongly associated with capital availability. Ellis (1999) also emphasised that institutional variables guides the accessibility, interaction, utilisation, and functionality of these capitals.

4.2.1 Farm adaptation influences

Research has focussed on the personal and demographic (human capital) profiles of farming communities as factors influencing adaptation choices (Alam et al. 2016; Seidl et al. 2021). For instance, since educational attainment can boost farming households' cognitive and information interpretation abilities, educated farmers have been found more likely to engage in farm adaptation initiatives (Abid et al. 2015; Below et al. 2012; Roesch-McNally et al. 2017). Earlier studies have signified that farm adaptation increased with farmer age (Deressa et al. 2009), while others have found age was inversely related with adaptation (Roesch-McNally et al. 2017). There is generally no clarity in earlier studies on the influence of gender, with some revealed that households with female heads had a much more tendency to adopt adaptation practices (Arunrat et al. 2017); while others suggesting females had a lower propensity to do so (Seidl et al. 2021; Yarong and Minpeng 2021).

Research has also concentrated on the links between farmers' "climate change perceptions and farm adaptation" choices (Arbuckle et al. 2013; Seidl et al. 2021; Zhang et al. 2020). The studies of Zhai et al. (2018) and Khan et al. (2020) pointed out that the propensity of engaging in farm adaptation increases with believing in climate change. Although studies such as Yarong and Minpeng (2021) and Le Dang et al. (2014) outlined a positive link between climate risk perception and farm adaptation intention, they did not consequently control for the likely endogeneity of perceptions of climate change on adaptation decisions. There are also now an expanding number of research works signifying that such a relationship represents a "feedback loop" (Nauges and Wheeler 2017; Wheeler et al. 2013). A research in Australia by Wheeler et al. (2013) noted that although the plan to adopt some practices in the future (e.g., improving irrigation efficiency and altering crop mix) statistically significantly increases with climate change risk perception, the adoption plans of other practices (e.g., overall farm practice and purchasing farmland) decreases. There also observed an endogenous association between perceptions to climate change and adaptation decisions (improving irrigation efficiency, altering crop mix, purchasing farmland, and overall farm practices). Moreover, Seidl et al. (2021) also illustrated that farming communities outlook relating to the changing climate strongly and positively determined the adoption of expansive and accommodating adaptation decisions in Australia. Their study also reported that perceptions to climate change was shown to be endogenously linked with farm adaptation decisions (expansive and accommodating practices). If such a relationship is not controlled for, it has the potential to significantly bias estimates. To our knowledge, Wheeler et al. (2021) was the first study to look at the influences of Australian farmers' climate change perceptions on farm adaptation practices, employing panel data. They underlined that there was a feedback loop between farmers' outlook in relation to the changing climate and adaptation behaviour over a five-year period, representing that those irrigators who thought that the changing climate imposed a risk in the earlier period were shown to have a higher propensity to apply less risky farm practices – which subsequently decreased their climate change perceptions after five-years and vice versa.

The other routinely stated influences of adaptation include variables related with physical capital (Abid et al. 2015; Alam et al. 2016; Below et al. 2012). These include livestock, extents of land, and market access. In this regard, Duffy et al. (2021) and Trinh et al. (2018) indicated that land holding was positively related with adaptation practices. Abid et al. (2015) and Tessema et al. (2019) also documented a negative relationship between farm adaptation practices and market distance.

Influences related to natural capital such as rainfall, water and location have also found to be relevant on adaptation practices (de Jalón et al. 2018; Tessema et al. 2019). Financial capital influences such as income, wealth, credit availability, and non-farm enterprises on adaptation initiatives have been clearly articulated (Nauges et al. 2021; Ouédraogo et al. 2017; Roesch-McNally et al. 2017; Tessema et al. 2019; Zhai et al. 2018). For instance, Duffy et al. (2021) revealed that planned farm adaptation increases with farm revenue in Vitenam.

Social capital such as affiliation with several organisations (farmers group, water user groups and environmental clubs) and extension service could also have a profound impact on adaptation decisions (Below et al. 2012; Wheeler et al. 2013; Wheeler et al. 2017). Interaction and dialogue with other actors possessing diverse sets of views, exposure, attitudes and responsibilities may prompt the exchange of ideas, ways of performing practices, experiences and information – including valuable adaptation practices – and subsequently may motivate farmers in carrying out adaptation decisions. Moreover, the influence of past farmer behaviour has been also proposed as a determining factor in the adoption of future adaptation practices (Fielding et al. 2008; Seidl et al. 2021; Wheeler et al. 2013). In Australia, Seidl et al. (2021)

and Wheeler et al. (2013) tested this claim and offered evidence that past adaptation practices were a significant and positive predictor of irrigators' future adaptation decisions.

There have been some studies comparing planned and actual farm adaptation within the literature. For example, Wheeler et al. (2013) examined various irrigation planned and actual farm practices in Australia and found that, while planned practices were shown to somewhat correspond with actual practices in years of no climate anomalies, large deviations were observed between these practices when there was an intense drought and significant government intervention. In these situations, actual farm behaviour outweighed planned behaviour. Using a cross-sectional survey, Niles et al. (2016) reported an enormous deviation among planned and actual farm behaviour in New Zealand.

4.2.2 SSA literature on farm adaptation influences

In general, the existing research regarding farm adaptation in SSA appears largely focused on actual farm behaviour (e.g., Below et al. 2012; de Jalón et al. 2018; Deressa et al. 2009; Tessema et al. 2019); with planned farm behaviour rarely studied. For instance, de Jalón et al. (2018) studied the actual adoption of fourteen individual practices using a cross-sectional dataset from nine SSA countries, and illustrated that various influences have differential impact on practice adoption. Using a cross-sectional data for Tanzania, Below et al. (2012) also analysed the actual adoption of 33 individual adaptation practices by collating them into a single index, and revealed that farm adaptation was influenced by various forms of capital resources. In Ethiopia, Deressa et al. (2009) assessed adoption of five practices by smallholder farmers and concluded that each practice was executed to a varying degree, with adoption associated with numerous influences. Hence, increased research on future behaviour in SSA may assist to develop policy programs to encourage future smallholder farmer's adaptation behaviour.

Similar to literature findings from developed countries (Dinh et al. 2017; Wheeler et al. 2013; Wheeler et al. 2014); present farm adaptation research works in SSA has heavily focussed more so on climate risk behaviour than studying farmer behaviour in reaction to other changes – such as project interventions and market dynamics (Ouédraogo et al. 2017; Tessema et al. 2019). Employing cross sectional data, Ouédraogo et al. (2017) investigated how farming communities across five SSA countries had adjusted their farming processes over the previous ten years before the survey – and found that climate risks, market forces, and land availability and productivity were among others triggering their farm adoption decisions (e.g., increasing land area, composting and adjusting planting period).

Employing a new technique that intended to manage response bias, Tessema et al. (2019) studied the adoption of seven farm practices in Ethiopia by eliciting farmers to state their adoption rationales, splitting by climate change and other changes. They found only the adoption of four out of seven practices were significantly related with climate change. Another research work within South Africa by Wilk et al. (2013) highlighted that the production of smallholder and large-scale farmers was hampered by policy change and absence of relevant support systems – on top of the impact of climate change.

4.2.3 Farm adaptation summary

Until now, it appears that the literature has concerned ordinarily on cross-sectional data to quantify farm adaptation (Duffy et al. 2021; Le Dang et al. 2014; Zhang et al. 2020) with inadequate attention into adaptation over time and consistency of actual and planned farm behaviour (Niles et al. 2016; Wheeler et al. 2013). In the broadest term, studies examining the consistency of planned and actual farm practices were not only scant numbers but also concentrated and skewed within developed countries. Given the heterogeneity between developed and developing countries in many aspects, greater analysis on farmers' adaptation plans in developing countries would fill an important gap.

Given that small-scale irrigation farmers are most likely to adopt similar farm practices in response to both climate change and other uncertainties – and that our baseline survey did not make any explicit distinctions between which farm adaptation practices were intended for climate related and other factors – this study explores farm adaptation in relation to future uncertainties as a whole. Within this context, irrigation farmers may adopt farm adaptation practices individually or in combination to counteract potential shocks (e.g., climate change, sickness), to boost the profitability of farm, or to achieve both. This study expands the literature by revealing the level of similarity/difference between planned and actual farm adaptation practices – as measured over a three-year interval – using two waves of survey data collected from the same irrigation households in 2014 and 2017. By doing so, this study offers key insights to policymakers about the relevance of designing different sets of policies that target specific adaptation practices by smallholder farmers. In addition, our study overcomes potential endogeneity concerns associated with climate perceptions and farm adaptation models, using a control function approach.

4.3 Data and research methodology

4.3.1 Survey overview and area

This study uses irrigation farm household survey information gathered by an *Australian Centre for International Agricultural Research* (ACIAR) sponsored project. The project was originally started in 2013 in six-irrigation areas within three countries including Mozambique, Tanzanian and Zimbabwe – with the purposes of enhancing agricultural outcomes through the application of two project interventions: "agricultural innovation platforms" and "monitoring tools" (see Stirzaker et al. 2017; van Rooyen et al. 2017 for interventions application details). The project undertook two farm household surveys: the first survey (baseline) in times of the initial launch of the project during 2014 and the other irrigation survey (end of project survey) at the completion of the project in 2017.

We analyse farm adaptation practices in two different settings: 1) planned farm adaptation behaviour using the 2014 cross-sectional dataset; and 2) the consistency of planned and actual farm adaptation practices over the three-year period, using both household datasets from 2014 and 2017. More specifically, the analysis of the planned farm adaptation stated in 2014 explores adaptation practices to be undertaken over the three years between 2014 and 2017. The second part of the analysis compares and contrasts farm adaptation practices – planned in 2014 – with actual farm adaptations undertaken between 2014 and 2017, using farm household survey data collected respectively in 2014 and 2017. More details are provided in the following section.

4.3.1.1 Baseline survey

The baseline survey took place from May to July 2014 with the purpose of capturing baseline farm situation prior to the actual initiation of the project. The data was obtained through face-to-face interviews of irrigation household' heads or any other household member actively engaged in household decision-making. The survey covered many details: demographic profiles; attitudes; asset ownership (household asset, farm asset, financial asset and housing conditions); land and livestock holdings; on-farm income (dryland crop, irrigated crop, and livestock sale); and off-farm income (e.g., seasonal work, agricultural labour, self-employment, small business etc.). It also gathered data on agriculture related spending (e.g., irrigation water, livestock input, fertiliser, insecticide, pesticide, transport and non-family labour); non-agriculture spending (such as education, health care, food, social events, personal transportation and housing); farm-decision making and farm adaptation practices; food security situation; perceptions towards climate; irrigation practices; and irrigation water distribution. Information on irrigator's overall values and views on numerous issues have been also captured in the survey.

Table 4.1 Sample respondents across six SSA irrigation schemes in 2014 (n=371) and 2014-2017 (n=263)

	Cross-sectional data: 2014		*Two waves of data: 2014-2017*	
Schemes	***n***	***%***	***n***	***%***
Mkoba	68	18.33	54	20.53
Silalatshani	97	26.15	69	26.24
Kiwere	90	24.26	54	20.53
Magozi	97	26.15	75	28.52
25 de Setembro	14	3.77	11	4.18
Khanimambo	5	1.35	–	–
Total[a]	371	100	263	100

Note: [a] In the baseline survey, which was carried out in 2014, 402 irrigation farm households were interviewed within six irrigation schemes. Since information on some of the key variables was missed, only 371 were comprised for the final regression analysis in this study. Although 282 farming households were reinterviewed in both the baseline and end of the project surveys, due to missing data only 263 were utilised for the regression modelling in the two waves of data analysis.

In general, the total number of farming households practicing irrigation in each of the six irrigation schemes varied, spanning from approximately 27 irrigation households in Khanimambo to 512 households in Magozi. By recognising this level of distinction, the project applied various sets of different sampling methodologies to select study participants. In Tanzanian case study areas (Kiwere and Magozi), the project utilised stratified sampling process on the grounds of irrigation households location within the scheme, asset base and gender. There were quite a small number of irrigation households working in Khanimambo, 25 de Setembro and Mkoba schemes. With this in mind, the project intended to include every irrigators working in these survey areas. For a variety of reasons, however, information on all households was not obtained. Furthermore, the project also applied a purposive way of sampling to draw study respondents in Silalatshani scheme. In the baseline survey, 402 irrigation households from all project schemes were interviewed. Given the missing data, information from 371 farmers was utilised in this study to quantify the influences on planned adaptation strategies. Table 4.1 highlights the respondents across the six irrigation schemes in SSA, both for the cross-sectional analysis using 2014 data only, and the corresponding households that were resurveyed in 2017 at the end of project.

4.3.1.2 End of project survey

The project undertook the second wave (end of project) of the survey during 2017 to quantify the changes that had occurred over the three-year period. In this survey, the required data was also obtained through face-to-face interviews of irrigation household' heads or another household member actively involved in decision-making. Consistent with the baseline survey, a variety of information was collected. The survey gathered information with respect to the applied interventions such as involvements in AIP events, whether or not a farm household granted monitoring tools and "willingness to pay" towards monitoring tools access (Abebe et al. 2020; Bjornlund, H et al. 2020).

At the end of project survey, an attempt was made to reinterview all previous farm households (n=402), which resulted in 373 irrigation households interviewed in total. For a diverse range of reasons such as migration and death, only a portion of those farmers (n=282) involved in the baseline survey were reinterviewed, resulting in an attrition rate around 30% (see Table C.13, Appendix C for attrition test results, which signifies no issues of attrition bias). It is worth noting that irrigation facilities in the Khanimambo scheme were greatly impacted by natural disaster before the end of the project survey in 2017, after which a large amount of land became fallow. Therefore, it was necessary to remove this scheme from the 2017 survey analysis. Because of this factor, along with missing values, this study uses a sample size of 263 farmers (see Table 4.1) who were interviewed in both the baseline and end of project surveys to investigate the consistency of (and influences on) planned and actual farm practices over the three-year time interval.

4.3.2 Dependent and independent variables

4.3.2.1 Dependent variables for cross-sectional analysis of planned farm adaptation

The cross-sectional analysis used the baseline survey dataset from 2014. It consists of two broad categories of dependent variables: 1) index based and 2) binary dummy adaptation practices (Tables 4.2 and 4.3). For this study, the index-based farm adaptation practices were measured in two different ways: fractional and count variables. This is mainly for the purposes of testing the sensitivity of findings to measurement differences. Hence, while we used fractional adaptation variables (percentage of expansive, accommodating, contractive and total practices planned to be executed – to the maximum number of proposed farm practices in the respective indexes asked in the survey) as our main variables of analysis, we used count adaptation variables for sensitivity testing. In the baseline survey, sixteen alternative individual farm adaptation methods were identified, including: increasing irrigated land; dryland area; livestock holding; crop diversification for both risk mitigation and labour purposes; specialising in a particular crop production; and acquiring productivity improving agricultural implements. The questions regarding each of the sixteen techniques were designed in a "yes/no" format. Accordingly, farmers were asked in 2014 to state whether they planned to adopt these practices from 2014-2017. The index-based dependent variables used here were specified following Wheeler et al. (2013), by collating the sixteen practices into three categories as planned *expansive, accommodating* and *contractive* indexes – with the underlining premise that they may have differential impact on the overall farm production (either increasing, decreasing or restructuring) (see Table 4.2 for a detailed explanation of each practice).

In this study context, *expansive practices* denote actions planned to be taken by farming households to increase the magnitude of the farm/associated activities. Some of the activities encompassed in this category include increasing the size of irrigated land, dryland and livestock holding (seven practices assigned). On the other hand, *accommodating practices* signify actions that change the composition of farm activities, including actions such as diversification or specialisation (four practices were assigned). Lastly, *contractive practices* indicate those activities that would potentially decrease the overall production of the farm, including decreasing irrigation land and livestock holdings (five practices were assigned). We also created an additional total farm adaptation index by combining all sixteen practices together.

For the count dependent variables, the values of each index were formed simply by counting the number of farm adaptation practices allocated in the respective indexes. As such, each index value potentially ranged from zero (if the farmer did not intend to adopt any of the proposed practices) to the maximum number of practices possible (e.g., seven for the expansive index). The fractional dependent variables were quantified as the ratio of the number of planned adaptation practices (count) stated to be applied by a given farming household over the next three years, to the maximum numbers of practices (counts) possible (within a range between zero and one) (see Table 4.3). Note, the greater an irrigation farm household scored on the fractional and count adaptation practice index, the higher the level of farm adaptation.

4.3.2.2 Dependent variables for two waves of data analysis in 2014 and 2017

For the two-wave data analysis, we used data collected in both 2014 and 2017. It should be noted that in the 2017 survey, the question indicating whether a farm household adopted a particular farm adaptation practice (in the form of a yes/no response) was not asked in exactly the same way under the 2014 survey. However, information on the actual intensities of some of the farm practices were recorded in the 2014 and 2017 surveys. For this reason, we relied on the actual farm practice intensities implemented in 2014 and 2017 to construct dummy variables for actual farm adaptations during the year 2017 (a proxy for actual adaptation practice). Note, since data on the actual intensity of some of the sixteen potential adaptive actions was unavailable or incomplete (e.g., consumption data) in either survey, our analysis here had to be restricted to four different practices regarding irrigation land area, dryland area, livestock holding and crop diversification.[12]

Therefore, using the actual intensity of these four practices (see Table C.14 in Appendix C), we created seven dummy variables (two dummies from each practice, with the exception of crop diversification[13]) that represent the actual adaptation practices used. Firstly, we computed the change in actual intensities of each farming practice by subtracting the actual intensities collected in the baseline survey (2014) from those obtained at the end of project survey (2017). Next, we divided irrigators into three categories according to the values of these changes. That is, “positive change” (if intensities in 2017 were greater than 2014); “no change” (if intensities in 2017 were equal to 2014); and “negative change” (if intensities in 2017 were less than 2014) (see Table C.14 of Appendix C). Secondly, we generated the actual farm adaptation indicator dummies for 2017, using the practice change variables created under the first step. As

[12] Crop diversification variable for this study was constructed by counting the number of crop varieties grown by farm households in 2014 and 2017.

[13] In the 2014 survey, planned farm adaptation practice data that indicates the reduction in the number of crop varieties grown was not asked, only planned crop diversification was asked. Because of this, we only constructed one dummy variable that denoted the actual crop diversification in 2017 and compared this with the planned crop diversification in 2014.

highlighted above, except crop diversification, we created two dummy variables (increasing vs decreasing size of the practices) for each actual farm practice. The practice was said to be increased (e.g., irrigated land, dryland, livestock holding, or numbers of crops grown) if the change in the intensities of the practices between 2014 and 2017 was positive (and assigned a value of one) – and not increased if the change was zero or negative (and assigned values of zero). In contrast, the practice was classified as 1=decreased if the change in the intensities was negative and 0=not decreased if the change was zero or positive (see Table C.15 in Appendix C). Finally, the seven dummy variables were used as actual farm adaptation dependent variables in 2017 to compare with planned farm adaptation practices identified in 2014.

4.3.2.3 Independent variables

A diverse array of independent variables was considered in this study to predict the adaptation decisions of small-scale irrigators, based on findings from prior research (Abebe et al. 2020; Arunrat et al. 2017; Khan et al. 2020; Seidl et al. 2021; Wheeler et al. 2013). Some of these independent variables include household head gender, age, education, land size, livestock holdings, extension services, asset ownership (such as car, motorbike or bicycle), ownerships of ox or donkey cart; farming experience; on-farm and off-farm income, credit availability, experience in using adaptation practices and climate perceptions over the previous decade.

Of particular interest is the independent variable of climate perceptions using farming households' overall views in relation to temperature variability in their area. Farming households were asked to consider the general trends of temperature in their area over the previous decade through "yes/no" questions. Farmers who answered "yes" that they believed temperature conditions had changed were asked a follow-up question regarding their beliefs on the direction of temperature change (1=increased, 2=decreased, 3=become more unpredictable and 4=pattern changed). We created a binary dummy climate perception[14] variable, where 1=climate perception dummy if farmers cited that temperature trends have been increasing or becoming more unpredictable over the past decade and 0=belief that temperatures have decreased, pattern changed/or not changed at all over the past decade.

[14] In this study, we use the term "climate perception" instead of "climate change perception" since the timeframe used to measure farm household's perception of temperature trend in the baseline survey was limited to ten years and referred to temperature perceptions only.

The household's previous farm adaptation was also used. Aside from planned adaptation practices, the survey also gathered data on previous adaptation experiences of all practices. In other words, farmers were asked in 2014 to indicate whether they had adopted these sixteen practices over the past three years, from 2011-2014. Hence, their respective past adaptation practices were incorporated as another independent variable (following the same processes described above). Tables 4.2 and 4.3, and Figures 4.1 and 4.2 provide greater detail.

For the two waves of data analysis (n=263) across the same irrigation household, involving the comparison of planned (2014-2017) and actual (2017) adaptation practices, we used the same sets of influences (drawn from the baseline survey in 2014) with those used for the cross-sectional analysis (n=371). More specifically, for the modelling of actual adaptation practices already implemented in 2017, the data collected in 2014 were used as independent variables instead of the 2017 independent variables. This is primarily because of the possibility that many of the potential independent variables collected in 2017 could be endogenous to actual adaptation practices in 2017. Secondly, some of the key independent variables (e.g., credit access, climate perception, asset ownership) found in the baseline survey were not included in the end of project survey, making it difficult to look at the influence of these variables on actual farm adaptation decisions. Lastly, some of the other independent influences considered are fixed between the two surveys, over the three-year interval (e.g., gender, education, scheme dummies). Bearing in mind these issues, the same sets of independent variables obtained from the baseline survey (2014) were utilised to explore both planned adaptation practices stated in 2014 and actual adaptation practices implemented by 2017. Because of these reasons, the sample size across the two waves of analysis was 263 rather than 526 (which would have been the sample size if panel data analysis were employed).

4.3.3 Econometric methodologies

Given the variety of dependent variable forms (e.g., as both fractional, count and binary variables), several estimation methods were employed, as detailed below.

4.3.3.1 Fractional probit model

For modelling the fractional dependent variables (percentage of expansive, accommodating, contractive and total adaptation practices planned to be used), we employed the fractional probit regression model to examine the influences of farm adaptation decisions. This model is most frequently applied in settings where the dependent variable with its value varies within the intervals of zero and one (Papke and Wooldridge 1996). In addition, given previous research findings that perception of climate was likely endogenous in the adaptation decision model (Nauges and Wheeler 2017; Wheeler et al. 2013), there was a need to control for this. Our fractional probit model for each planned adaptation index was defined as:

$$Farm\_adpt_i = \alpha Perception_i + x_i \beta + u_i \qquad [4.1]$$

where $Farm\_adpt_i$ signifies the four farm adaptation indexes, comprising either planned expansive, accommodating, contractive and total farm indexes by irrigator i; $Perception_i$ is farming households' climate perception, which is expected to be endogenously correlated with farm adaptation decisions; x_i designates sets of exogenous independent variables; α and β are coefficients indicating the influence of various features on farm adaptation decisions; and u_i are error terms. The same independent variables were used with the exception of past adaptation practice experiences – where their respective previous farm adaptation practices were used as an additional independent variable.

Following recent works such as Nauges and Wheeler (2017), this study utilised the "control function approach" (Wooldridge 2015) to solve endogeneity concerns arising from climate perception. According to Wooldridge (2015), the control function approach is comparatively easy to use and has less binding working assumptions. It entails an instrumental variable postulated to be linked with climate perceptions but not with the error term. This study used an "environmental investment index" that was created from responses to the following two related statements: *1) "investing in long term environmental benefits is more important than attending to traditional/cultural/social activities or lifestyle";* and *2) "decisions about investments at my farm are more about immediate livelihood benefits/solving problems, rather than about long-term environmental benefits".*[15] Survey participants were asked their level of agreement to these statements using seven point "Likert scales" (1=extremely agree to 7=extremely disagree), and the environmental investment index took the average of responses to these two statements. The relevancy of the environmental investment index as a seemly instrument to climate perception was assessed using F-tests (Table C.5 in Appendix C). The test result

[15] We reversed irrigators' responses to the second statement as follows: "7=extremely disagree", "6=strongly disagree"; "5= disagree"; "4=neutral"; "3=agree"; "2=strongly agree" and "1=extremely agree", so as to make it compatible with the responses to the first statement in computing the environment investment index variable.

highlighted that this variable was shown to be a desirable instrument (with F-statistics>10, or very close to 10).

In general, remedying the likely endogenous links between climate perception and farm adaptation decision through a control function approach consists of the following two steps. The first one is the estimation of the determinants of climate perception through an OLS approach and subsequently, predicting the residuals ($\hat{\eta}_i$):

$$Perception_i = x_i\pi + \varphi Env\_index_i + \eta_i \qquad [4.2]$$

where $Perception_i$ represents farming households' perception of climate; x_i represents a set of factors assumed to influence climate perception, which are the same as those expressed in Equation 4.1; Env_index_i is the environmental investment index; π and φ are coefficients; and η_i is the error term.

The second step was the investigation of the farm adaptation decision by incorporating the predicted residual ($\hat{\eta}_i$) as an extra independent variable together with all factors defined above in Equation 4.1 using the fractional probit model, which is respecified as:

$$Farm\_adpt_i = \alpha Perception_i + x_i\beta + \hat{\eta}_i\mu + \varepsilon_i \qquad [4.3]$$

where $\hat{\eta}_i$ denotes the predicted residual calculated from climate perception equation; μ are the coefficients of predicted residuals (control function); and the definition of all other parameters and variables remains the same as previously. The statistical significance of the coefficients of predicted residuals in Equation 4.3 was used to make a decision in relation to whether climate perception was endogenous to farm adaptation practices. A non-significant coefficient would signify that climate perception was exogenous, demonstrating that the issue of endogeneity would not be a serious matter and that the fraction probit model without $\hat{\eta}_i$ could potentially offer reliable inferences. Note that for the analysis encompassing the control function approach, bootstrapping standard errors with 1,000 replications were employed in the second stage.

The test results indicated that climate perception was shown to be endogenous with expansive, accommodating and total farm adaptation practices, but not with contractive farm adaptation practices (Table 4.4). Moreover, the endogeneity of climate perception was also tested with other methods including "*Durbin's chi-square test*" as well as *"Wu-Hausman's F-test"* (Table C.4 in Appendix C). These tests also substantiated the results reported using the control function approach.

We also carried out a series of extra sensitivity testing of our index dependent variable measurement. Specifically, various other methods such as OLS and Poisson regression models suited to our count dependent variables combined with the control function approach were employed. Moreover, we also further explored the sensitivity of results using "seemingly unrelated regression" method.[16] Results remained relatively robust.

4.3.3.2 Recursive bivariate probit model

Regarding the sixteen individual adaptation practices (Table 4.2), these were modelled as dependent variables using probit regression models, also taking into consideration the likely endogeneity of climate perceptions through the use of "recursive bivariate probit model". This model is routinely applied in such cases (Green 2012; Maddala 1983).

For a given irrigation farming household i with sixteen individual planned farm adaptation practices and climate perception, the recursive bivariate probit model was:

$$q_i^* = x_i\alpha + u_i, \qquad q_i = 1 \text{ } if \text{ } q_i^* > 0, \, q_i = 0 \text{ } otherwise \qquad [4.4]$$

$$y_i^* = x_i\beta + q_i\tau + \varepsilon_i, \qquad y_i = 1 \text{ } if \text{ } y_i^* > 0, \, y_i = 0 \text{ } otherwise \qquad [4.5]$$

where q_i^* and q_i represents the latent and observed climate perception respectively. Similarly, y_i^* and y_i also represent the latent and observed planned individual farm adaptation practices respectively; x_i are independent variables presumed to influence both irrigators' farm adaptation decisions and climate perceptions;[17] α, β and τ are coefficients; and u_i and ε_i are

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[16] When the error terms of the three index decision models *(expansive, accommodating and contractive)* are significantly correlated, estimating these models simultaneously through SUR approach could offer more reliable and efficient inferences than the separate estimation of each decision model (Zellner 1962). We performed a correlation test and the result highlighted that the correlation between expansive and accommodating, expansive and contractive, and accommodating and contractive indexes were shown to be 0.63, 0.33 and 0.49 (*with Breusc h-Pagan test of independence:* χ^2*=276.04 and P value=0.00*) respectively (Table C.7 of Appendix C). It suggests that the decision to use each index was not determined independently and thus, SUR could be a tenable approach to capture this dependence of decision-making. However, the comparison of estimated results from SUR and OLS indicated that these two methods offered very similar results; so that we reported results with both methods (Table C.8, Appendix C).

[17] We used the same sets of independent variables for both index and individual farm adaptation practices modelling.

error terms having a zero mean and a correlation coefficient of ρ_i. One of the binding requisites in exploring the adaptation decision in the Equation 4.5 is "exclusion restriction" (Maddala 1983). In particular, there must be a minimum of one extra exogenous variable contained within the climate perception model in Equation 4.4 but not within the adaptation decision model in Equation 4.5. This variable – in our study – is the *environment investment index*. Note that it was used as an instrumental variable in both the index and individual adaptation dependent variable estimations.

A Wald test (obtained from recursive bivariate probit model estimation) helped determine the endogeneity of climate perception in the sixteen possible adaptation decision equations. It evaluated the null hypothesis that there was insignificant links among the error terms of adaptation decisions (Equation 4.4) and climate perceptions (Equation 4.5) – in contrast to the alternative hypothesis that there was a statistically significant association. The test results indicated that climate perception was shown to be endogenous only in three particular practices (increased irrigated area, specialised crops for income purpose and disposed dryland area) out of the sixteen possible farm adaptation practice models (see Tables C.10, C.11 and C12 in Appendix C). Therefore, we applied the recursive bivariate probit model when climate perception was found to be endogenous and the binary probit model otherwise.

4.3.3.3 Binary probit model

The methodology above details the cross-sectional modelling using the 2014 baseline data. This section describes the modelling methods used for the two waves of data analysis. As the core aim is the comparison of planned adaptation behaviour in 2014 with actual behaviour adopted by 2017, only farming households interviewed in both baseline and end of project surveys were used (n=263). Seven (binary) farm adaptation practices were common to both surveys, hence binary probit[18] modelling was utilised to explore the determinants of both

[18] In the two waves of data analysis (n=263), we tested endogeneity within all seven planned farm adaptation practice models by employing the Wald test obtained from the recursive bivariate probit model estimation. The result signified that climate perception was found exogenous across all models. Consequently, we used binary probit regression (Table 4.5). In contrast, as the independent variables drawn from the 2014 survey were used for the seven actual farm adaptation practices modelling, we assumed that climate perception stated in 2014 would be exogenous with actual farm adaptation practices implemented in 2017. For this reason, we also used the binary probit model for actual farm adaptation practice modelling (Table 4.5).

planned and actual farm adaptation practices. For the farming household i with seven alternative individually planned or actual farm adaptation practices; the binary probit model was:

$$y_i = x_i\beta + u_i \qquad [4.6]$$

where y_i represents individual planned or actual farm adaptation decisions; x_i are sets of independent variables including climate perceptions; β are coefficients; and u_i is the error term.

Various tests were done to analyse estimation working assumptions in relation to our survey data including variance inflation factors (VIF) and correlation coefficients for "serious multicollinearity", which revealed no VIFs>10 (Table C.1, Appendix C) and no correlation coefficients>0.7 (Table C.2, Appendix C). In addition, the correlation coefficients of planned individual farm adaptation practices and error terms of index adaptation practices are also illustrated in Tables C.6 and C.7 of Appendix C, respectively. Outliers were identified for some variables. The problems of outliers were alleviated with the application of "Winsorizing" techniques. In particular, the upper as well as the lower-end 1% of outlier data were changed with 99 percentile and 1 percentile values respectively to minimise likely bias. Furthermore, robust standard errors were estimated to increase the precision of the results. Attrition tests were also carried out to detect whether households who were not reinterviewed at the end of project survey, were statistically significantly different (e.g., in terms of education, gender, age etc.) in contrast with households who appeared in both surveys. The test suggested that these two groups of households had statistically insignificant variations – indicating that attrition seemed to happen randomly (see Table C.13, Appendix C).

4.4 Results

4.4.1 Descriptive results

4.4.1.1 Cross-sectional analysis

Table 4.2 reports the descriptive statistics of past (2011-2014) and planned (2014-2017) farm adaptation practices. Out of the sixteen potential farm practices in Table 4.2, crop intensification (47%) was the most mentioned adaptation practice; followed by increasing livestock holding (45%) and crop production specialisation (41%). In contrast, contractive practices were only implemented by around 10% of irrigators from 2011-2014 (except decreasing livestock practice). In terms of what irrigators planned to do in the next three years from 2014, increasing livestock holding (63%), production intensification (60%) and acquiring agricultural implements (58%) were among the most prioritised actions. Again, only a small number of irrigators planned any contractive practices. These simple statistics highlight that irrigation households are more focussed on farm adaptation practices that potentially help to expand farming operations than measures reducing farming.

Table 4.2 Descriptive statistics of past and planned individual farm adaptation practices from 2011-2014 to 2014-2017 across six SSA irrigation schemes as at 2014 (n=371)

Index farm adaptation practices	*Individual farm adaptation practices*	*Unit of measurements*	*Responses* Last 3 years (2011-2014)	Next 3 years (2014-2017)	*Difference*[a]
Expansive practices	Increased irrigated area[b]	1=yes; 0=otherwise	0.26	0.47	0.21***
	Acquired more irrigated area	1=yes; 0=otherwise	0.27	0.47	0.20***
	Acquired more dryland area	1=yes; 0=otherwise	0.18	0.36	0.18***
	Acquired agricultural implements	1=yes; 0=otherwise	0.34	0.58	0.24***
	Intensified crop production	1=yes; 0=otherwise	0.47	0.60	0.13***
	Sold more crop production	1=yes; 0=otherwise	0.27	0.40	0.12***
	Increased livestock	1=yes; 0=otherwise	0.45	0.63	0.18***
Accommodating practices	Diversified crops for risk purposes	1=yes; 0=otherwise	0.33	0.52	0.19***
	Specialised crops for income purposes	1=yes; 0=otherwise	0.41	0.48	0.06*
	Diversified crops for labour purposes	1=yes; 0=otherwise	0.20	0.26	0.06**
	Consumed more crop production	1=yes; 0=otherwise	0.35	0.44	0.09**
Contractive practices	Decreased irrigated area	1=yes; 0=otherwise	0.10	0.13	0.03
	Disposed irrigated land	1=yes; 0=otherwise	0.10	0.10	0.00
	Disposed dryland area	1=yes; 0=otherwise	0.09	0.13	0.04
	Disposed agricultural implements	1=yes; 0=otherwise	0.10	0.13	0.03
	Decreased livestock	1=yes; 0=otherwise	0.27	0.22	-0.05

Notes: [a] Proportional equality test: ***$p \leq 0.01$; **$p \leq 0.05$; *$p \leq 0.1$

[b] Note that adaptation practices related to the increasing or decreasing of the irrigated land area indicates how much land was irrigated over the previous three years (or planned to be irrigated in the coming three years), including multiple crops. For example, if a farmer grows two crops on the same land during a year, the area would be counted twice. Whereas practices concerning acquiring or disposing of irrigated area indicates whether farm households have increased or decreased the area they controlled in the previous three years – or planned to undertake these practices in the next three years, irrespective of the number of times an area was irrigated.

Table 4.2 also displays the proportional equality test results of past and planned farm adaptation practices. With the exception of contractive adaptation practices, a statistically significant difference was observed between past and planned adaptation practices – with planned practices shown to be higher than previous adaptation practices. For instance, while nearly a quarter of faming households increased their irrigation land area on average from 2011-2014, double this amount planned to increase irrigation area in the coming three years from 2014 onwards ($p \leq 0.01$). The fact that the livelihoods of most farming households in developing countries are strongly tied with agriculture (e.g., land and livestock), with minimal options elsewhere, the insignificant differences of past and planned adaptation practices for the contractive index are expected. In a similar research in Australia, Wheeler et al. (2013) revealed a strong and significant divergence among planned and actual behaviour 1) in times of comparatively suitable climate conditions, planned farm behaviour was shown to be fairly extensive than actual behaviour; and 2) it was less than actual behaviour in times of external shocks, such as climate anomalies and government intervention. Table C.3, Appendix C also presented the paired t test results of past and planned indexes, with similar results to Table 4.2.

Figure 4.1 presented the percentage of farming households adopting several adaptation practices. Broadly, when the number (count) of potential farm practices were small, the proportion of actual past practices (2011-2014) was relatively shown to be higher than the respective planned practices (for 2014-2017). These patterns changed after a certain threshold number of practices (typically, after the seventh practice); such that the proportion of planned practices was higher than actual past practices. This result implied that when farmers undertook adaptive changes and noticed the returns from these changes, they appeared to be more likely to make subsequent changes in the future. Almost 80% of respondents intended to implement a minimum of one practice. Whereas approximately one fifth of farming households were not interested in any kind of adaptation practice during the next three years, and 12% of farmers planned to carry out only one practice. At the other end of the scale, only 3% of the respondents stated they planned to implement all the proposed adaptation practices within the coming three years.

Figure 4.1 The percentage of actual and planned individual farm adaptation practices across six SSA irrigation schemes from 2014-2017 (n=371)

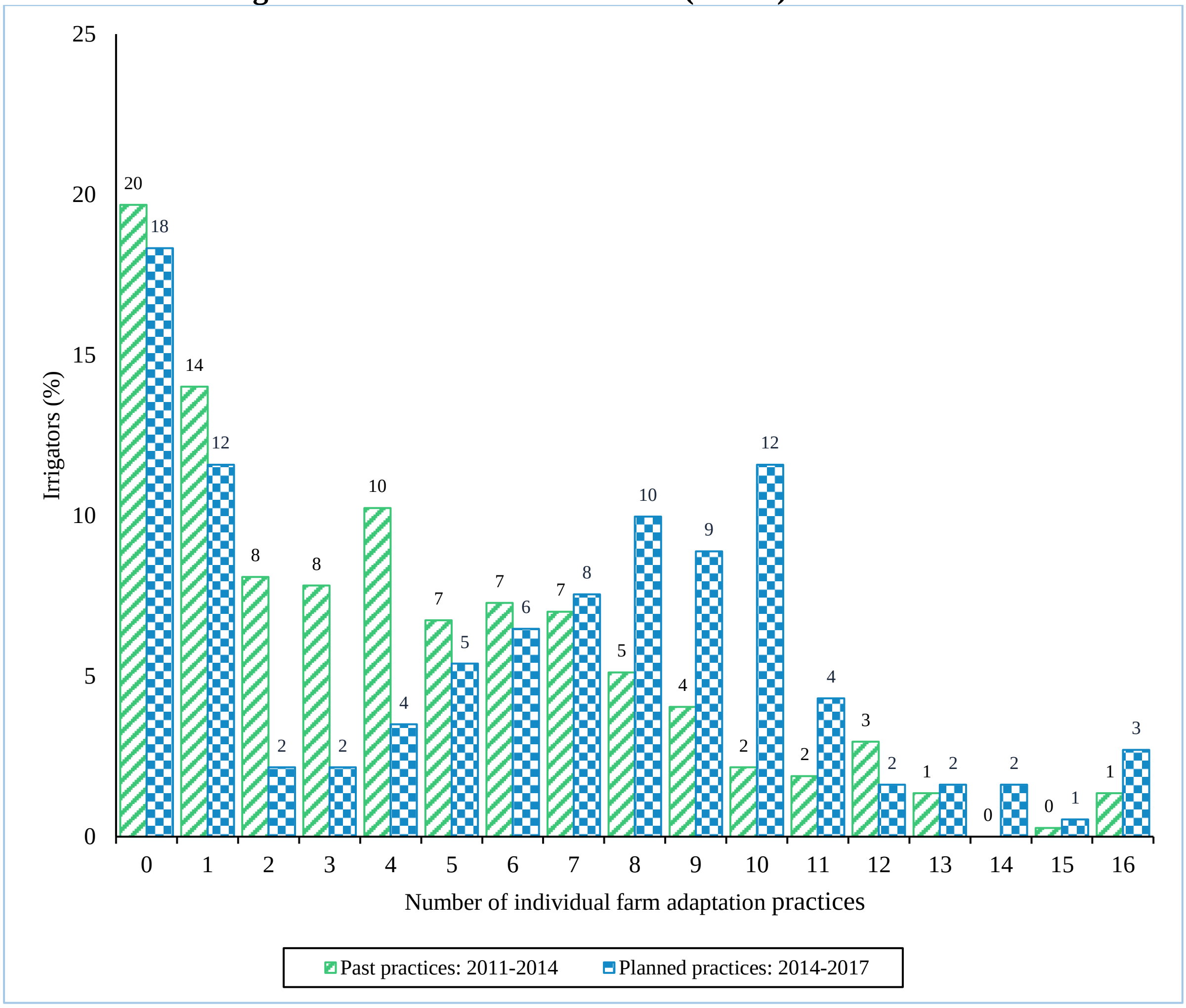
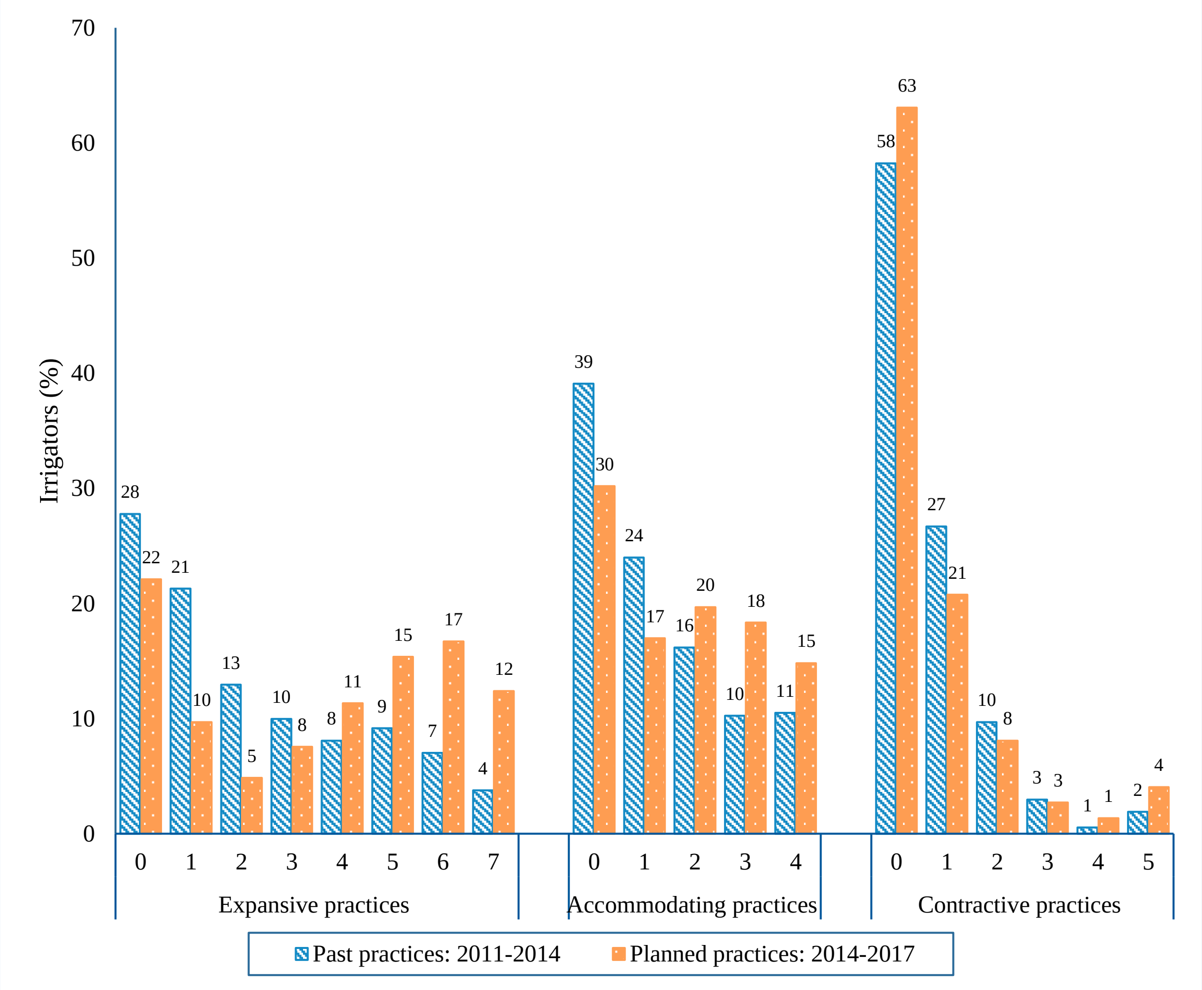


Figure 4.2 illustrates the share of farmers planning to undertake expansive, accommodating and contractive farm adaptation practices as an index. On average, the overwhelming share of farmers planned to engage in practices intended to increase the size of the farm or to make it more productive, i.e., expansive and accommodating practices, relative to contractive adaptation practices. For example, about 63% of households are not planning to carry out any contractive adaptation practices. 12% and 15% of irrigators are planning to undertake all sets of practices collated under expansive and accommodating indexes respectively; while only 4% of respondents indicated they planned to implement all five contractive adaptation practices.

Figure 4.2 The percentage of past (2011-2014) and planned (2014-2017) expansive, accommodating and contractive farm adaptation practices across six SSA irrigation schemes (n=371)



The descriptive results of the independent variables employed for the cross-sectional investigation are illustrated in Table 4.3. Nearly two-thirds of households had car, motorbike or bicycle. Moreover, a quarter also had ox or donkey cart. The average income revenues from the sale of crops and animal products was USD874 and USD562 from off-farm sources. Table 4.3 also highlights that only 14% of irrigators had obtained credit from financial institutions, other institutions or individuals – and that almost two-thirds obtained advice pertaining to crop production from extension officers. 71% of households described that temperature in their area was in general increasing or becoming more unpredictable over the last decade.

Table 4.3 Summary results of variables across six SSA irrigation schemes in 2014 (n=371)

Variables	*Unit of measurements*	*Mean*	*Std. Dev.*	*Min*	*Max*
Dependent variables					
Fractional dependent variables					
Percentage of planned expansive index	Share of planned expansive adaptation practices (i.e., increased irrigated area, acquired more irrigated area, acquired more dryland area, acquired agricultural implements, intensified crop production, sold more crop production and increased livestock) from the total set of expansive adaptation practices asked in the survey	0.50	0.36	0	1
Percentage of planned accommodating index	Share of planned accommodating adaptation practices (i.e., diversified crops for risk purposes, specialised crops for income purposes, diversified crops for labour purposes and consumed more crop production) from the total set of accommodating adaptation practices asked in the survey	0.43	0.36	0	1
Percentage of planned contractive index	Share of planned contractive adaptation practices (i.e., decreased irrigated area, disposed irrigated land, disposed dryland area, disposed agricultural implements and decreased livestock) from the total set of contractive adaptation practices asked in the survey	0.14	0.25	0	1
Percentage of planned total index	Share of all planned total adaptation practices from the total set of adaptation practices asked in the survey	0.37	0.28	0	1
Count dependent variables					
Planned expansive index	Sum of planned expansive adaptation practices	3.51	2.53	0	7
Planned accommodating index	Sum of planned accommodating adaptation practices	1.71	1.44	0	4
Planned contractive index	Sum of planned contractive adaptation practices	0.71	1.23	0	5
Planned total index	Sum of all planned total adaptation practices	5.92	4.48	0	16
Independent variables					
Household head gender: male	1=male; 0=otherwise	0.72	0.45	0	1
Household head age	Age of the head of household in years	51.71	16.47	18	92
Household head education: primary school	1=attended primary school; 0=otherwise	0.66	0.47	0	1
Household head education: secondary school or above	1=attended secondary school or above; 0=otherwise	0.19	0.39	0	1

Table 4.3 (continued)

Variables	*Unit of measurements*	*Mean*	*Std. Dev.*	*Min*	*Max*
Household size	Number of persons	5.52	2.29	1	10
Farming experience	Dryland farming experience in years	25.23	16.16	0	70
Car/motorbike/bicycle	1=own car, motorbike or bicycle; 0=otherwise	0.63	0.48	0	1
Ox/donkey cart	1=own ox/donkey cart; 0=otherwise	0.25	0.43	0	1
Livestock holding[a]	Tropical livestock units (TLU)	3.25	5.34	0	23.52
On-farm income[b, c]	Income from crop sale and animal product sale in USD (in 2014 prices)	873.60	1296.33	0	7611.79
Off-farm income	Income from off-farm activities in USD (in 2014 prices)	561.93	1041.05	0	5977.39
Total land	Hectares of total farmland	1.71	1.35	0.2	7
Environment investment index	Irrigators' average levels of agreement on the benefits long-term environmental investment versus investing to attend traditional/cultural/social activities or lifestyle and investing in immediate livelihood befits/solving problems (1=extremely disagree to 7=extremely agree)	4.31	0.88	1	7
Source of advice on crop production	1=extension officer; 0=otherwise	0.67	0.47	0	1
Credit access	1=accessed loan from financial institutions/other institutions/individuals; 0=otherwise	0.14	0.33	0	1
Climate perception	1=temperature has increased/become more unpredictable over the past 10 years; 0=otherwise	0.71	0.45	0	1
Percentage of past expansive index	Share of past expensive adaptation practices (i.e., increased irrigated area, acquired more irrigated area, acquired more dryland area, acquired agricultural implements, intensified crop production, sold more crop production and increased livestock) from the total set of expansive adaptation practices asked in the survey	0.32	0.31	0	1
Percentage of past accommodating index	Share of past accommodating adaptation practices (i.e., diversified crops for risk purposes, specialised crops for income purposes, diversified crops for labour purposes and consumed more crop production) from the total set of accommodating adaptation practices asked in the survey	0.32	0.34	0	1

Table 4.3 (continued)

Variables	*Unit of measurements*	*Mean*	*Std. Dev.*	*Min*	*Max*
Percentage of past contractive index	Share of past contractive adaptation practices (i.e., decreased irrigated area, disposed irrigated land, disposed dryland area, disposed agricultural implements and decreased livestock) from the total set of contractive adaptation practices asked in the survey	0.13	0.20	0	1
Percentage of past total index	Share of all past total adaptation practices from the total set of adaptation practices asked in the survey	0.26	0.24	0	1
Past expansive index	Sum of past expansive adaptation practices	2.24	2.14	0	7
Past accommodating index	Sum of past accommodating adaptation practices	1.29	1.35	0	4
Past contractive index	Sum of past contractive adaptation practices	0.67	1.02	0	5
Past total index	Sum of all past total adaptation practices	4.19	3.82	0	16
Scheme: Mkoba	1=Mkoba; 0=otherwise	0.18	0.39	0	1
Scheme: Kiwere	1=Kiwere; 0=otherwise	0.24	0.43	0	1
Scheme: Magozi	1=Magozi; 0=otherwise	0.26	0.44	0	1
Scheme: 25 de Setembro	1=25 de Setembro; 0=otherwise	0.04	0.19	0	1
Scheme: Khanimambo	1=Khanimambo; 0=otherwise	0.01	0.12	0	1

Notes: [a] Conversion values employed to calculate TLU variable includes "Cattle=0.7; donkey=0.5; Pig=0.2; Sheep=0.1; Goat=0.1; chicken=0.01; Duck=0.02 and rabbit=0.01" (Ghirotti 1993; Maass et al. 2012).

[b] Exchange rate in 2014: 1USD=1653.23 Tanzanian Shilling; 1USD=31.53 Mozambique Metical (World Bank 2019).

[c] During the 2014 survey, all income and expense related information for Zimbabwe were collected in USD.

The summary results of sixteen proposed planned adaptation practices that served as dependent variables in the recursive bivariate probit/binary probit models are shown in Table 4.2. In addition, the descriptive results of dependent and independent variables utilised for the two waves of analysis are reported under Appendix C (Table C.15 and Table C.16).

4.4.2 Regression results

Regression findings are displayed under this section, with the first section outlining the cross-sectional analysis using the 2014 baseline dataset; and the second section the modelling of the two waves of survey datasets collected in 2014 and 2017.

4.4.2.1 Planned index farm adaptation practices: cross-sectional analysis

The fractional probit model results are presented in Table 4.4. In addition, regression results (using either recursive bivariate probit or binary probit models, depending on exogeneity test results) for the sixteen proposed individual planned adaptation practices are reported in Appendix C (Tables C.10, C11 and C12). In the broadest term, most of the statistically significant results correspond with findings in the earlier literature. For conciseness, the focus here is on the fractional probit model index adaptation results (Table 4.4), however all other 2014 cross-sectional dataset (n=371) results are illustrated under Tables C.10-C12 of Appendix C.

Table 4.4 presents results for the four indexes (i.e., expansive, accommodating, contractive and total). Note that, with the exception of livestock holding and source of advice, the same variables along with the same coefficient signs were found to be statistically significant for the indexes of expansive, accommodating and total (Table 4.4). As pointed out in Wheeler et al. (2013), both expansive and accommodating measures are expected to contribute positively towards agricultural production. In particular, those farmers who intend to remain in agriculture will be more likely to plan for expansive and accommodating practices rather than contractive practices. In addition, the number of practices included in both expansive and accommodating indexes altogether (11 practices, or 69% of the total index); were much higher than the number of practices in the contractive index (5 practices), signifying that it is not surprising the effects of expansive and accommodating practices altogether outweighed contractive practices. Consequently, the total index followed a similar trend to the expansive and accommodating practices. Namely, it was predicted by the same sets of influences – including the similarity in the signs of the statistically significant coefficients.

Table 4.4 Fractional probit regression results of planned expansive, accommodating, contractive and total farm adaptation practices across six SSA irrigation schemes in 2014 (n=371)

Variables	*Expansive index*	*Accommodating index*	*Contractive index*	*Total index*
Male	0.01	0.12	-0.28*	-0.02
	(0.10)	(0.11)	(0.15)	(0.08)
Age	-0.01*	-0.01**	-0.00	-0.01*
	(0.00)	(0.00)	(0.01)	(0.00)
Primary school	0.39***	0.26*	-0.02	0.23**
	(0.11)	(0.14)	(0.15)	(0.10)
Secondary school or above	0.16	-0.07	-0.19	0.05
	(0.15)	(0.17)	(0.18)	(0.12)
Household size	0.01	0.02	0.02	0.01
	(0.02)	(0.02)	(0.02)	(0.01)
Farming experience	-0.00	0.00	-0.01	-0.00
	(0.00)	(0.00)	(0.01)	(0.00)
Car/motorbike/bicycle	0.29***	0.21*	-0.04	0.17**
	(0.10)	(0.12)	(0.14)	(0.08)
Ox/donkey cart	0.18	0.02	0.44**	0.14
	(0.12)	(0.17)	(0.18)	(0.11)
Livestock	-0.02*	0.00	0.02	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)
On-farm income	-0.00	-0.00	-0.00***	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Off-farm income	-0.00**	-0.00**	0.00	-0.00**
	(0.00)	(0.00)	(0.00)	(0.00)
Total land	0.07**	0.14***	0.12***	0.09***
	(0.03)	(0.05)	(0.05)	(0.03)
Source of advice	0.24**	0.17	0.29**	0.17*
	(0.12)	(0.13)	(0.15)	(0.09)
Credit access	0.70***	0.64***	0.30*	0.53***
	(0.18)	(0.20)	(0.16)	(0.14)
Climate perception	-1.34**	-1.61**	0.03	-1.08**
	(0.64)	(0.72)	(0.13)	(0.51)
Past adaptation index	1.29***	1.63***	1.64***	1.27***
	(0.22)	(0.17)	(0.31)	(0.23)
Mkoba	0.21	0.08	0.31	0.18
	(0.15)	(0.17)	(0.19)	(0.13)
Kiwere	0.67***	-0.01	1.63***	0.60***
	(0.22)	(0.24)	(0.27)	(0.18)
Magozi	1.13***	0.19	1.62***	0.78***
	(0.22)	(0.22)	(0.25)	(0.17)
25 de Setembro	-0.03	-0.36	1.06**	0.02
	(0.57)	(0.86)	(0.45)	(0.47)
Khanimambo	-0.28	-0.64	0.76**	-0.20
	(1.82)	(1.85)	(0.32)	(1.22)
Control function	1.21*	1.54**	–	1.00*
	(0.67)	(0.76)		(0.53)
Constant	-0.38	-0.07	-2.65***	-0.66
	(0.65)	(0.73)	(0.37)	(0.52)
AIC	406.46	433.61	278.95	449.25
BIC	496.54	523.68	365.11	539.33
Observations[a]	371	371	371	371
Pseudo R^2	0.30	0.23	0.22	0.18
Wald χ^2	504.90***	258.28***	202.20***	437.90***
Log pseudo likelihood	-180.23	-193.81	-117.48	-201.63

Notes: Bootstrap standard errors are in parentheses (with 1,000 replications) when climate perception was endogenously associated with farm adaptation, otherwise robust standard errors are in parentheses.
***$p\leq0.01$; **$p\leq0.05$; *$p\leq0.1$

[a] For the cross-sectional analysis with index dependent variables, the sensitivity of results to sample size difference was tested (e.g., using the full sample employed in the cross-sectional analysis (n=371) versus those used in the two waves of analysis (n=263)). Tests suggest that some results were sensitive to sample size (see Table 4.4 and Table C.9, Appendix C) and thus, we report both results.

The results showed that education (primary school) and either car/motorbike/bicycle ownership had a positive and statistically significant influence on planned expansive, accommodating and total adaptation indexes. Similarly, household head age, off-farm income and perception of climate correlated statistically significantly and inversely with the three adaptation indexes.

Interestingly, the results also revealed that the four farm adaptation practices had some common sets of influences. More specifically, total land area in hectares; credit access from various streams including financial institutions other institutions or individuals; and previous experiences in adopting a particular farm adaptation practice positively and significantly encouraged irrigation farm households planned expansive, accommodating, contractive and total indexes in the planned three year period. Broadly, farmers with larger land, credit services access and prior adaptation experiences had a higher tendency to execute all adaptation practices. Extension advice was also a statistically significant and positive influence on all adaptation indexes – with the exception of the accommodating index – such that receiving advice from extension officers induced farmers' interest in planning expansive, contractive and total practices from 2014 onwards. The statistically insignificant impacts of extension advice in the accommodating index are somewhat unexpected given the expectation that adoption of these practices – such as diversification and specialisation – would require considerably greater levels of expertise and information.

In addition to being impacted by those variables common to most indexes, there are also significant variables explicit to contractive indexes. Among these, on-farm income strongly and negatively influenced the decision to plan contractive practices; while household head gender also appeared to have a negative, yet weaker statistical significance, on these practices. Male-headed households had a lower preference to implement contractive practices compared with female-headed households. In contrast, households that own an ox/donkey cart had a greater statistically significant inclination to plan for contractive practices, signifying the potential for greater off-farm income. Moreover, a negative statistically significant association was revealed between livestock holdings and planned expansive irrigation farm practices. Namely, irrigators with larger livestock herds – as opposed to those having fewer herds – were less inclined to exercise expansive practices, also indicating greater opportunity for non-irrigated income.

4.4.2.2 Sensitivity analysis to dependent variables measurement difference

Results from the sensitivity analysis to changing the measurement of index adaptation practices are presented under Table C.8 of Appendix C. The findings suggested that most of the results from OLS, Poisson and SUR models seem to be reasonably similar to the fractional probit model (Table 4.4) results. Broadly, these additional sensitivity tests indicate that findings were comparatively stable to different dependent variable measurements (fractional vs count variables).

4.4.2.3 Comparison of planned and actual individual farm adaptation practices: two waves of data analysis

Table 4.5 reports the results from households interviewed in both surveys (n=263) of: a) the binary probit model results for the seven proposed planned individual farm adaptation practices, stated in the 2014 baseline survey to be implemented over the next three years, from 2014-2017; and b) their actual[19] adoption of these practices after three years, obtained from the 2017 survey. The results in Table 4.5, compare factors affecting a given farm adaptation practice during its planning and actual implementation stages, over a three-year period. In Table 4.5, to aid comparison between differing results and the number of models, only statistically significant results are reported (significance levels, which are denoted by asterisks along with coefficient signs). The full modelling results with coefficients and standard errors are reported under Table C.17, Appendix C.

Table 4.5 results highlight that differing factors were shown to influence the decision to plan – versus actually implement – specific farm adaptation actions. For instance, male-headed

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[19] In computing actual farm adaptation practices implemented as at 2017, there were very few percentages of irrigators whose actual farm adaptation practice intensities remained the same between 2014 and 2017 (only 3.8% for irrigation land area, 11.8% for dryland area and 6.1% for livestock holding) (Table C.14, Appendix C). As a consequence, the values of dummy variables indicating the *"increasing"* and *"decreasing"* types of actual farm adaptation practices in 2017 (e.g., increased irrigated area vs decreased irrigated area) used in the two-wave analysis were found to be very similar (lacks considerable variation), showing that the *"increasing"* variable was almost the flipside of the *"decreasing"* variable. As a result, except the sign of the coefficients, the same statistically significant (but not all) variables influenced both the *"increasing"* and their respective *"decreasing"* actual farm adaptation practices. This is specifically the case for irrigation and livestock-based practices.

households had a statistically significant and negative effect only on the plan to implement one adaptation practice over the next three years (decreasing livestock holding). However, it was shown to significantly determine (positively or negatively, depending on practice types) the actual uses of five farm adaptation practices after three years period in 2017 (increased irrigated area, acquired more dryland area, diversified crops for risk purposes, decreased irrigated area and disposed dryland area). Also, primary school education of the household head positively and significantly determined planned adaptation practices, however had no significant role on the decision to apply all actual farm adaptation practices. Conversely, attending secondary school or above did not influence planned farm adaptation, however it significantly influenced the actual uses of two farm adaptation practices (acquired more dryland area and decreased livestock) (Table 4.5). This influence of education on adaptation practices might be related with 1) the time gap between the two decisions (three years) resulting in farmers forming decisions differently during the planning and actual execution stages, meaning that education influences each decision differently; and/or 2) our uses of different units of measurement for planned and actual practices.

The other observed difference was in terms of the role past adaptations played in farm adaptation decisions. In contrast to expectations, except for “disposed dryland area”, no statistically significant association between previous farm adaptation experience and actual adaptation was found. This implies that farmers’ actual use of farm adaptation practices did not rely on their preceding adaptation experience. However, past adaptations did have a strongly significant positive effect on the seven proposed individual planned adaptation practices (see also Table 4.4 and Table C.8 in Appendix C). Household head age, livestock holding, and off-farm income also had a differential influence on certain planned and actual farm adaptation practices.

Table 4.5 Summary of binary probit regression results of the comparison of planned and actual individual farm adaptation practices for the period 2014-2017 (n=263)

	Planned future farming adaptation practices (using 2014 survey data responses for 2014-2017)							***Actual farming adaptation practices (using 2017 survey data responses for the period 2014-2017)***						
Variables	*Increased irrigated area*	*Acquired more dryland area*	*Increase livestock*	*Diversify crops for risk and labour purposes*	*Decrease irrigated area*	*Disposed dryland area*	*Decrease livestock*	*Increased irrigated area*	*Acquired dryland area*	*Increased livestock*	*Diversified crops for risk and labour purposes*	*Decreased irrigated area*	*Disposed dryland area*	*Decreased livestock*
Male	-	-	-	-	-	-	$-^{***}$	$+^{***}$	$+^{***}$	-	$+^{**}$	$-^{**}$	$-^{***}$	-
Age	$-^{**}$	-	-	$-^{*}$	-	-	-	-	$-^{*}$	-	-	-	-	-
Primary school	$+^{**}$	$+^{**}$	$+^{***}$	$+^{***}$	-	-	-	-	-	-	-	-	-	-
Secondary school or above	-	-	-	-	-	-	-	-	$-^{**}$	-	-	-	-	$+^{*}$
Household size	-	$-^{*}$	-	-	-	-	-	-	$-^{***}$	-	-	-	$+^{***}$	-
Farming experience	-	$-^{**}$	-	-	-	$-^{**}$	-	-	$+^{**}$	$-^{**}$	-	-	-	$+^{*}$
Car/motorbike/bicycle	$+^{*}$	-	-	$+^{**}$	$-^{*}$	-	-	-	-	$+^{**}$	$+^{**}$	$-^{**}$	-	$-^{*}$
Ox/donkey cart	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Livestock	-	-	-	-	$+^{*}$	-	-	-	-	-	-	-	-	-
On-farm income	-	-	$+^{*}$	-	-	-	-	-	-	$-^{***}$	-	-	-	$+^{**}$
Off-farm income	-	-	-	-	-	-	-	-	-	$-^{*}$	-	-	-	-
Total land	-	-	-	-	-	$+^{***}$	$+^{*}$	$-^{**}$	$-^{***}$	$+^{**}$	$-^{*}$	$+^{**}$	$+^{***}$	$-^{**}$
Source of advice	$+^{*}$	$+^{**}$	-	$+^{*}$	$+^{*}$	-	-	$+^{*}$	-	-	-	-	$+^{**}$	$+^{**}$
Credit access	-	-	$+^{**}$	$+^{***}$	-	$+^{*}$	$+^{**}$	-	-	-	-	-	-	$-^{*}$
Climate perception	-	-	-	$-^{***}$	-	$-^{**}$	-	-	-	$+^{**}$	-	-	$+^{**}$	-
Past adaptation practice	$+^{***}$	$+^{***}$	$+^{***}$	$+^{***}$	$+^{***}$	$+^{***}$	$+^{***}$	-	-	-	-	-	$-^{**}$	-
Country: Tanzania[a]	$+^{***}$	$+^{***}$	$+^{**}$	-	$+^{***}$	$+^{***}$	$+^{***}$	$-^{***}$	$-^{*}$	-	-	$+^{***}$	-	$+^{*}$
Constant	-	$-^{***}$	$-^{**}$	$-^{*}$	$-^{***}$	$-^{***}$	$-^{**}$	$+^{**}$	$+^{***}$	$+^{*}$	-	$-^{***}$	$-^{***}$	$-^{***}$
Observations	263	263	263	263	263	263	263	263	263	263	263	263	263	263
Pseudo R^2	0.55	0.44	0.49	0.46	0.45	0.41	0.29	0.23	0.14	0.09	0.10	0.33	0.22	0.11
Wald χ^2	115.35^{**}	113.92^{**}	101.57^{*}	93.22^{***}	81.77^{***}	81.40^{***}	72.39^{***}	69.22^{***}	48.08^{***}	27.95^{**}	26.32^{*}	79.88^{***}	62.76^{***}	30.63^{**}
Log pseudo likelihood	-81.91	97.69	-88.76	-94.36	-53.47	-53.89	-91.14	-129.60	-154.98	-155.61	-121.96	-107.74	-127.07	-142.66

Notes: $^{***}p\leq0.01$; $^{**}p\leq0.05$; $^{*}p\leq0.1$

'-' represents a non-significant coefficient

[a] Since all irrigators in some irrigation schemes did not plan to and actually implement some individual farm adaptation practices (e.g., *"acquire more dryland area"*, *"decrease irrigated area"* and *"disposed dryland area"* by 25 de Setembro scheme irrigators, *"disposed dryland area"* by Silalatshani and Magozi schemes irrigators), it was difficult to include scheme dummies in the modelling. Therefore, country dummy was used in the two waves of data analysis.

As shown in Table 4.5, there are also some situations where similar statistically significant independent variables influence the same farm adaptation practices – both when they were planned in 2014 and when they were actually implemented in 2017. For example, household size statistically significantly and negatively influenced both planned and actual implementation of acquiring more dryland area. Likewise, car/motorbike/bicycle ownership was also significantly and positively linked with crop diversification, and negatively associated with decreasing irrigated land area – in both planned and actual adaptation models. The propensity of planning to – and actually increasing – irrigated area significantly increases with extension services. As well, climate perceptions (disposed dryland area), previous adaptation experiences (disposed dryland area), land area (decreased livestock), credit access (decreased livestock), on-farm income (increased livestock) and farming experience (acquired more dryland area) also significantly affected planned and actual farm adaptation practices (some), but with opposite coefficient signs. One reason for the opposite sign results might be measurement scale difference between planned and actual farm adaptation practices.

4.5 Discussion

This study looked at planned and actual farm adaptation techniques by irrigation farm households in six irrigation schemes of SSA. The findings indicated that, when interviewed in 2014, just over 80% of irrigation households planned to adopt a minimum of one farm adaptation practice out of the potential sixteen farm practices listed, over the next three years. However, fewer than 5% planned to adopt all of the proposed farm adaptation practices. In terms of factors affecting the decision to plan to implement various adaptation practices – depicted in the form of indexes (categorised as expansive, accommodating, contractive and total practices) – a wide range of farm, farmer, natural capital and institutional variables were shown to determine farming household planning decisions.

In particular, age of the household head was statistically significantly inversely related with planned expansive ($p \leq 0.1$), accommodating ($p \leq 0.05$) and total ($p \leq 0.1$) adaptation practices, suggesting that older irrigators were significantly less likely to engage in those practices believed to expand farm size/associated activities (such as increasing irrigation land, acquiring dryland and increasing livestock holdings). Our finding in this regard corresponds to earlier studies (Khan et al. 2020; Niles et al. 2016; Wheeler et al. 2013). Besides, farmers who attended primary school had a much larger propensity to plan to perform expansive ($p \leq 0.01$), accommodating ($p \leq 0.1$) and total ($p \leq 0.05$) indexes compared with those with no formal education at all. This could be because education enhances knowledge and skills around interpreting data within farming societies – and indeed the positive influence of education on farm adaptation is in accordance with other studies (Abid et al. 2016; Yarong and Minpeng 2021).

Female-headed households were shown to be statistically significantly positively associated with planning to adopt contractive practices in general ($p \leq 0.1$). This finding is probably reflecting the incidence of chronic gender related deviations through which female-headed farming households in SSA typically face greater challenges in getting desirable resources, education, jobs and technologies for better life (Bako and Syed 2018; Manero and Wheeler 2022). A similar gender finding was revealed by Deressa et al. (2009) in Ethiopia, but our result differed to the findings of Arunrat et al. (2017) in Thailand and Yarong and Minpeng (2021) in China.

Land size had a strong and positive relationship with all four adaptation indexes, a finding that corresponds to previous literature (Arunrat et al. 2017; Zhai et al. 2018). The fact that land is the single most crucial resource for agricultural activities of smallholder farmers is expected. Having a greater land might incentivise households to broaden their activities by planning expansive and accommodating based practices. In contrast, farming households with greater land also have greater opportunity to sell, lease out or share farm a part of their holding in order to fund their agricultural and non-agricultural related expenses (e.g., financing education, health, food) or to establish new enterprises. Livestock holding was the other significant determinant of the plan to use expansive adaptation practices, although its influence was weak and negative ($p \leq 0.1$) – a result consistent with Mulwa et al. (2017) in Malawi, although Deressa et al. (2009) concluded that livestock contributed positively towards farm adaptation in Ethiopia. It should be noted that the effects of livestock on adaptation decisions are context specific. Traditionally, livestock is a default activity and farming communities who are not interested in selling their livestock instead use them as a wealth accumulation mechanism. Hence, when animals were sold, they were underweight and attracted low prices. On the other hand, livestock could become a significant income generator to fund other activities (e.g., land expansion becomes attractive to produce good feed or pasture), if the practice is modernised with relevant services such as better husbandry and feed.

A significant and positive effect of car/motorbike/bicycle was also found on farm adaptation. Farmers with a car/motorbike/bicycle were more likely to plan to engage in expansive ($p \leq 0.01$), accommodating ($p \leq 0.1$) and total ($p \leq 0.05$) indexes. Given transport is a widespread challenge for rural areas in SSA (van Rooyen et al. 2017), this ownership may help farmers more easily reach market centres and thus be able to supply their produce in a more timely manner. Furthermore, owning a car/motorbike/bicycle could also be seen as an indicator for wealth, and it is believed that farmers with greater wealth are easily able to cover agricultural-related outlays – including farm adaptations – and consequently might encourage further investment in expansive, accommodating and total indexes.

In addition, the adoption of the contractive index significantly and negatively correlated with on-farm income ($p \leq 0.01$). Farmers who obtained higher farm revenues were unlikely to plan for increased contractive practices. The on-farm income influences on adaptation practices are also discussed in other research works (Abid et al. 2016; Arunrat et al. 2017). Likewise, off-farm income was statistically and negatively related to expansive, accommodating and total practices ($p \leq 0.05$), possibly for the reason that this variable enable farmers to avoid financial related burdens through which they may change their livelihood systems gradually from farm to non-farm activities. This was consistent with results reported by Mulwa et al. (2017) in Malawi, but differed to the Australian off-farm income findings by Seidl et al. (2021). Similarly, contractive indexes significantly increases with ox/donkey cart ownership ($p \leq 0.05$), a result somehow directly related to the off-farm income findings outlined previously.

In accordance with findings in the literature, such as Arunrat et al. (2017) in Thailand, credit from various streams including financial institutions, other institutions or individuals positively and significantly correlated with all adaptation indexes. On the one hand, credit availability may assist farmers in funding their farming business, therefore fostering adaptation. On the other hand, because of the availability of credit, farmers may encouraged to invest in other livelihood mechanisms and new non-farm enterprise pathways.

Obtaining information from extension officers also had a statistically significant positive impact in encouraging the decision to adopt expansive ($p \leq 0.05$), contractive ($p \leq 0.01$) and total ($p \leq 0.1$) adaptation practices. Due to the paucity of well-developed information sharing platforms and outlets, along with lower level literacy of farming households in several underdeveloped countries, extension officers have long been served as a viable and desirable forms of advice (Wheeler et al. 2017). Our finding here corresponds with previous studies (Deressa et al. 2009; Khan et al. 2020).

The planned uses of expansive, accommodating and total indexes ($p \leq 0.05$) was statistically significantly negatively associated with whether farmers thought that the temperature conditions of their area had increased or become more unpredictable over the past decade.

Although this finding contrasted to Seidl et al. (2021), it substantiated findings reported in Wheeler et al. (2013) – both studies being from Australia. Another important finding from this study was that climate perception was endogenously linked with the plan to adopt the three indexes (expansive, accommodating and total), which is evident from the positive and significant control function coefficients and had to be controlled for. This result demonstrated the presence and implications of reverse causality – climate perception and the three adaptation indexes influenced one another, rather than the customarily posited linear relationship that goes from climate perception to adaptation. Overall, the result emphasised that ignoring this endogenous relationship would compromise inferences of climate perception on farm practices.

In line with findings from Seidl et al. (2021) and Wheeler et al. (2013) in Australia, and Roesch-McNally et al. (2017) in the USA, past adaptation practices had a strong and positive association with all four indexes ($p \leq 0.01$) – affirming irrigation households with previous experience in certain practices were more likely encouraged to adopt more of these practices over the next time-period. This might be for the reason that previous experience could offer farmers greater information on the possible benefits and costs of these practices. In addition, the result may also be linked with the notions of "habit" (Ajzen 2002) and path dependency.

As well as exploring planned farm adaptation using cross-sectional data, this study looked at the consistency of planned and actual farm adaptation practices, using two wave survey data from the same households over a three-year interval (Table 4.5). The findings indicated statistically significant differences were observed between planned and actual farm adaptation practices (except for the activity of increased livestock) in which actual farm adaptation practices were shown to be much higher than planned farm adaptation practices – demonstrating the inconsistency of planned and actual farm practices over time (see Table C.15 in Appendix C). The estimated results also highlighted that there was often heterogeneity in relation to the variables influencing both planned and actual adaptation practices. However, some variables did consistently influence both planned and actual practices (e.g., household size and extension services). Our finding conforms to Niles et al. (2016) who revealed that influences of actual practice differed to the planned practice in the context of New Zealand farmers.

The potential justification as to why planned and actual farm adaptation practice varies over time could be because of the absence of suitable resources and changing situations including government policies, development intervention programs, resource availability and the overall economic performance over the course of time. However, for our case study, it is entirely possible that it was a result of the project's intervention (e.g., the establishment of agricultural innovation platforms and other irrigation support measures). As a result, numerous concerns related with farm-land, water bills and many other issues that previously impeded irrigation practices were addressed (e.g., Parry et al. 2020). This could have prompted farmers to take a greater role in the sector and broaden their farm activities. In addition, it is possible that the discrepancy between planned and actual behaviour could partly be a result of variations in the question formats used to measure adaptation variables across the two surveys. Therefore, policy-makers should have to consider all these potential reasons for deviations between planned and actual behaviours when formulating farm adaptation programs.

In view of the above, it is possible to draw the following insights. First, the study suggests the roles of expanding education and training facilities in rural areas in order to further promote planned farm adaptation. Second, increasing the accessibility of financial resources could also be desirable pathways for encouraging farm adaptation decisions. This requires the establishment of functional credit service programs and other related services such as insurance that can accommodate the interests and contexts of rural farming communities. The government may play a leading role in this process by formulating attractive and favourable regulatory frameworks, policies and incentives that encourage the engagement of the private sector in the credit market. Parallel to credit market development, a significant effort is also required to create market connections, so that farmers can make sure in their ability to sell crops at prices allowing them to pay back loans. Furthermore, efforts should be done to modernise the overall extension system. Given extension officers are the single most nearby dependable advice option for farmers (Wheeler et al. 2017), policies that commit to enrich the training, education and outreach programs could likely succeed in empowering the capacities of extension workers. Lastly, attention should also be focussed on ensuring "gender equality" within rural communities.

Our study has the following limitations. Firstly, this study focused on farm adaptation behaviour by combining datasets from three countries, mainly because the sample size of individual countries was not large enough to model separately, which may consequently make it difficult to draw inferences applicable for a particular country. This implies that additional research with larger samples would be needed in order to further explore farm adaptation behaviour in more detail and substantiate our findings. Secondly, because of the deviations in survey questions asked, measurement variations exist between planned and actual farm adaptation practices and consequently they might not be directly comparable. Finally, additional work on the intensities and differences of adaptation (rather than broad measures of yes/no) would be useful to reveal further insights, as well as understanding how adaptation changes over a much more extended time horizon, given the timespan of our study was relatively short.

4.6 Conclusion

This study explored farm adaptation behaviour using household survey data from six irrigation schemes in three SSA countries. The study a) examined planned farm adaptation behaviour in a cross-sectional setting, using 2014 as a baseline; and b) compared planned and actual adaptation behaviour over the three-year timespan of 2014-2017, using two waves of farm surveys of the same households. Adaptation were measured in sixteen practices, and further split into three categories: expansive (e.g., increased irrigated area, acquired more irrigated area, acquired more dryland area, acquired agricultural implements, intensified crop production, sold more crop production and increased livestock); accommodating (e.g., diversified crops for risk purposes, specialised crops for income purposes, diversified crops for labour purposes and consumed more crop production); contractive (e.g., decreased irrigated area, disposed irrigated land, disposed dryland area, disposed agricultural implements and decreased livestock). A total index was also created by composing the sixteen individual farm adaptation practices.

Expansive, accommodating and total adaptation practices were found to be influenced by similar sets of variables. While education and car/motorbike/bicycle ownership significantly increased the likelihood of planning to adopt expansive, accommodating and total practices; other variables such as household head age, off-farm income and climate perception were negatively associated with the propensity of using these three categories of practices in the future. Likewise, total land area, credit access, previous farm adaptation experience and extension advice (except accommodating practices) were generally shown to statistically significantly and positively increase irrigator likelihood of planning to undertake all four practices. On-farm income, male household head and ox/donkey cart ownership were found to statistically significantly negatively influence contractive practices.

The results from the two waves of data analysis indicated that there was heterogeneity in relation to the influences determining irrigation households' planned adaptation practices in 2014 – versus their actual implementation three years later in 2017. One interesting finding in this regard was that while previous adaptation experience was the significant positive determinant of planned adaptation, it played an insignificant role on actual adaptation. In general, the findings suggest that intervention programs focussing on increasing the availability and quality of education facilities, extension services and finance, while assuring gender balance within rural communities, may help SSA irrigators in adapting to an uncertain future.

Chapter 5 Conclusion

This thesis harnessed data from an ACIAR-funded irrigation development project implemented within six case study irrigation schemes in three countries (Tanzania, Mozambique and Zimbabwe). The underlying notion of the project was that irrigation schemes are diverse by their very nature in terms of actors involved at different levels, expertise requirements, institutions, water management, infrastructure developments and many other factors (van Rooyen et al. 2017). In this context, intervention programs that accommodate most of these elements are more likely to achieve their objectives. The ACIAR-funded project implemented two interventions concurrently, namely *AIPs and monitoring tools*. While AIPs were anticipated to overcome institutional (e.g., market, policy, tenure, transport) related impediments, monitoring tools were expected to induce learning through practice and societal-level learnings in water management.

The overall focus of this thesis was to investigate: a) SSA small-scale irrigation farming communities' willingness to adopt monitoring tools; b) how the two irrigation development interventions (AIP and monitoring tools) impact various irrigation household outcomes; and finally, c) influences associated with farm adaptation behaviour across the schemes and over time. The thesis employed two phases of irrigation household survey data gathered three years apart – the first during the initial stages of the project in 2014, to capture baseline information relating to irrigation households, their farming practices and other demographics at the project commencement. Subsequently, an end-of-project survey (targeting as many of the same baseline respondents as possible) was carried out in 2017, to ascertain changes in living conditions, irrigation practices, information access, decision-making and other potential impacts over the life of the project.

The following section presents summary results of the three case study chapters, the policy implications of these findings, and the contribution of this thesis to the current literature. It concludes with a discussion of the research limitations of this thesis and offers suggestions for future research.

5.1 Summary of results

5.1.1 Chapter 2: WTP for monitoring tools

Chapter 2 presents empirical findings in relation to the willingness of irrigation households to adopt monitoring tools. The monitoring tool studied under this chapter is known as the "Chameleon Sensor", which comprised two elements: 1) Chameleon Sensor array; and 2) Chameleon Sensor reader (Stirzaker et al. 2017). In guiding irrigation via chameleon, while it is necessary for a farmer to install sensor arrays on their private farm plots, there is a possibility that sensor readers can be shared among irrigation households within a scheme as it is a handheld device and that there would be just one reading over a one to two week time period. Taking this facet into account, the thesis explored the adoption willingness towards sensor arrays and readers individually (as irrigation communities may have a divergent WTP for them). Overall, this monitoring tool is relatively new and still at the stage of pre-commercialisation – and is yet to be released on the market. Given this tool was introduced to the farming communities for the first time as part of the project and offered free of charge, it was imperative to assess farm household preferences expressed in the form of WTP for their future adoption. Such information helps shed more information on the future market adoption of the products. Consequently, farm household data gathered during the completion of the project in 2017 from four small-scale irrigation schemes was utilised for the analysis (n=234). A contingent valuation framework was employed with the purpose of eliciting irrigator adoption preferences, which were then analysed through a Tobit model.

The results highlighted that farmer preferences towards both sensor arrays and readers were significantly influenced by similar variables, including being situated downstream of the scheme and the location of pre-existing monitoring tools within the scheme – both being location-related variables. More specifically, farmer WTP for both sensor arrays and readers was shown to be statistically significantly and positively associated with downstream plot location – suggesting that farmers who owned plots in the downstream of the scheme had a much higher propensity of WTP as opposed to those in the other parts of the scheme. Furthermore, there was an observed strong positive relationship between installed monitoring tools and neighbours' willingness to adopt sensor arrays and readers – indicating a positive neighbourhood effect. This result highlights that farming households with plots near to installed monitoring tools were shown to have a far greater WTP when compared to those with plots further away. In addition, higher water costs were shown to be a positive driver of irrigator's adoption willingness for the sensor array and reader, illustrating the relevance of economic factors driving potential adoption.

Along with the influences outlined above, there were also distinct variables influencing the WTP for the sensor reader. The results showed a divergence of sensor reader adoption with regards to gender – in that female-headed households demonstrated a far greater WTP when compared to male-headed households. However, households with male heads were shown to have a much higher WTP for sensor readers if they had obtained a higher education. Furthermore – as expected – farm households with a greater understanding around the potential advantages of monitoring tools reported a higher WTP than those without that knowledge. Lastly, it was evident that farmers indicated an average sensor array WTP of USD10 and a sensor reader WTP of USD9 (based on conservative estimations that sought to tackle hypothetical bias) – which together represent a small portion of the present pre-commercialisation price of these technologies.

5.1.2 Chapter 3: AIPs and monitoring tool impact on households

In Chapter 3, we examined the influences that irrigation development interventions (AIPs and monitoring tools) had on various household outcomes across five irrigation schemes. The study employed irrigation household survey information derived from the end-of-project survey (n=361 for AIPs and n=241 for monitoring tools). Household outcomes investigated included: on-farm income, off-farm income, child education and food shortage reduction. Doubly robust regression estimation was used to measure the influences of the two project interventions, with a diverse number of other methods employed to examine the robustness of the results. Overall, the findings highlighted that engagement in either AIPs or monitoring tools statistically significantly increased on-farm income, as well as enhanced irrigation household capacity to fund child education – with differing impacts evident between the two interventions. Irrigation households taking part in AIP programs seemed to have a statistically significantly reduced annual food shortages and increased income obtained from non-farm activities. By contrast, the analysis showed no significant influence from the uses of monitoring tools with respect to off-farm income and food shortage reduction.

Another important finding is that, in relative terms, irrigation interventions appeared more useful for male-headed households – perhaps, signifying entrenched cultural factors, whereby female-headed households encountering unfavourable environments in harnessing the benefits from such interventions. This issue may compromise efforts to improve human development (education and health), asset creation, and productivity in general. Ultimately, female-headed households may be hampered in taking full advantage of such irrigation intervention projects. In addition to examining the influence of project interventions on participating irrigation households, Chapter 3 sought to reveal if the project caused spillover effects by relaxing the "stable unit treatment value assumption" and employing the approach of Cerulli (2017). It was shown that the AIP intervention significantly led to an increased on-farm income of nearby irrigators who did not actually engage in AIPs, although the extent of this gain was small. Similarly, the monitoring tools intervention also increased on-farm income of nearby non-participants. Finally, there appeared to be no statistically significant spillover effects from either intervention in relation to the remaining outcome variables (i.e., off-farm income, education and food shortage).

5.1.3 Chapter 4: Farm adaptation behaviour

Chapter 4 quantifies farm adaptation practices planned by irrigators for the coming three years from 2014 onwards, in response to the large arrays of uncertainties associated with irrigation farming in SSA. It also assessed planned and actual adaptation behaviour stability over these three years (using the baseline survey as well as the end of project survey); utilising both cross-sectional (n=371) and multiple year survey analysis (n=263). Sixteen farm adaptation practices, drawn from the 2014 baseline project survey, were included in the cross-sectional analysis. Based on their expected impact on farm production (either increasing, decreasing or restructuring), the sixteen practices were sorted into three indexes, namely: expansive (seven practices); accommodating (four practices); and contractive (five practices). The sixteen practices were also summed together to create a "total adaptation index", which was also analysed. Fractional probit regression – in conjunction with a control function approach (to overcome the likely endogeneity of the climate perception variable) – was employed, in order to examine the influences associated with farm household adaptation behaviour. The results highlighted that around 80% of respondents in 2014 intended to carry out at least one adaptation practice over the coming three years. Overall, it was revealed that farming households with a larger land holding, prior adaptation experiences and credit facilities were statistically significantly more likely to carry out a practice in one of the four indexes (i.e., expansive, accommodating, contractive and total). Furthermore, education and wealth of irrigators significantly increased their adoption of expansive, accommodating and total indexes; whereas age, off-farm income and climate perception of irrigators significantly decreased the possibility of adopting these same three indexes. In particular, the results pertaining to climate perception indicated a significant endogenous links between climate perception and farm adaptation behaviour, illustrating the relevance of remedying endogeneity to gain a powerful inference.

Tracing farm adaptation progress (namely seven agricultural practices) over the course of three years from 2014 was also examined in Chapter 4. The analysis integrated the two waves of survey information (baseline and end-of-project) following the same farming households across both surveys, and analysed this information through a binary probit model. The analysis highlights an obvious divergence with respect to what irrigators planned to do and what they actually did, over the course of three years. Notably, actual farm adaptation practices as at 2017 exceeded planned practices in 2014. Results also emphasised that, in most cases, there is a clear asymmetry in terms of the variables determining planned and actual practices by farm households across the three-year period. There were only a small number of cases where identical factors significantly influenced planned and actual practices in equal measure.

5.2 Policy implications

The findings from this thesis highlight several implications for irrigation in SSA. The investigation in Chapter 2 showed that non-participating farmers in close proximity to the provided monitoring tools had a much larger WTP propensity for monitoring tools – signifying the relevance of social learning and seeing irrigation outcomes from the tools (e.g., Parry et al. 2020). Accordingly, policy mechanisms that encourage social learning through various initiatives involving demonstration and experience sharing would likely assist in advancing the use of irrigation monitoring tools. The results also highlighted an increased tools adoption willingness due to higher water costs – suggesting that economic measures may be required to induce greater use of water management innovations.

Despite the high WTP for monitoring tools specified by the overwhelming proportion of farmers, the specified WTP did not reflect the full price of these tools, suggesting that a sole dependence on economic mechanisms may not lead to desired levels of adoption. As a result, sharing part of the financial outlay of monitoring tools through external partners may be imperative for their sustained use. This is particularly reasonable from the public viewpoint, given that monitoring tools are knowledge-oriented and would have social benefits in addition to gains made by adopting farmers. Therefore, as irrigators are operating in a shared setting – including infrastructure, water and waterways – adoption of these tools would have considerable external effects, often not reflected within the market, making co-finance a more attractive option for farmers. Furthermore, given cost is one of many impediments to implementing water management innovations – particularly for subsistence farmers, expanding financial availability (e.g., credit support) may further foster adoption.

Under Chapter 3, it was shown that engagement in AIP activities was positively associated with greater on-farm income, education, food shortage reduction and off-farm income. These results illustrate that, instead of solely concentrating on technology solutions, irrigation development initiatives tackling a large variety of impediments (market, finance, technical, tenure, policy) are more likely to enhance schemes and expand both productivity and profitably. Hence, policy strategies that frame and develop agricultural interventions to reflect the complexity of irrigation and account for a vast range of actors and ingredients are more likely to succeed in facilitating agricultural change in SSA. In addition, the study demonstrates that AIP and monitoring tools generated a significantly positive on-farm income spillover effect on non-participating irrigation households, with the reported gains from monitoring tools exceeded those of AIPs. This result emphasises the importance of capturing the likely spillover effects of development programs and policymakers should therefore be mindful in accommodating such effects throughout the design phase up until the monitoring and evaluation process – so that resources may be allocated in a socially desirable manner.

The results reported in Chapter 3 also highlighted that project influences are varied, according to household head gender, reflecting current gender "inequality" across SSA. This finding indicates that policymakers should consider appropriate policy instruments (e.g., altering land policy) in an effort to deter gender discrepancy across all levels of irrigation farming. Other actors such as NGOs and civil societies may have a part to play in this process by applying pressure (e.g., lobbying) on government bodies in influencing policy reforms, or through consultancies, financing, as well as conducting awareness campaign programs.

As highlighted above, Chapter 4 examined farm adaptation behaviour across the irrigation schemes and over the three-year study period. Planned farm adaptation was statistically significantly and positively associated with education, and the availability of finance and extension services – indicating that policy tools cognisant of these three variables are desirable to accelerate planned adaption actions. Since farming encompasses a lot of uncertainties, selecting a beneficial farm adaptation practice from many alternative ones requires a great deal of specialised skills, experience and expertise – however the reality is that illiteracy appeared to be a serious matter in a number of countries in SSA (World Bank 2021e). Accordingly, funding the expansion of educational facilities would be one mechanism to foster farm adaptation and overall economic and social growth. Smallholder farmers are also generally working in surroundings where the options to fund investments are often limited. This could clearly hamper productivity as well as overall viability of farming, which in turn would reduce capability of implementing adaptation measures. Accordingly, policy mechanisms that increase availability of credit – tailored towards small-scale irrigation farmers – could trigger the uptake of farm adaptation practices.

Furthermore, as the overwhelming share of farming households in developing economies rely on extension officers to seek advice in regards to farming (Wheeler et al. 2017), investing in modernising the extension system through a series of activities (education, training, outreaching, demonstrations and experience sharing) could also be a favourable policy device for progressing planned adaptation practices. Analogous to the findings revealed under Chapter 3, the empirical results indicated that – in contrast to irrigation households headed by males – female-headed ones are typically encouraged to carry out contractive planned adaptation practices – often resulting in poor outcomes in terms of farm production. Once again, this result underscores that comprehensive policy actions need to be implemented to handle gender inequalities and their associated negative outcomes. Under Chapter 4, it was also found that farmers' planned adaptation behaviour was inconsistent with their actual adaptation behaviour carried out three years later – while in several cases planned and actual behaviour were predicted by different factors. The implication here is that policy-makers need to be cognisant of these disparities when formulating farm adaptation polices and interventions.

5.3 Contributions to the literature

The empirical studies within this thesis have contributed to three broad spheres of agricultural and water research: a) adoption of irrigation management innovations; b) irrigation development intervention outcomes; and c) farm adaptation behaviour. The assessments of the adoption demand of small-scale farmers towards irrigation management technologies is the first area of literature that this thesis adds to. At the international level, a large quantity of innovations believed to assist irrigation have been introduced (Gu et al. 2020), although they have generally been adopted by a small fraction of farming communities (Annandale et al. 2011; Ibragimov et al. 2021; Nicol et al. 2010). A lack of integration between the innovation and local expertise and resources is among the routinely specified causes of partial adoption of these innovations. Examining the willingness of farm households to adopt irrigation management innovations could be a useful mechanism to obtain preference information, allowing various groups to harness this information in producing innovations well suited to farmers. To date, there have been no detailed studies exploring the demand of these technologies by small-scale farmers. Chapter 2 of this thesis expands on this knowledge by examining farm household's WTP for Chameleon Sensor arrays and readers. It specifically showed the relevance of neighbourhood influences in accelerating innovation use. This is of particular interest for policymakers as irrigation management innovations entail a substantial public good component, while their adoption is not exclusively regulated through the mainstream market – therefore co-financing via external bodies is highly advantageous.

Although there are a growing number of agricultural interventions such as AIPs being implemented across Africa, to date the current knowledge around how these interventions can best achieve production growth is limited. Accordingly, Chapter 3 extends the literature by examining the value of two irrigation interventions – AIPs and monitoring tools, – which were implemented conjunctively with the purpose of enhancing irrigation viability. The household indicator outcomes were calculated as both objective-based variables (on-farm income and food shortage) and perception-based variables (child education and off-farm income). The thesis also contributes to the understanding of spillover effects linked with development programs, which are not extensively covered in the current empirical literature.

While it is known that the farming sector in SSA faces many uncertainties such as climate anomalies, market forces, government regulations, political volatility and development interventions, there is still much to be learnt about planned and actual adaptation behaviours. There has not been much research done to date, that has tracked the same farmers over time and tried to understand the changing influences on their behaviour (a study by Wheeler et al. (2021) is a notable outlier in the literature in this regard). Chapter 4 provides two contributions in this context, namely: a) empirically examining planned farm adaptation to a variety of uncertainties within a cross-sectional setting, and the comparison of planned and actual adaptation behaviours of the same farmers over a three-year period; and b) methodologically overcoming the endogeneity of climate perceptions relating to adaptation behaviour, using a control function approach.

5.4 Limitations and future research

The relatively small sample observation, especially in some schemes, is the core limitation confronting this thesis. The data used originates from irrigation development interventions in six irrigation schemes within three countries of SSA. Overall, there is a great deviation in the total number of farm households among the studied schemes, with a small number recorded in Khanimambo and a reasonably large number in Magozi. While almost the entire households working in the smaller schemes were interviewed as part of the survey, this was not the case for the larger schemes. As a result, in the baseline survey, 402 households across all irrigation schemes participated, whereas 373 households took part in the end-of-project survey. Missing information and attrition between the two irrigation surveys also impacted the data used in this thesis. Taking into consideration these factors, three of the empirical chapters in this thesis employed pooled information of all sample households across all studied schemes, which may reduce the ability to draw inferences for a specific scheme or country. Therefore, additional research incorporating a larger volume of observations, unique to the relevant study region, would further aid understanding.

In addition to data challenges, project implementation realities impact upon methodological inferences. In Chapter 3, while the two interventions (AIPs and monitoring tools) were implemented contemporaneously with the possibility of influencing one another, this thesis investigated their impacts separately – given the available observations was too low to analyse their combined effects via a suitable econometric approach. For example, instead of defining the interventions – AIPs or monitoring tools – independently, as a dichotomous participate/non-participate question, it would be worthy examining the joint roles of the two interventions within a "multivalued treatment effect" setting (Cattaneo 2010). One possible arrangement for this could be made by splitting all sample households into four categories such as: *participated in both interventions; participated in AIPs only; participated in monitoring tools only; and participated in neither intervention.* In this manner, we could test the question whether the relative advantages of engagement in both interventions exceeds that of participating in a single intervention, along with neither of the interventions. Data limitations precluded our ability to do this. Therefore, it would be beneficial for future studies to avoid dualistic classifications (such as participate/non-participate) and instead employ multivalued treatment effect classifications when studying development initiatives.

While two waves of irrigation survey data were present for this thesis, only the end-of-the project survey was utilised instead of data from both surveys (panel data) in Chapter 3. This was mainly because: 1) the sample size was not large enough to facilitate panel data analysis (given only around 282 of the same irrigators appeared in the two surveys); and 2) some of the variables thought to influence AIPs and monitoring tools were not encompassed in the baseline survey. Indeed, future efforts to understand irrigation development interventions on poverty, equity, agricultural production, quality of food consumed and education enrolment; with a detailed series of panel data would be highly useful. This is particularly important for AIPs and monitoring tools in which the roles of these two initiatives in delivering the required gains are not sufficiently covered within the current literature.

Furthermore, as the household survey data did not contain comprehensive information relating to the plot distances between irrigation households within irrigation schemes, we instead developed similarity indexes of spillover effects using other proxy indicators – determined according to the working hypothesis of the implemented project and logical intuitions. While estimates resulting from this index provided some meaningful clues, the index may fail in identifying the extent of similarity among irrigation households – in turn negatively influencing the reported results in Chapter 3. Future studies may resolve this limitation by incorporating detailed locational variables into their analyses (similar to Manero et al. (2019)). One mechanism that could aid spillover analysis is upgrading the design of survey questionnaires to accommodate many more situations and information – given that a large share of surveys did not comprise appropriate locational variables in the data collection process. Specifically, in the design of household surveys, incorporating some variables that enabled to gather information on the actual location of farmers (living areas) and their respective plots would open a straightforward way to determine spillover effects.

Finally, it is also prudent to be mindful of the results from the two waves of analysis, presented in Chapter 4. The fact is that actual farm adaptation practices in 2017 were not gathered via "yes/no" format, as they were for planned practices in 2014. As a result, proxies were constructed for some variables, and hence, caution must be advised, as the reported results might not completely reflect adaptation patterns. As such, Chapter 4's data analysis would be far more powerful if greater information on actual and planned farm adaptation practices were available. At the same time, having more information about climate change perceptions and beliefs would also be highly useful, to more fully understand the relationship between perceptions and behaviour.

Overall summary

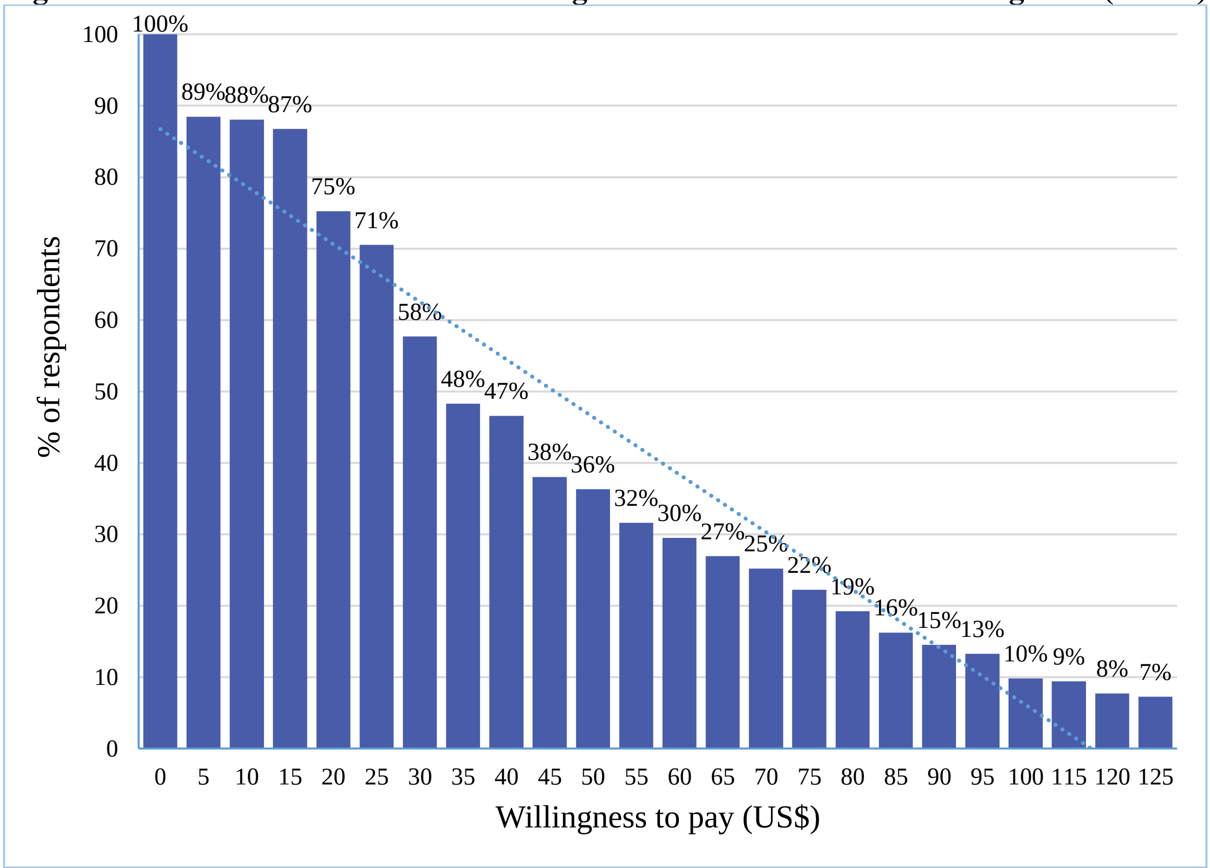
Overall, this thesis has utilised several unique data sets to identify the wide range of influences associated with monitoring tool adoption, farm adaptation and household living outcomes in six irrigation schemes in SSA. It has provided many key insights on improving irrigator economic and social welfare in small-scale irrigation schemes and identifying future research needs. The findings contribute to the literature by highlighting that projects committed to fostering social learning and institutional development – such as markets – can significantly impact irrigation household outcomes. To foster further adoption, understanding the influences on existing farmer adoption and farmers' WTP for innovations will help shape future policy programs designed to maximise societal net gains in SSA countries.

Appendix A Additional Materials for Chapter 2

Table A.1 Summary statistics of WTP answers for access to monitoring tools

		% with positive WTP	
Schemes	***Sample (n)***	***Array***	***Reader***
Mkoba	52	85%	81%
Kiwere	81	94%	93%
25 de Setembro	26	100%	96%
Silalatshani	75	81%	79%
Total (Pooled)	234	89%	86%

Figure A.1 Cumulative distribution of irrigators' total WTP for monitoring tools (n=234)



Appendix B Additional Materials for Chapter 3

Table B.1 Some of the irrigation practice impediments raised and solutions from AIP meetings/events

Country	***Examples of identified impediments***	***Solutions from AIPs***
Zimbabwe	Cultivating low value traditional staple crops	Trained farmers to cultivate varieties with high market values and demands
		Allowed farmers to determine the varieties they would like to grow
	Outstanding irrigation water payments to the government	Persuaded the government to reduce the burden
	Knowledge gap on farming	Arranged workshops and training programs to enhance the capacity of farmers
		Established demonstration plots to train farmers on enhanced farming practices
		Organised study visit programs to prompt "farmer-to-farmer" learning, experimentation and experience sharing
Tanzania	Substandard quality inputs and supply deficit in the market	Connected farmers to relevant input producers, sellers and other bodies working on the input sector
		Created awareness to farmers in relation to the use of organic fertiliser
	Knowledge gap on farming	Arranged capacity building trainings in collaboration with other bodies working in the sector
		Established demonstration plots to train farmers on meaningful farming practices
		Organised visit programs to boost "farmer-to-farmer" learning, and experience sharing
	Limited market access	Created new market opportunities and outlets
		Built grain storage technologies to prevent output losses and store output until prices increased
		Introduced new technologies (e.g., rice mills) to enable farmers supply value-added produce to market
	Continuous disputes on farm land borders among irrigators	Maps were prepared to demarcate each farmers' land border and thus, minimised potential disputes
Mozambique	Credit constraint	Connected farmers to credit markets
	Restricted market access	Established market connection/channels with potential product demanders
		Trained farmers and convinced them to concentrate on the cultivation of high value varieties
	Issues related with unused farm lands	Dispersed fallow land resources to young households
	Old and collapsed irrigation infrastructure	Mobilised resources from development partners and repaired broken infrastructure

Sources: Adapted from Bjornlund, H et al. (2020); Chilundo et al. (2020) and Mdemu et al. (2020)

Table B.2 Summary statistics across five SSA irrigation schemes in 2017

Variables	Definition	Unit	AIP (n=361)				Monitoring tools (n=241)			
			Mean	*Std. Dev*	*Min*	*Max*	*Mean*	*Std. Dev*	*Min*	*Max*
Dependent variables										
On-farm income	Gross farm household revenue from crop and animal product sale	USD (in 2017 prices)	1132.41	1435.24	0	6990.26	1200.74	1500.49	0	6990.26
Child education	Change in household's capacity to pay for child education over the past four years	1=improved; 0=otherwise	0.50	0.50	0	1	0.47	0.50	0	1
Food insecurity	Number of months farm household faces food shortage in a year	Months	6.51	3.79	0	12	6.16	3.77	0	12
Off-farm income	Change in household's off-farm income over the past four years	1=improved; 0=otherwise	0.39	0.49	0	1	0.39	0.49	0	1
Interventions										
AIP	Participation in AIP events	1=participated in AIP events; 0=otherwise	0.75	0.43	0	1	–	–	–	–
Tools use	Access to monitoring tools	1=received tools; 0=otherwise	–	–	–	–	0.39	0.49	0	1
Independent variables										
Age	Household head age	Years	52.13	16.05	20	100	55.23	16.03	20	100
Male	Household head gender	1=male; 0=otherwise	0.77	0.42	0	1	0.75	0.44	0	1
Primary school	Household head education level	1=attended primary school; 0=no formal school	0.70	0.46	0	1	0.64	0.48	0	1
Secondary school or above	Household head education level	1=attended secondary school or above; 0=no formal school	0.23	0.42	0	1	0.29	0.45	0	1
Household size	Number of household members	Person	5.75	2.35	1	12	5.88	2.48	1	12
Better health	Household head health position	1=good; 0=otherwise	0.78	0.41	0	1	0.75	0.44	0	1
Livestock[a]	Livestock holding	Tropical livestock units (TLU)	4.35	7.83	0	45.48	4.48	6.49	0	30.23
Crop land	Cultivated land area	Hectare	2.15	1.74	0.30	10.80	2.27	1.97	0.3	14.50
Media access	Access to information services	1=any household member access information service from media; 0=otherwise	0.91	0.29	0	1	0.88	0.33	0	1
Information access	Access to information services	1=any household member access information service from shows/trade fairs; 0=otherwise	0.80	0.40	0	1	0.73	0.44	0	1
Tool use	Access to monitoring tools	1=received tools; 0=otherwise	0.27	0.44	0	1	–	–	–	–
AIP	Participation in AIP events	1=participated in AIP events; 0=otherwise	–	–	–	–	0.74	0.44	0	1

Table B.2 (continued)

Variables	*Definition*	*Unit*	*AIP (n=361)* Mean	Std. Dev	Min	Max	*Monitoring tools (n=241)* Mean	Std. Dev	Min	Max
Membership	Affiliation to farmer group or community-based organisation	1=member; 0=otherwise	0.93	0.26	0	1	0.91	0.28	0	1
Downstream location	Plot location within the scheme	1=downstream; 0=otherwise	0.33	0.47	0	1	0.31	0.46	0	1
Mkoba	Irrigation scheme	1=Mkoba; 0=otherwise	–	–	–	–	0.22	0.41	0	1
Kiwere	Irrigation scheme	1=Kiwere; 0=otherwise	–	–	–	–	0.36	0.48	0	1
25 de Setembro	Irrigation scheme	1=25 de Setembro; 0=otherwise	–	–	–	–	0.12	0.32	0	1
Country: Tanzania	Country	1=Tanzania; 0=otherwise	0.54	0.50	0	1	–	–	–	–

Notes: [a] Conversion values employed to generate TLU variable includes "Cattle=0.7; donkey=0.5; Pig=0.2; Sheep=0.1; Goat=0.1; chicken=0.01; Duck=0.02 and rabbit=0.01" (Ghirotti 1993; Maass et al. 2012).

'–' represents not applicable

Table B.3 Differences in key variables by household head gender across five SSA irrigation schemes in 2017

	AIP (n=361)			*Monitoring tools (n=241)*		
Variables	*Male (n=277)*	*Female (n=84)*	T/χ^2 *test*	*Male (n=180)*	*Female (n=61)*	T/χ^2 *test*
On-farm income	1294.39	598.27	696.12***	1390.96	639.44	751.52***
Off-farm income	0.39	0.39	0.00	0.39	0.36	0.03
Male household member size	3.14	2.27	0.87***	3.26	2.26	1.00***
Female household member size	2.78	2.93	0.15	2.89	2.82	0.07
Household size (total)	5.91	5.20	0.71**	6.15	5.08	1.07***
Crop land	2.36	1.48	0.88***	2.52	1.55	0.97***
Livestock holding	4.85	2.69	2.16**	5.11	2.62	2.49***

Note: ***p≤0.01; **p≤0.05; *p≤0.1

Table B.4 Impacts of AIP events participation by household head gender across five SSA irrigation schemes in 2017

	On-farm income		*Child education*		*Food insecurity*		*Off-farm income*	
Estimation strategies	*Male (n=277)*	*Female (n=84)*	*Male (n=277)*	*Female (n=84)*	*Male (n=277)*	*Female (n=84)*	*Male (n=277)*	*Female (n=84)*
IPWRA	465.09***	158.60	–	-0.16	-0.88*	-2.20***	–	-0.01
	(165.99)	(148.83)		(0.10)	(0.45)	(0.70)		(0.09)
AIPW	474.58***	211.71	–	-0.13	-0.87*	-2.25**	–	-0.00
	(168.05)	(170.30)		(0.11)	(0.49)	(0.90)		(0.09)
RA	462.50***	229.71	–	-0.13	-0.61	-2.11**	–	-0.01
	(162.12)	(172.24)		(0.10)	(0.52)	(0.90)		(0.09)
PSM	498.84***	119.13	0.19***	-0.08	-0.82**	-2.06**	0.20***	-0.08
	(126.25)	(97.88)	(0.06)	(0.13)	(0.36)	(1.02)	(0.06)	(0.09)
IPW	478.78***	131.10	0.20***	-0.16	-0.92*	-1.63	0.19***	-0.17
	(168.39)	(131.91)	(0.07)	(0.12)	(0.51)	(1.00)	(0.06)	(0.11)
OLS	481.68***	-45.51	–	–	–	–	–	–
	(179.92)	(135.96)						
Binary Probit	–	–	0.20***	-0.15	–	–	0.20***	-0.06
			(0.08)	(0.14)			(0.07)	(0.13)
Poisson	–	–	–	–	-0.06	-0.24**	–	–
					(0.08)	(0.11)		

Notes: Robust standard errors in parentheses
***p≤0.01; **p≤0.05; *p≤0.1
'–' represents not applicable
For the dummy dependent variables, we reported the marginal effects in the binary probit model

Table B.5 Impacts of monitoring tools by household head gender across five SSA irrigation schemes in 2017

	On-farm income		***Child education***		***Food insecurity***		***Off-farm income***	
Estimation strategies	*Male (n=180)*	*Female (n=61)*	*Male (n=180)*	*Female (n=61)*	*Male (n=180)*	*Female (n=61)*	*Male (n=180)*	*Female (n=61)*
IPWRA	686.12^{***}	-236.49	–	–	–	–	–	–
	(218.34)	(196.38)						
AIPW	686.53^{***}	-245.28	–	–	–	–	–	–
	(222.91)	(205.35)						
RA	618.36^{***}	-286.16	–	–	–	–	–	–
	(222.90)	(226.30)						
PSM	408.85^{*}	-106.89	0.32^{***}	0.16	0.73	-2.39^{*}	0.031	-0.08^{***}
	(209.28)	(202.58	(0.06)	(0.10)	(0.75)	(1.27)	(0.07)	(0.01)
IPW	695.93^{***}	-23.92	0.28^{***}	0.05	0.15	-1.96^{**}	0.04	-0.12
	(216.64)	(189.18)	(0.07)	(0.12)	(0.61)	(0.77)	(0.07)	(0.10)
OLS	577.32^{**}	-189.10	–	–	–	–	–	–
	(250.22)	(226.76)						
Binary Probit	–	–	0.32^{***}	0.09	–	–	0.06	-0.18
			(0.08)	(0.16)			(0.08)	(0.14)
Poisson	–	–	–	–	0.09	-0.11	–	–
					(0.10)	(0.18)		

Notes: Robust standard errors in parentheses

***p≤0.01; **p≤0.05; *p≤0.1

'–' represents not applicable

For the dummy dependent variables, we reported the marginal effects in the binary probit model

Table B.6 Variance inflation factors (VIF) of independent variables across five SSA irrigation schemes in 2017

	VIF	
Variables	***AIP***	***Monitoring tools***
Age	1.50	1.64
Male	1.26	1.43
Primary school	3.38	4.46
Secondary school or above	3.72	4.72
Household size	1.12	1.23
Better health	1.27	1.28
Livestock	1.14	1.44
Crop land (ln)	1.21	1.43
Media access	1.22	1.31
Information access	1.12	1.16
AIP	–	1.27
Tool use	1.10	–
Membership	1.19	1.19
Downstream location	1.05	1.12
Mkoba	–	1.80
Kiwere	–	2.58
25 de Setembro	–	1.76
Country: Tanzania	1.99	–
Mean VIF	1.59	1.86

Note: '–' represents not applicable

Table B.7 Pearson correlation coefficients of independent variables across five SSA irrigation schemes in 2017 (n=361)

Variables		*A*	*B*	*C*	*D*	*E*	*F*	*G*	*H*	*I*	*J*	*K*	*L*	*M*	*N*
A	Age	1													
B	Male	-0.15	1.00												
C	Primary school	-0.06	0.12	1.00											
D	Secondary school or above	-0.02	-0.03	-0.83	1.00										
E	Household size	0.08	0.13	0.03	-0.09	1.00									
F	Better health	-0.35	0.19	0.08	0.00	0.03	1.00								
G	Livestock	0.13	0.12	-0.07	0.09	0.14	0.03	1.00							
H	Crop land (ln)	-0.07	0.29	0.05	-0.06	0.18	0.12	0.22	1.00						
I	Media access	-0.24	0.23	-0.01	0.02	0.09	0.15	0.02	0.17	1.00					
J	Information access	-0.13	0.12	0.11	-0.14	0.05	0.11	-0.04	0.07	0.22	1.00				
K	Tools use	0.05	0.03	-0.08	0.13	0.12	0.09	0.05	0.10	0.02	-0.03	1.00			
L	Membership	-0.23	0.13	0.14	-0.15	0.05	0.27	-0.05	0.08	0.20	0.16	0.05	1.00		
M	Downstream location	0.05	-0.05	-0.10	0.07	0.06	-0.05	-0.02	-0.06	0.06	0.04	-0.09	0.03	1.00	
N	Country: Tanzania	-0.48	0.27	0.33	-0.36	-0.05	0.30	-0.17	0.18	0.29	0.28	-0.17	0.30	0.03	1.00

Note: As agricultural innovation platforms have been applied in five schemes and monitoring tools only in four schemes, the number of observations available for AIP (n=361) and monitoring tools (n=241) assessment were different. For this reason, while we assessed the correlation coefficients using both AIP and monitoring tools database separately, we decided to report only results using the AIP database, given that the AIP database consists of large number of observations than monitoring tools database. The correlation results using monitoring tools database are available up on request.

Table B.8 Probit model results: AIP events and monitoring tools across five SSA irrigation schemes in 2017

	Coefficients		*Marginal effects*	
Variables	***AIP***	***Monitoring tools***	***AIP***	***Monitoring tools***
Age	0.01*	0.01	0.003*	0.002
	(0.01)	(0.01)	(0.002)	(0.003)
Male	-0.03	0.003	-0.01	0.001
	(0.20)	(0.234)	(0.06)	(0.089)
Primary school	0.01	0.78*	0.002	0.30*
	(0.30)	(0.41)	(0.091)	(0.16)
Secondary school or above	0.35	1.00**	0.11	0.38**
	(0.33)	(0.44)	(0.10)	(0.17)
Household size	-0.04	0.05	-0.01	0.02
	(0.03)	(0.04)	(0.01)	(0.02)
Better health	0.22	0.45**	0.07	0.17**
	(0.20)	(0.23)	(0.06)	(0.09)
Livestock	0.001	0.02	0.001	0.01
	(0.009)	(0.02)	(0.03)	(0.01)
Crop land (ln)	-0.06	-0.02	-0.02	-0.01
	(0.14)	(0.17)	(0.04)	(0.07)
Media access	0.38	-0.08	0.12	-0.03
	(0.26)	(0.30)	(0.08)	(0.12)
Information access	0.60***	-0.06	0.18***	-0.02
	(0.18)	(0.21)	(0.06)	(0.08)
AIP	–	0.26	–	0.10
		(0.23)		(0.09)
Tools use	0.40**	–	0.12**	–
	(0.19)		(0.06)	
Membership	0.44	0.15	0.13	0.06
	(0.30)	(0.36)	(0.09)	(0.14)
Downstream location	-0.36**	-0.16	-0.11**	-0.06
	(0.16)	(0.19)	(0.05)	(0.07)
Mkoba	–	0.36	–	0.14
		(0.28)		(0.11)
Kiwere	–	0.71**	–	0.27**
		(0.31)		(0.12)
25 de Setembro	–	1.42***	–	0.54***
		(0.37)		(0.14)
Country: Tanzania	0.28	–	0.09	–
	(0.21)		(0.06)	
Constant	-1.10*	-2.81***		
	(0.62)	(0.75)		
Wald chi^2	37.13***	34.31***		
Log pseudo likelihood	-185.26	-142.50		
Percent correctly predicted (%)	77.01	65.98		
Pseudo R^2	0.09	0.12		
Observations	361	241		

Notes: Robust standard errors in parentheses

***$p\leq0.01$; **$p\leq0.05$; *$p\leq0.1$

'–' represents not applicable

Figure B.1 Overlap diagram of AIP events and monitoring tools across five SSA irrigation schemes in 2017

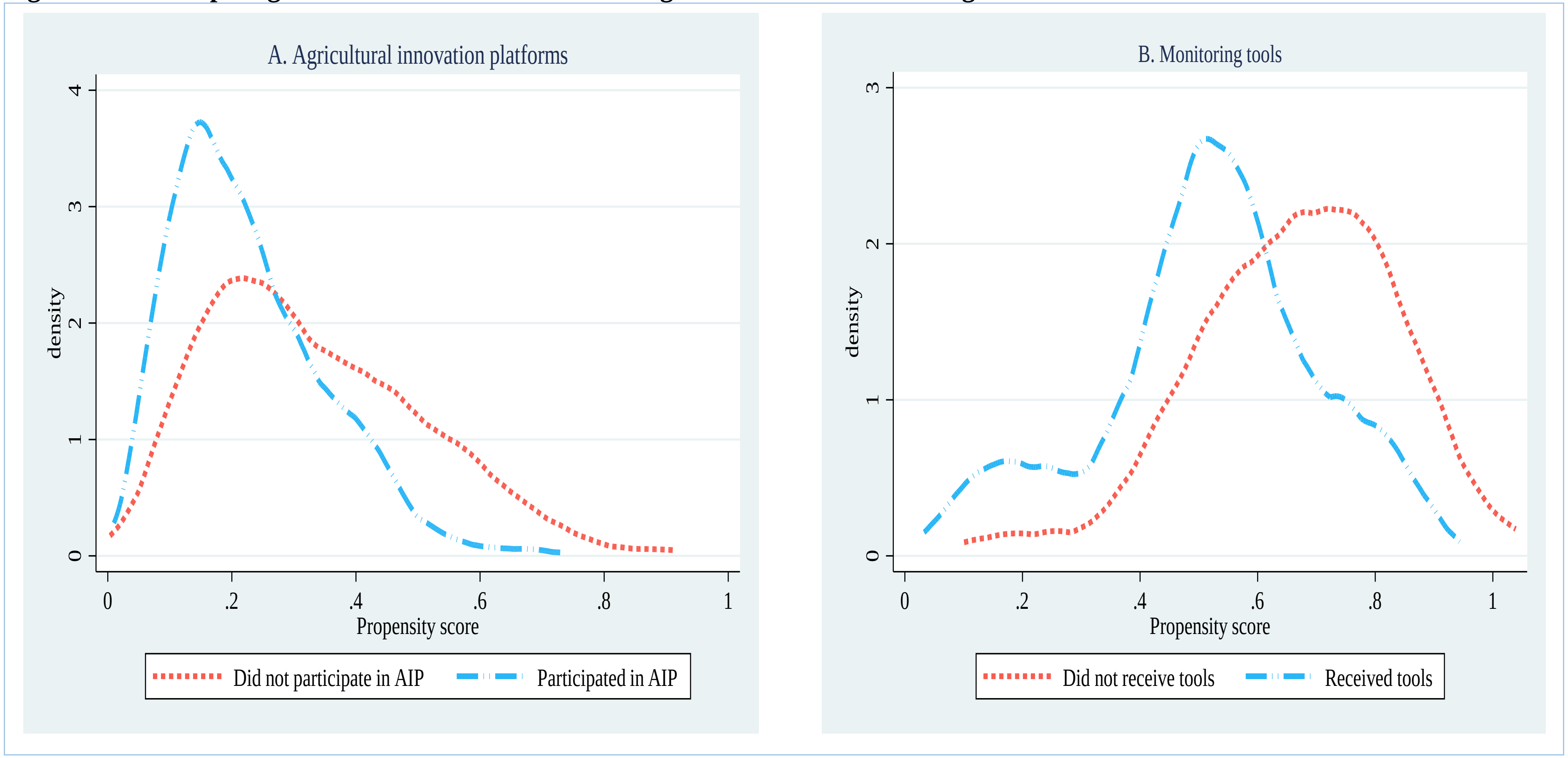


Table B.9 Over-identification tests for IPWRA, AIPW and IPW approaches across five SSA schemes in 2017

	AIP		***Monitoring tools***	
Dependent variables	χ^2	***Prob*** > χ^2	χ^2	***Prob*** > χ^2
On-farm income	5.39	0.99	7.27	0.98
Child education	5.39	0.99	7.27	0.98
Food insecurity	5.39	0.99	7.27	0.98
Off-farm income	5.39	0.99	7.27	0.98

Notes: Over-identification test involved the assessments of independent variables patterns between intervention recipients and non-recipients. It tests the null hypothesis that the patterns of independent variables incorporated in the modelling were balanced between *AIP (or monitoring tools*) intervention participants and non-participants versus the alternative hypothesis that patterns were not balanced.

As the same independent variables were utilised to examine the influences of AIPs or monitoring tools on all dependent variables, the over-identification test results were shown to be similar for all dependent variables for AIP or monitoring tools.

Table B.10 Independent variables balancing tests for IPW, IPWRA and AIPW across five SSA schemes in 2017

	AIP				*Monitoring tools*			
	Standardised differences		*Variance ratio*		*Standardised differences*		*Variance ratio*	
Variables	***Raw***	***Weighted***	***Raw***	***Weighted***	***Raw***	***Weighted***	***Raw***	***Weighted***
Age	-0.06	-0.01	0.89	0.97	-0.16	0.07	0.91	1.08
Male	0.13	0.00	0.85	1.00	0.16	0.02	0.83	0.98
Primary school	-0.02	0.01	1.01	0.99	0.01	0.03	1.00	0.98
Secondary school or above	0.07	0.00	1.09	1.01	0.09	0.02	1.09	1.01
Household size	-0.1	0.00	0.9	0.99	0.23	-0.05	0.95	0.84
Better health	0.25	0.07	0.73	0.92	0.37	-0.01	0.62	1.01
Livestock	-0.05	0.05	1.39	1.69	0.07	-0.01	1.33	0.81
Crop land (ln)	0.05	0.05	1.10	1.06	0.17	0.00	1.05	1.01
Media access	0.30	-0.01	0.47	1.02	0.19	-0.02	0.63	1.06
Information access	0.45	0.00	0.57	0.99	0.17	-0.01	0.83	1.01
AIP	–	–	–	–	0.39	-0.01	0.61	1.01
Tool use	0.29	-0.02	1.43	0.98	–	–	–	–
Membership	0.28	0.01	0.43	0.96	0.28	-0.05	0.39	1.14
Downstream location	-0.22	-0.01	0.86	0.99	-0.16	0.02	0.87	1.02
Mkoba	–	–	–	–	-0.11	0.07	0.86	1.09
Kiwere	–	–	–	–	0.18	0.00	1.11	1.00
25 de Setembro	–	–	–	–	0.42	0.00	2.78	1.01
Country: Tanzania	0.25	0.02	0.98	1.00	–	–	–	–
Number of observations	361	361	361	361	241	241	241	241
Treated observations	270	179.70	270	179.70	95	118.80	95	118.80
Control observations	91	181.3	91	181.3	146	122.2	146	122.2

Note: '–' represents not applicable

Table B.11 Independent variables balancing tests for PSM approach across five SSA irrigation schemes in 2017

	AIP				*Monitoring tools*			
	Standardised differences		*Variance ratio*		*Standardised differences*		*Variance ratio*	
Variables	***Raw***	***Matched***	***Raw***	***Matched***	***Raw***	***Matched***	***Raw***	***Matched***
Age	-0.06	-0.09	0.89	0.9	-0.16	0.07	0.91	1.04
Male	0.13	-0.02	0.85	1.02	0.16	0.08	0.83	0.91
Primary school	-0.02	-0.02	1.01	1.02	0.01	0.02	1.00	0.99
Secondary school or above	0.07	0.06	1.09	1.09	0.09	0.03	1.09	1.03
Household size	-0.10	-0.06	0.90	0.94	0.23	0.02	0.95	0.98
Better health	0.25	0.10	0.73	0.89	0.37	-0.04	0.62	1.04
Livestock	-0.05	0.01	1.39	1.54	0.07	0.04	1.33	0.83
Crop land (ln)	0.05	0.01	1.10	1.03	0.17	0.04	1.05	0.98
Media access	0.30	-0.01	0.47	1.03	0.19	0.04	0.63	0.91
Information access	0.45	0.04	0.57	0.95	0.17	0.01	0.83	0.99
AIP	–	–	–	–	0.39	0.02	0.61	0.98
Tool use	0.29	0.00	1.43	1.00	–	–	–	–
Membership	0.28	-0.06	0.43	1.21	0.28	-0.03	0.39	1.08
Downstream location	-0.22	-0.03	0.86	0.98	-0.16	-0.01	0.87	0.99
Mkoba	–	–	–	–	-0.11	-0.02	0.86	0.98
Kiwere	–	–	–	–	0.18	-0.05	1.11	0.97
25 de Setembro	–	–	–	–	0.42	0.08	2.78	1.22
Country: Tanzania	0.25	0.03	0.98	1.00	–	–	–	–
Number of observations	361	722	361	722	241	482	241	482
Treated observations	270	361	270	361	95	241	95	241
Control observations	91	361	91	361	146	241	146	241

Note: '–' represents not applicable

Figure B.2 Kernel destiny diagrams for PSM approach across five SSA irrigation schemes in 2017

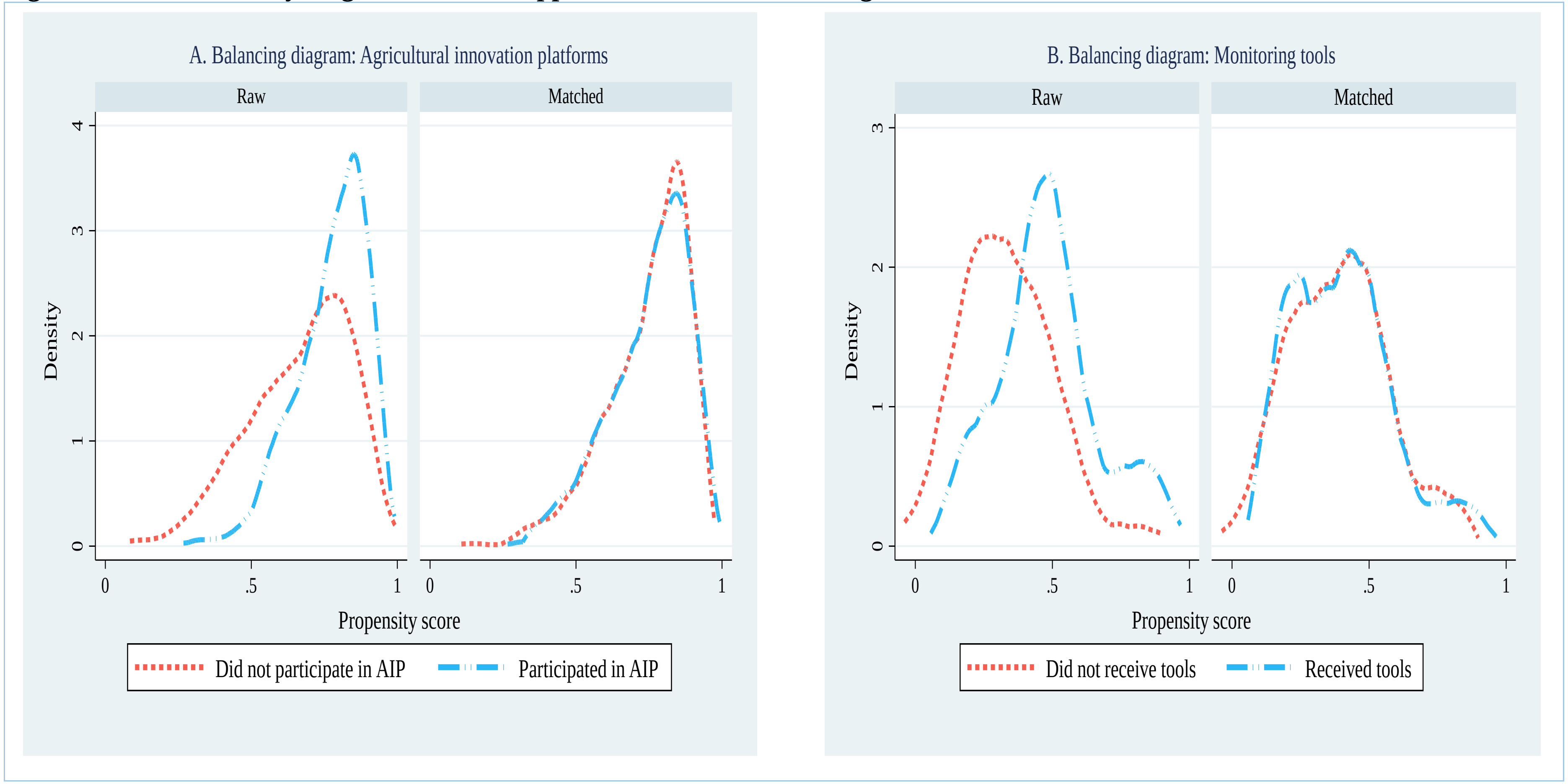
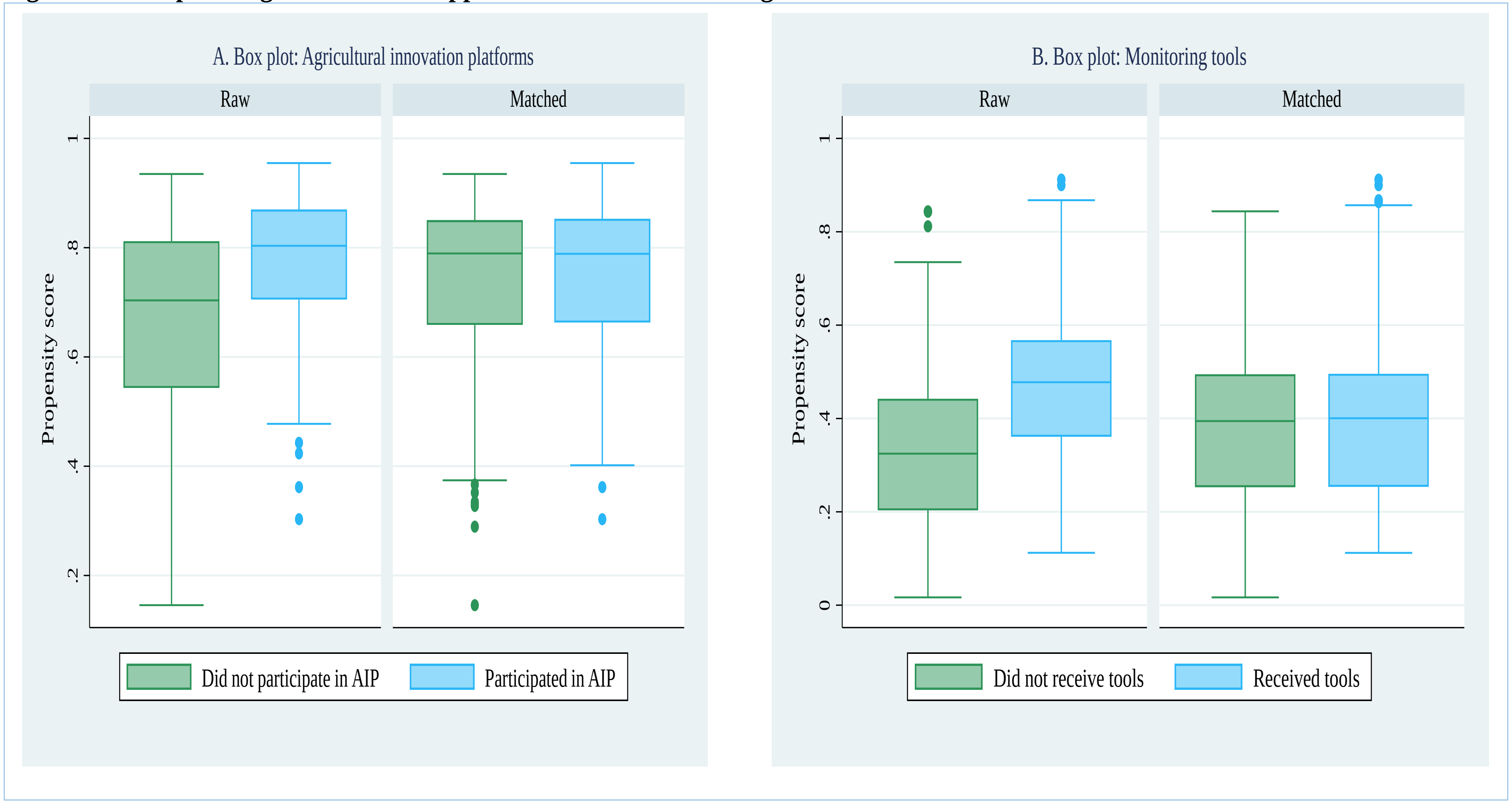


Figure B.3 Box plot diagrams for PSM approach across five SSA irrigation schemes in 2017



Appendix C Additional Materials for Chapter 4

Table C.1 Variance inflation factors (VIF) of independent variables across six SSA irrigation schemes in 2014 (n=371)

	VIF			
Variables	***Expansive index***	***Accommodating index***	***Contractive index***	***Total index***
Male	1.54	1.54	1.54	1.54
Age	2.25	2.25	2.26	2.24
Primary school	2.09	2.09	2.08	2.09
Secondary school or above	2.18	2.17	2.16	2.18
Household size	1.26	1.26	1.26	1.26
Farming experience	1.9	1.89	1.91	1.9
Car/motorbike/bicycle	1.36	1.36	1.36	1.36
Ox/donkey cart	2.08	2.07	2.08	2.08
Livestock	1.46	1.46	1.46	1.46
On-farm income	1.64	1.64	1.64	1.64
Off-farm income	1.27	1.28	1.27	1.27
Total land	1.45	1.44	1.44	1.45
Source of advice	1.82	1.82	1.83	1.82
Credit access	1.19	1.22	1.19	1.19
Climate perception	1.09	1.07	1.07	1.08
Past adaptation index	1.46	1.24	1.13	1.38
Mkoba	1.74	1.75	1.72	1.74
Kiwere	3.55	3.52	3.54	3.64
Magozi	3.42	3.26	3.24	3.41
25 de Setembro	1.87	1.87	1.87	1.87
Khanimambo	1.39	1.39	1.39	1.39
Mean VIF	1.81	1.79	1.78	1.81

Table C.2 Correlation coefficients of independent variables across six irrigation schemes in SSA in 2014 (n=371)

	Variables	***A***	***B***	***C***	***D***	***E***	***F***	***G***	***H***	***I***	***J***	***K***
A	Male	1.00										
B	Age	-0.10	1.00									
C	Primary school	0.10	-0.10	1.00								
D	Secondary school or above	0.01	0.00	-0.68	1.00							
E	Household size	0.13	0.15	0.03	-0.08	1.00						
F	Farming experience	-0.08	0.62	0.05	-0.09	0.15	1.00					
G	Car/motorbike/bicycle	0.32	-0.17	0.04	0.02	0.05	-0.07	1.00				
H	Ox/donkey cart	-0.01	0.35	-0.16	0.21	0.01	0.28	0.02	1.00			
I	Livestock	0.07	0.10	-0.12	0.13	0.13	0.11	0.15	0.41	1.00		
J	On-farm income	0.15	-0.08	0.04	-0.02	0.22	0.00	0.10	-0.17	0.16	1.00	
K	Off-farm income	-0.07	0.07	-0.10	0.22	0.13	-0.03	-0.07	0.09	0.12	0.15	1.00
L	Total land	0.17	0.17	0.03	0.01	0.26	0.27	0.10	0.10	0.16	0.40	0.06
M	Source of advice	-0.22	0.23	-0.09	0.10	-0.09	0.09	0.01	0.36	0.26	-0.25	0.04
N	Credit access	0.12	-0.04	0.04	0.03	0.04	0.01	-0.11	-0.10	-0.05	0.12	-0.04
O	Climate perception	-0.01	0.01	-0.03	-0.03	-0.02	0.01	0.00	0.11	0.03	-0.05	-0.12
P	Past adaptation index	0.22	-0.24	0.14	-0.04	0.03	-0.16	0.20	-0.20	-0.02	0.15	-0.09
Q	Mkoba	-0.37	0.28	-0.07	0.14	-0.22	0.09	-0.09	0.24	-0.02	-0.22	0.12
R	Kiwere	0.27	-0.23	0.11	-0.12	0.09	-0.08	0.25	-0.32	-0.19	0.03	-0.18
S	Magozi	0.14	-0.33	0.23	-0.20	-0.01	-0.19	0.09	-0.33	-0.05	0.19	-0.06
T	25 de Setembro	0.00	0.12	-0.13	0.08	0.20	0.09	-0.23	-0.12	-0.11	0.29	0.19
U	Khanimambo	-0.14	0.05	0.08	-0.06	0.02	0.16	-0.15	-0.01	-0.03	0.16	0.18

Table C.2 (continued)

	Variables	*L*	*M*	*N*	*O*	*P*	*Q*	*R*	*S*	*T*	*U*
A	Male										
B	Age										
C	Primary school										
D	Secondary school or above										
E	Household size										
F	Farming experience										
G	Car/motorbike/bicycle										
H	Ox/donkey cart										
I	Livestock										
J	On-farm income										
K	Off-farm income										
L	Total land	1.00									
M	Source of advice	-0.02	1.00								
N	Credit access	0.04	-0.23	1.00							
O	Climate perception	0.03	0.00	0.11	1.00						
P	Past adaptation index	0.12	-0.16	0.08	0.00	1.00					
Q	Mkoba	-0.13	0.33	0.00	-0.01	-0.14	1.00				
R	Kiwere	0.08	-0.35	0.02	-0.03	0.27	-0.27	1.00			
S	Magozi	-0.06	-0.17	0.04	-0.09	0.26	-0.28	-0.34	1.00		
T	25 de Setembro	0.08	-0.28	0.22	-0.03	-0.14	-0.09	-0.11	-0.12	1.00	
U	Khanimambo	0.15	-0.17	0.09	0.02	-0.10	-0.06	-0.07	-0.07	-0.02	1.00

Table C.3 Paired t-test differences of past and planned indexes across six irrigation schemes in SSA in 2014 (n=371)

Variables	*Past 3 years (2011-2014)* *Mean*	*Next 3 years (2014-2017)* *Mean*	*t-test*
Expansive index (fractional)	0.32	0.50	0.18***
Accommodating index (fractional)	0.32	0.43	0.11***
Contractive index (fractional)	0.13	0.14	0.01
Total index (fractional)	0.26	0.37	0.11***
Expansive index (count)	2.23	3.51	1.28***
Accommodating index (count)	1.29	1.71	0.42***
Contractive index (count)	0.67	0.70	0.03
Total index (count)	4.19	5.92	1.73***

Note: ***p≤0.01; **p≤0.05; *p≤0.1

Table C.4 Exogeneity test of climate perception across six SSA irrigation schemes in 2014 (=371)

Variables	*Durbin chi-square test*	*Wu-Hausman F test*
Expansive index (fractional)	5.59**	5.32**
Accommodating index (fractional)	8.18***	7.85***
Contractive index (fractional)	0.26	0.24
Total index (fractional)	6.56**	6.26**
Expansive index (count)	5.59**	5.32**
Accommodating index (count)	8.18***	7.85***
Contractive index (count)	0.26	0.24
Total index (count)	6.56**	6.26**

Note: ***p≤0.01; **p≤0.05; *p≤0.1

Table C.5 Instrumental variable validity test of environment investment index across six SSA irrigation schemes in 2014 (=371)

Variables	*Partial R-squared*	*F-stat*	*Prob > F*
Expansive index (fractional)	0.028	9.941	0.002
Accommodating index (fractional)	0.028	10.164	0.002
Total index (fractional)	0.029	10.519	0.001
Expansive index (count)	0.028	9.941	0.002
Accommodating index (count)	0.028	10.164	0.002
Total index (count)	0.029	10.519	0.001

Note: The instrumental variable test for contractive index was not conducted in Table C.5, Appendix C since contractive index found to be exogenously related with climate perception (Table C.4, Appendix C).

Table C.6 Correlation coefficients of planned individual farm adaptation practices across six SSA irrigation schemes in 2014 (n=371)

	Individual farm practices	***A***	***B***	***C***	***D***	***E***	***F***	***G***	***H***	***I***	***J***	***K***	***L***	***M***	***N***	***O***	***P***
A	Increased irrigated area	1.00															
B	Acquired more irrigated area	0.74	1.00														
C	Acquired more dryland area	0.59	0.58	1.00													
D	Acquired agricultural implements	0.59	0.59	0.48	1.00												
E	Intensified crop production	0.51	0.53	0.40	0.63	1.00											
F	Sold more crop production	0.25	0.31	0.30	0.47	0.45	1.00										
G	Increased livestock	0.37	0.42	0.23	0.51	0.45	0.35	1.00									
H	Diversified crops for risk purposes	0.58	0.55	0.47	0.63	0.67	0.38	0.44	1.00								
I	Specialised crops for income purposes	0.28	0.31	0.28	0.37	0.44	0.32	0.22	0.43	1.00							
J	Diversified crops for labour purposes	0.24	0.21	0.15	0.32	0.40	0.40	0.37	0.40	0.28	1.00						
K	Consumed more crop production	0.41	0.37	0.34	0.52	0.48	0.50	0.47	0.47	0.32	0.50	1.00					
L	Decreased irrigated area	0.22	0.21	0.26	0.24	0.23	0.31	0.15	0.30	0.24	0.19	0.24	1.00				
M	Disposed irrigated land	0.26	0.24	0.25	0.26	0.23	0.24	0.18	0.28	0.22	0.24	0.18	0.47	1.00			
N	Disposed dryland area	0.28	0.25	0.24	0.27	0.21	0.16	0.23	0.28	0.22	0.29	0.23	0.43	0.45	1.00		
O	Disposed agricultural implements	0.25	0.16	0.15	0.19	0.26	0.21	0.23	0.30	0.31	0.44	0.34	0.31	0.42	0.51	1.00	
P	Decreased livestock	0.29	0.33	0.25	0.35	0.30	0.24	0.32	0.33	0.20	0.32	0.33	0.33	0.30	0.42	0.27	1.00

Table C.7 Correlation coefficient of error terms of planned index adaptation practices across six SSA irrigation schemes in 2014 (n=371)

Variables	*Expansive index*	*Accommodating index*	*Contractive index*
Expansive index	1.00		
Accommodating index	0.63	1.00	
Contractive index	0.33	0.49	1.00
Breusch-Pagan test of independence		276.04***	

Note: ***p≤0.01; **p≤0.05; *p≤0.1

Table C.8 Sensitivity test results to adaptation index measurement differences across six SSA irrigation schemes in 2014 (n=371)

	OLS				*Poisson*				*SUR*		
Variables[a]	*Expansive index*	*Accommodating index*	*Contractive index*	*Total index*	*Expansive index*	*Accommodating index*	*Contractive index*	*Total index*	*Expansive index*	*Accommodating index*	*Contractive index*
Male	0.03	0.12	-0.23*	-0.09	-0.01	0.06	-0.33*	-0.03	0.02	0.12	-0.22*
	(0.19)	(0.12)	(0.13)	(0.34)	(0.08)	(0.10)	(0.20)	(0.08)	(0.19)	(0.12)	(0.12)
Age	-0.02**	-0.01**	-0.00	-0.03*	-0.00	-0.01	-0.00	-0.00	-0.01*	-0.01**	-0.00
	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)
Primary school	0.73***	0.25*	-0.10	0.86**	0.33***	0.25*	0.05	0.26**	0.72***	0.26*	-0.10
	(0.20)	(0.15)	(0.13)	(0.41)	(0.10)	(0.13)	(0.21)	(0.11)	(0.19)	(0.15)	(0.13)
Secondary school or above	0.24	-0.17	-0.23*	-0.19	0.25*	0.09	-0.31	0.15	0.22	-0.15	-0.23*
	(0.27)	(0.18)	(0.13)	(0.51)	(0.13)	(0.16)	(0.29)	(0.14)	(0.25)	(0.17)	(0.13)
Household size	0.02	0.02	0.00	0.05	0.01	0.02	0.03	0.01	0.02	0.02	0.00
	(0.03)	(0.02)	(0.02)	(0.06)	(0.01)	(0.02)	(0.03)	(0.01)	(0.03)	(0.02)	(0.02)
Farming experience	-0.00	-0.00	-0.00	-0.01	-0.00	0.00	-0.01	-0.00	-0.00	0.00	-0.00
	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)
Car/motorbike/bicycle	0.54***	0.27*	-0.04	0.78**	0.16**	0.17*	-0.12	0.14*	0.53***	0.26*	-0.04
	(0.20)	(0.14)	(0.12)	(0.39)	(0.07)	(0.10)	(0.20)	(0.08)	(0.20)	(0.13)	(0.12)
Ox/donkey cart	0.31	0.05	0.10	0.51	0.21	0.12	0.60**	0.21	0.30	0.04	0.09
	(0.24)	(0.18)	(0.11)	(0.45)	(0.13)	(0.15)	(0.24)	(0.13)	(0.23)	(0.18)	(0.12)
Livestock	-0.03*	0.00	0.02	-0.00	-0.01	0.00	0.02	-0.00	-0.03*	0.00	0.02
	(0.02)	(0.01)	(0.01)	(0.04)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
On-farm income	-0.00	-0.00	-0.00***	-0.00	-0.00	-0.00	-0.00**	-0.00	-0.00	-0.00	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Off-farm income	-0.00**	-0.00***	0.00	-0.00**	-0.00**	-0.00**	0.00	-0.00*	-0.00**	-0.00***	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Total land	0.14**	0.17***	0.13**	0.46***	0.05**	0.09***	0.12**	0.07***	0.13*	0.17***	0.13**
	(0.07)	(0.05)	(0.06)	(0.15)	(0.02)	(0.03)	(0.06)	(0.02)	(0.07)	(0.05)	(0.06)
Source of advice	0.53**	0.24	0.41**	1.16**	0.08	0.09	0.29	0.11	0.53**	0.25	0.40**
	(0.23)	(0.17)	(0.21)	(0.51)	(0.06)	(0.09)	(0.19)	(0.07)	(0.24)	(0.17)	(0.20)
Credit access	1.53***	0.80***	0.20	2.70***	0.50***	0.48***	0.37	0.50***	1.51***	0.79***	0.21
	(0.34)	(0.23)	(0.19)	(0.69)	(0.10)	(0.14)	(0.23)	(0.12)	(0.32)	(0.20)	(0.19)
Climate perception	-2.62**	-2.10**	0.04	-5.23**	-0.89**	-1.21**	0.05	-0.91**	-2.52**	-1.96***	0.03
	(1.20)	(0.85)	(0.12)	(2.53)	(0.36)	(0.53)	(0.18)	(0.43)	(1.03)	(0.62)	(0.13)
Past adaptation index	0.39***	0.54***	0.45***	0.42***	0.10***	0.27***	0.31***	0.06***	0.44***	0.53***	0.49***
	(0.06)	(0.05)	(0.09)	(0.08)	(0.02)	(0.03)	(0.06)	(0.01)	(0.05)	(0.04)	(0.07)
Mkoba	0.46	0.09	0.18*	0.72	0.39**	0.10	0.62	0.34**	0.44	0.10	0.18
	(0.30)	(0.18)	(0.10)	(0.55)	(0.16)	(0.18)	(0.39)	(0.17)	(0.28)	(0.17)	(0.11)
Kiwere	1.80***	0.06	1.27***	3.15***	0.84***	0.21	2.54***	0.83***	1.73***	0.10	1.23***
	(0.42)	(0.29)	(0.26)	(0.91)	(0.18)	(0.21)	(0.42)	(0.19)	(0.39)	(0.25)	(0.25)

Table C.8 (continued)

	OLS				*Poisson*				*SUR*		
Variables[a]	***Expansive index***	***Accommodating index***	***Contractive index***	***Total index***	***Expansive index***	***Accommodating index***	***Contractive index***	***Total index***	***Expansive index***	***Accommodating index***	***Contractive index***
Magozi	2.69***	0.33	1.20***	4.20***	1.01***	0.34*	2.50***	0.97***	2.61***	0.37	1.17***
	(0.42)	(0.25)	(0.22)	(0.83)	(0.18)	(0.20)	(0.40)	(0.18)	(0.38)	(0.23)	(0.21)
25 de Setembro	0.05	-0.25	0.82***	0.49	-0.05	-0.32	1.51*	-0.02	0.09	-0.23	0.81**
	(0.68)	(0.42)	(0.31)	(1.33)	(1.21)	(2.43)	(0.88)	(0.95)	(0.66)	(0.41)	(0.33)
Khanimambo	-0.26	-0.43	0.57*	-0.15	-0.66	-1.32	1.23**	-0.55	-0.21	-0.43	0.55*
	(0.64)	(0.48)	(0.30)	(1.14)	(6.75)	(6.36)	(0.57)	(4.83)	(0.63)	(0.48)	(0.33)
Control function	2.41*	2.02**	–	4.97*	0.81**	1.14**	–	0.85*	2.28**	1.88***	–
	(1.26)	(0.89)		(2.66)	(0.37)	(0.56)		(0.45)	(1.07)	(0.65)	
Constant	2.51**	1.93**	-0.35	4.61*	0.59	0.32	-2.71***	1.14**	2.37**	1.79***	-0.34
	(1.21)	(0.86)	(0.30)	(2.55)	(0.40)	(0.57)	(0.55)	(0.46)	(1.07)	(0.66)	(0.29)
AIC	1339.57	1079.37	1071.31	1840.69	1410.73	1089.45	745.93	1927.76	3199.02	3199.02	3199.02
BIC	1429.64	1169.45	1157.46	1930.76	1500.80	1179.52	832.08	2017.84	3465.33	3465.33	3465.33
Observations	371	371	371	371	371	371	371	371	371	371	371
Adjusted R^2/Pseudo R^2	0.68	0.51	0.34	0.61	0.27	0.19	0.27	0.30	0.70	0.54	0.38
Wald χ^2/F-test	1236.06***	633.93***	9.53***	854.74***	365.75***	238.34***	362.04***	317.70***	931.05***	536.55***	261.24***
Log pseudo likelihood	–	–	–	–	-682.37	-521.73	-350.97	-940.88	–	–	–

Notes: Bootstrap standard errors are in parentheses (with 1, 000 replications) when climate perception was endogenously associated with farm adaptation, otherwise robust standard errors are in parentheses.

$^{***}p\leq0.01$; $^{**}p\leq0.05$; $^{*}p\leq0.1$

'–' represents not applicable

[a] The key focus of this analysis is to look at the sensitivity of estimated results to dependent variable measurement differences (count farm adaptation practices vs fractional farm adaptation practices). Hence, this analysis (Table C.8, Appendix C) shows estimated results of planned adaptation practices measured as fractional variable; while the results of planned adaptation practice measured with count variable are reported in Table 4.4.

Table C.9 Sensitivity test results to sample size difference with various estimators across five SSA irrigation schemes in 2014 (n=263)

	OLS				*Poisson*				*Fractional probit*				*SUR*		
Variables[a]	*Expansive index*	*Accommodating index*	*Contractive index*	*Total index*	*Expansive index*	*Accommodating index*	*Contractive index*	*Total index*	*Expansive index*	*Accommodating index*	*Contractive index*	*Total index*	*Expansive index*	*Accommodating index*	*Contractive index*
Male	0.24	0.21	-0.24*	0.11	0.07	0.10	-0.20	0.01	0.12	0.18	-0.30*	0.02	0.24	0.21	-0.24*
	(0.21)	(0.14)	(0.14)	(0.40)	(0.08)	(0.11)	(0.26)	(0.09)	(0.11)	(0.12)	(0.18)	(0.09)	(0.21)	(0.14)	(0.14)
Age	-0.02**	-0.02**	-0.00	-0.03	-0.01*	-0.01*	-0.00	-0.01	-0.01**	-0.01**	0.00	-0.01	-0.02**	-0.01**	-0.00
	(0.01)	(0.01)	(0.01)	(0.02)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)
Primary school	1.07***	0.33*	0.01	1.58***	0.44***	0.44***	0.36	0.43***	0.57***	0.35**	0.19	0.39***	1.04***	0.39**	0.01
	(0.22)	(0.19)	(0.15)	(0.43)	(0.13)	(0.15)	(0.32)	(0.13)	(0.11)	(0.17)	(0.19)	(0.10)	(0.22)	(0.17)	(0.15)
Secondary school or above	0.46	-0.52*	-0.09	0.35	0.32**	0.20	0.03	0.27*	0.29*	-0.33	0.05	0.18	0.41	-0.38*	-0.09
	(0.29)	(0.30)	(0.14)	(0.52)	(0.15)	(0.18)	(0.41)	(0.15)	(0.15)	(0.26)	(0.23)	(0.12)	(0.29)	(0.23)	(0.15)
Household size	0.03	0.00	-0.02	0.01	0.02	0.01	-0.01	0.01	0.02	0.00	-0.01	0.01	0.03	0.00	-0.02
	(0.04)	(0.03)	(0.02)	(0.07)	(0.01)	(0.02)	(0.04)	(0.01)	(0.02)	(0.02)	(0.03)	(0.01)	(0.04)	(0.03)	(0.02)
Farming experience	0.00	0.00	-0.01	0.00	0.00	0.00	-0.01	0.00	0.00	0.00	-0.01	0.00	0.01	0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.02)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)
Car/motorbike/bicycle	0.14	0.30	-0.13	0.25	0.03	0.06	-0.35	0.02	0.08	0.22	-0.21	0.05	0.13	0.24	-0.13
	(0.21)	(0.19)	(0.14)	(0.42)	(0.07)	(0.10)	(0.23)	(0.08)	(0.10)	(0.17)	(0.16)	(0.08)	(0.21)	(0.17)	(0.13)
Ox/donkey cart	-0.13	0.06	0.07	-0.13	0.01	-0.03	0.20	0.03	-0.06	0.03	0.27	-0.02	-0.15	0.02	0.07
	(0.28)	(0.23)	(0.14)	(0.52)	(0.13)	(0.16)	(0.32)	(0.13)	(0.13)	(0.20)	(0.23)	(0.12)	(0.28)	(0.22)	(0.14)
Livestock	-0.02	0.00	0.01	0.00	-0.01	0.00	0.03*	-0.00	-0.01	-0.00	0.02	-0.00	-0.02	0.00	0.01
	(0.02)	(0.01)	(0.01)	(0.04)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
On-farm income	-0.00	0.00	-0.00**	-0.00	-0.00	-0.00	-0.00*	-0.00	-0.00	0.00	-0.00**	-0.00	-0.00	0.00	-0.00**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Off-farm income	-0.00	-0.00*	0.00	-0.00	-0.00	-0.00	0.00	-0.00	-0.00	-0.00	0.00	-0.00	-0.00	-0.00*	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Total land	0.17**	0.15**	0.16**	0.46**	0.06***	0.08***	0.20**	0.08***	0.08**	0.12**	0.17***	0.09***	0.17**	0.14**	0.16**
	(0.07)	(0.07)	(0.07)	(0.18)	(0.02)	(0.03)	(0.08)	(0.03)	(0.04)	(0.06)	(0.06)	(0.03)	(0.07)	(0.06)	(0.08)
Source of advice	0.74***	0.12	0.36	1.66***	0.15***	0.22**	0.33	0.21***	0.37***	0.08	0.28	0.26***	0.73***	0.21	0.36
	(0.26)	(0.23)	(0.24)	(0.58)	(0.06)	(0.09)	(0.25)	(0.07)	(0.13)	(0.18)	(0.18)	(0.10)	(0.26)	(0.20)	(0.23)
Credit access	0.95***	0.66***	0.30	1.96***	0.31***	0.27***	0.64**	0.37***	0.41***	0.59***	0.44**	0.39***	0.95***	0.65***	0.30
	(0.31)	(0.21)	(0.22)	(0.59)	(0.08)	(0.10)	(0.27)	(0.09)	(0.15)	(0.19)	(0.18)	(0.10)	(0.30)	(0.20)	(0.22)
Climate perception	-0.14	-2.09**	0.01	-0.47	-0.06	-0.12	0.01	-0.09	-0.08	-1.67**	0.01	-0.12	-0.16	-1.57***	0.02
	(0.21)	(0.95)	(0.14)	(0.41)	(0.06)	(0.09)	(0.22)	(0.07)	(0.10)	(0.81)	(0.15)	(0.08)	(0.21)	(0.55)	(0.14)
Past adaptation index	0.35***	0.58***	0.45***	0.41***	0.09***	0.30***	0.40***	0.07***	1.14***	1.75***	1.82***	1.23***	0.40***	0.54***	0.46***
	(0.06)	(0.06)	(0.11)	(0.08)	(0.01)	(0.03)	(0.08)	(0.01)	(0.19)	(0.20)	(0.37)	(0.22)	(0.05)	(0.04)	(0.09)
Mkoba	0.85***	0.18	0.09	1.22**	0.47***	0.13	0.45	0.36**	0.40***	0.13	0.19	0.27**	0.83***	0.22	0.09
	(0.29)	(0.20)	(0.13)	(0.55)	(0.16)	(0.17)	(0.48)	(0.16)	(0.14)	(0.19)	(0.24)	(0.12)	(0.30)	(0.20)	(0.14)
Kiwere	2.06***	-0.53	1.14***	3.43***	0.83***	0.16	2.22***	0.77***	0.78***	-0.48	1.53***	0.61***	1.94***	-0.31	1.13***
	(0.44)	(0.46)	(0.32)	(0.95)	(0.17)	(0.21)	(0.56)	(0.19)	(0.20)	(0.39)	(0.35)	(0.18)	(0.43)	(0.36)	(0.32)

Table C.9 (continued)

	OLS				Poisson				Fractional probit				SUR		
Variables[a]	***Expansive index***	***Accommodating index***	***Contractive index***	***Total index***	***Expansive index***	***Accommodating index***	***Contractive index***	***Total index***	***Expansive index***	***Accommodating index***	***Contractive index***	***Total index***	***Expansive index***	***Accommodating index***	***Contractive index***
Magozi	3.08***	0.02	1.06***	4.60***	1.04***	0.39**	2.21***	0.94***	1.32***	-0.09	1.47***	0.82***	2.97***	0.19	1.05***
	(0.35)	(0.34)	(0.25)	(0.74)	(0.16)	(0.19)	(0.51)	(0.17)	(0.16)	(0.29)	(0.30)	(0.14)	(0.35)	(0.29)	(0.25)
25 de Setembro	0.19	-0.30	0.43	0.82	-0.26	-0.39	-0.03	-0.28	-0.04	-0.59	0.21	-0.12	0.21	-0.24	0.43
	(0.58)	(0.40)	(0.27)	(0.98)	(0.51)	(0.51)	(0.98)	(0.49)	(0.39)	(0.98)	(0.45)	(0.30)	(0.63)	(0.40)	(0.29)
Control function	-	1.92*	–	–	–	–	–	–	–	1.52*	–	–	–	1.38**	–
		(0.99)								(0.84)				(0.56)	
Constant	0.48	2.37**	-0.28	0.38	-0.02	-0.55*	-2.80***	0.46*	-1.42***	0.36	-2.63***	-1.46***	0.46	1.82***	-0.27
	(0.60)	(1.04)	(0.34)	(1.12)	(0.24)	(0.28)	(0.75)	(0.25)	(0.30)	(0.88)	(0.45)	(0.23)	(0.59)	(0.69)	(0.35)
AIC	951.26	763.83	732.14	1303.67	1013.11	781.37	490.01	1362.33	294.48	320.17	193.77	330.32	2260.72	2260.72	2260.72
BIC	1026.28	842.42	807.15	1378.68	1088.12	856.39	565.02	1437.34	369.50	398.75	268.79	405.34	2489.34	2489.34	2489.34
Observations	263	263	263	263	263	263	263	263	263	263	263	263	263	263	263
R-squared	0.69	0.51	0.32	0.60	0.27	0.18	0.29	0.30	0.31	0.23	0.23	0.17	0.71	0.55	0.37
Wald χ^2/F-test	29.83***	464.51***	7.16***	20.31***	320.88***	220.54***	262.18***	269.42***	462.76***	191.74***	160.40***	378.55***	695.75***	370.06***	169.69***
Log pseudo likelihood	–	–	–	–	-485.55	-369.68	-224.00	-660.16	-126.24	-138.08	-75.88	-144.16	–	–	–

Notes: Bootstrap standard errors are in parentheses (with 1, 000 replications) when climate perception was endogenously associated with farm adaptation; otherwise, robust standard errors are in parentheses.

***p≤0.01; **p≤0.05; *p≤0.1

'–' represents not applicable

[a] This analysis aimed to examine the sensitivity of estimated findings to differences in sample size (e.g., using the full sample employed in the cross-sectional analysis (n=371) versus those used in the two waves of analysis (n=263)). Accordingly, this analysis (Table C.9, Appendix C) presents the results of planned adaptation practices using the sample utilised for the two waves of analysis (n=263), whereas Table 4.4 illustrated results with the full sample employed in the cross-sectional analysis (n=371).

Table C.10 Binary probit and recursive bivariate probit regression results of individual expansive farm adaptation practices across six SSA irrigation schemes in 2014 (n=371)

	Expansive practices[a]						
Variables	*Increased irrigated area*	*Acquired more irrigated area*	*Acquired more dryland area*	*Acquired agricultural implement*	*Intensified crop production*	*Sold more crop production*	*Increased livestock*
Male	0.07	0.14	0.12	-0.20	-0.05	-0.01	-0.47**
	(0.20)	(0.22)	(0.23)	(0.19)	(0.20)	(0.20)	(0.20)
Age	-0.02**	-0.02***	-0.00	-0.01	-0.01	0.00	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Primary school	0.52**	0.87***	0.52**	0.56**	0.47**	0.31	0.62***
	(0.25)	(0.28)	(0.26)	(0.22)	(0.23)	(0.27)	(0.21)
Secondary school or above	0.13	0.53	-0.11	0.48*	0.20	0.19	0.51**
	(0.28)	(0.33)	(0.32)	(0.28)	(0.27)	(0.30)	(0.25)
Household size	-0.00	-0.02	-0.06	0.05	0.02	0.02	0.01
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Farming experience	-0.01	0.00	-0.02***	0.01	-0.01	0.01	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Car/motorbike/bicycle	0.50***	0.25	0.45**	0.14	0.37*	0.30	0.09
	(0.19)	(0.19)	(0.19)	(0.19)	(0.19)	(0.20)	(0.19)
Ox/donkey cart	0.07	0.01	0.11	0.12	-0.28	0.14	0.66***
	(0.27)	(0.27)	(0.30)	(0.24)	(0.23)	(0.25)	(0.24)
Livestock	-0.03	-0.02	0.01	-0.03	0.00	-0.03*	-0.04*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
On-farm income	-0.00	0.00*	0.00	0.00	-0.00	-0.00	0.00**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Off-farm income	-0.00	-0.00	-0.00	-0.00**	-0.00	0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Total land	0.06	-0.15**	-0.07	-0.01	0.22**	0.15**	-0.01
	(0.07)	(0.06)	(0.07)	(0.09)	(0.09)	(0.06)	(0.08)
Source of advice	0.48**	0.78***	0.32	0.53**	0.44*	0.64***	0.59**
	(0.23)	(0.26)	(0.21)	(0.27)	(0.24)	(0.22)	(0.26)
Credit access	0.62**	0.72**	0.17	0.92***	0.87***	0.99***	1.04***
	(0.28)	(0.30)	(0.24)	(0.29)	(0.31)	(0.26)	(0.31)
Climate perception	-1.02***	-0.23	-0.09	-0.47**	-0.08	-0.21	-0.34
	(0.36)	(0.21)	(0.20)	(0.20)	(0.20)	(0.18)	(0.21)
Past adaptation practices	1.72***	1.24***	1.02***	1.63***	1.27***	1.62***	2.12***
	(0.25)	(0.24)	(0.24)	(0.25)	(0.18)	(0.19)	(0.23)
Country: Tanzania	1.17***	1.49***	1.31***	1.73***	1.05***	1.05***	1.35***
	(0.28)	(0.32)	(0.32)	(0.28)	(0.27)	(0.27)	(0.27)
Constant	-0.38	-1.00*	-1.30**	-1.60***	-1.46***	-2.72***	-2.02***
	(0.62)	(0.56)	(0.55)	(0.53)	(0.50)	(0.53)	(0.56)
Rho	0.36*	–	–	–	–	–	–
	(0.22)						
Observations	371	371	371	371	371	371	371
Pseudo R^2	–	0.52	0.41	0.50	0.41	0.36	0.47
Wald χ^2	209.52***	140.10***	125.00***	137.58***	125.17***	149.35***	138.03***
Log pseudo likelihood	-329.09	-122.60	-144.02	-125.51	-146.82	-158.77	-129.23

Notes: Robust standard errors in parentheses

***$p \leq 0.01$; **$p \leq 0.05$; *$p \leq 0.1$

[a] Recursive bivariate probit model when climate perception was endogenously linked with farm adaptation and binary probit model otherwise.

'–' represents not applicable

Table C.11 Binary probit and recursive bivariate probit regression results of individual accommodating farm adaptation practices across six SSA irrigation schemes in 2014 (n=371)

	Accommodating practices[a]			
Variables	*Diversified crops for risk purposes*	*Specialised crops for income purposes*	*Diversified crops for labour purposes*	*Consumed more crop production*
Male	0.04	-0.09	0.35*	0.30
	(0.22)	(0.19)	(0.20)	(0.21)
Age	-0.01	-0.00	-0.00	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Primary school	0.61**	0.07	0.47	0.65***
	(0.26)	(0.23)	(0.30)	(0.25)
Secondary school or above	0.36	-0.33	0.26	-0.03
	(0.30)	(0.26)	(0.34)	(0.28)
Household size	0.04	-0.00	0.02	0.03
	(0.04)	(0.03)	(0.04)	(0.04)
Farming experience	0.01	-0.01	0.00	0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Car/motorbike/bicycle	0.56***	0.26	0.00	0.06
	(0.21)	(0.16)	(0.20)	(0.20)
Ox/donkey cart	-0.15	-0.30	0.27	0.23
	(0.26)	(0.23)	(0.27)	(0.27)
Livestock	-0.00	0.02	-0.01	0.00
	(0.02)	(0.01)	(0.02)	(0.02)
On-farm income	-0.00	0.00	0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Off-farm income	0.00	-0.00***	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Total land	0.15	0.10	0.21***	0.12*
	(0.09)	(0.06)	(0.06)	(0.06)
Source of advice	0.36	0.53***	0.60***	0.21
	(0.25)	(0.19)	(0.23)	(0.23)
Credit access	0.93***	0.59***	0.42	0.19
	(0.27)	(0.19)	(0.28)	(0.31)
Climate perception	-0.43**	-0.84**	-0.31	-0.21
	(0.20)	(0.33)	(0.19)	(0.20)
Past adaptation practices	2.04***	1.24***	2.16***	2.32***
	(0.23)	(0.18)	(0.22)	(0.22)
Country: Tanzania	1.11***	0.10	0.18	0.33
	(0.29)	(0.24)	(0.27)	(0.27)
Constant	-1.88***	-0.22	-2.57***	-1.62***
	(0.53)	(0.57)	(0.57)	(0.54)
Rho	–	0.71**	–	–
		(0.29)		
Observations	371	371	371	371
Pseudo R^2	0.50	–	0.40	0.48
Wald χ^2	158.18***	195.99***	117.26***	154.20***
Log pseudo likelihood	-129.49	-391.07	-127.79	-133.26

Notes: Robust standard errors in parentheses

***p≤0.01; **p≤0.05; *p≤0.1

[a] Recursive bivariate probit model when climate perception was endogenously linked with farm adaptation and binary probit model otherwise.

'–' represents not applicable

Table C.12 Binary probit and recursive bivariate probit regression results of individual contractive farm adaptation practices across six SSA irrigation schemes in 2014 (n=371)

	Contractive practices[a]				
Variables	***Decreased irrigated area***	***Disposed irrigated land***	***Disposed dryland area***	***Disposed agricultural implements***	***Decreased livestock***
Male	-0.22	0.28	-0.37*	-0.13	-0.66***
	(0.30)	(0.24)	(0.19)	(0.26)	(0.25)
Age	-0.00	0.00	0.00	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Primary school	-0.41	-0.13	0.01	-0.04	-0.12
	(0.31)	(0.30)	(0.21)	(0.38)	(0.25)
Secondary school or above	-1.25***	-0.35	-0.38	-0.75*	0.04
	(0.45)	(0.40)	(0.26)	(0.43)	(0.31)
Household size	0.04	0.07	0.03	-0.04	0.01
	(0.05)	(0.04)	(0.04)	(0.05)	(0.04)
Farming experience	-0.00	-0.01	-0.02***	-0.00	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Car/motorbike/bicycle	-0.10	-0.03	-0.05	-0.19	0.16
	(0.25)	(0.24)	(0.18)	(0.26)	(0.20)
Ox/donkey cart	-0.00	-0.42	0.82**	0.01	0.45
	(0.47)	(0.39)	(0.41)	(0.38)	(0.32)
Livestock	0.02	0.01	0.00	0.04*	0.01
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)
On-farm income	-0.00	-0.00**	-0.00	-0.00**	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Off-farm income	-0.00	0.00	-0.00*	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Total land	0.06	0.10	0.20***	0.23***	0.10
	(0.09)	(0.08)	(0.06)	(0.08)	(0.07)
Source of advice	0.41*	0.20	0.04	0.72**	0.02
	(0.24)	(0.25)	(0.18)	(0.29)	(0.20)
Credit access	0.34	-0.01	0.63**	0.48	0.52**
	(0.29)	(0.33)	(0.30)	(0.32)	(0.23)
Climate perception	-0.11	0.16	-1.99***	-0.06	0.22
	(0.24)	(0.22)	(0.17)	(0.25)	(0.20)
Past adaptation practices	1.80***	1.25***	1.02***	2.68***	0.99***
	(0.27)	(0.26)	(0.27)	(0.33)	(0.18)
Country: Tanzania	1.61***	0.90**	1.63***	1.14**	1.70***
	(0.56)	(0.40)	(0.37)	(0.45)	(0.33)
Constant	-2.27***	-2.88***	-0.92	-2.36***	-1.90***
	(0.69)	(0.68)	(0.56)	(0.62)	(0.53)
Rho	–	–	13.22***	–	–
			(2.37)		
Observations	371	371	371	371	371
Pseudo R^2	0.39	0.26	–	0.51	0.27
Wald χ^2	102.29***	73.00***	392.98***	86.68***	81.98***
Log pseudo likelihood	-87.51	-87.47	-291.61	-70.17	-144.71

Notes: Robust standard errors in parentheses
***p≤0.01; **p≤0.05; *p≤0.1
[a] Recursive bivariate probit model when climate perception was endogenously linked with farm adaptation and binary probit model otherwise.
'–' represents not applicable

Table C.13 Attrition tests on key household characteristics across five SSA irrigation schemes in 2017 (n=381)

	Non-attritors (n=273)	***Attritors (n=108)***	***Difference***
Household characteristics	***Mean/percentage[a]***	***Mean/percentage***	***(t / χ^2 test)***
Male	0.71	0.77	-0.06
Age	51.31	52.01	-0.69
Primary school	0.64	0.67	-0.03
Secondary school or above	0.21	0.19	0.01
Household size	5.65	5.35	0.30
Farming experience	24.84	24.59	0.25
Car/motorbike/bicycle	0.62	0.68	-0.06
Ox/donkey cart	0.26	0.20	0.06
Livestock	3.30	2.86	0.44
On-farm income	872.99	811.46	61.52
Off-farm income	556.40	580.55	-24.14
Total land	1.67	1.75	-0.08
Source of advice	0.67	0.65	0.02
Credit access	0.13	0.15	-0.02
Environment investment index	4.32	4.29	0.03

Note: [a] Instead of using all the 402 farm households surveyed in the baseline survey, only 381 respondents were utilised for the attrition analysis. This is mainly because of 1) missing data and 2) all surveyed households from Khanimambo scheme were not incorporated in the analyses, given this scheme was severely impacted through flooding.

Table C.14 Actual farming practices intensities and changes across five SSA irrigation schemes in 2014 and 2017 (n=263)

	Actual farm practices intensities in 2014 and 2017			*Changes in actual farm practice intensities between 2014 and 2017*					
				Positive change: 2017>2014		*No change: 2017=2014*		*Negative change: 2017<2014*	
Farm adaptation practices	***Mean (2014)***	***Mean (2017)***	***Difference [a] (2017-2014)***	***n***	***%***	***n***	***%***	***n***	***%***
Irrigated area (ha)	0.74	0.98	0.24***	175	66.54	10	3.80	78	29.66
	(0.79)	(0.05)	(0.80)						
Dryland area (ha)	0.63	0.95	0.32***	150	57.03	31	11.79	82	31.18
	(0.85)	(0.95)	(1.08)						
Livestock holding (TLU)	3.38	4.72	1.34***	169	64.26	16	6.08	78	29.66
	(5.35)	(8.31)	(5.22)						
Crop diversification for risk	2.60	4.54	1.94***	207	78.71	34	12.93	22	8.37
and labour purposes	(0.09)	(0.12)	(0.11)						

Notes: Standard errors in parentheses

[a] Paired t-test of difference in means between 2017 and 2014

***$p \leq 0.01$; **$p \leq 0.05$; *$p \leq 0.1$

Table C.15 Proportional test difference of planned (2014-2017) vs actual (2017) farm adaptation practices across five SSA irrigation schemes in 2014 and 2017 (n=263)

	Planned practices: 2014–2017		*Actual practice in 2017*[a]		
Farm adaptation practices	***n***	***%***	***n***	***%***	***Difference***
Increased irrigated area (dummy)	128	48.67	175	66.54	0.18***
Decreased irrigated area (dummy)	32	12.17	78	29.66	0.17***
Acquired more dryland area (dummy)	100	38.02	150	57.03	0.19***
Disposed dryland area (dummy)	29	11.03	82	31.18	0.20***
Increased livestock (dummy)	165	62.74	169	64.26	0.02
Decreased livestock (dummy)	50	19.01	78	29.66	0.11***
Diversified crops for risk purposes (dummy)[b]	136	51.71	192	73.00	0.21***

Notes: ***p≤ 0.01; **p≤0.05; *p≤0.1

[a] The actual farm adaptation practice figures as well as proportional test results needs to be interpreted with caution, given both the *'increasing'* and *'decreasing'* indicator variables were constructed from the same practices. Probably this could be one reason as to why actual farm adaptation practices were greater than the planned farm adaptation practices.

[b] Crop diversification for risk and labour purpose in the baseline survey was asked separately for each farmer. However, in the end of the project survey, as crop diversification indicator dummy variable was constructed from the number of crop types grown by farmers, we are not able to know whether farming households diversify crops for risk, labour or for both purposes. With this in mind, we combined the baseline survey responses of crop diversification for risk and labour purpose together as one variable and used in the two waves of analysis.

Table C.16 Summary statistics of dependent and independent variables across five SSA irrigation schemes in 2014 and 2017 (n=263)

Definition of variables	*Unit of measurements*	*Mean*	*Std. Dev.*	*Min*	*Max*
Dependent variables: Planned individual farm adaptation practices (using 2014 survey data responses for 2014-2017)					
Increased irrigated area (planned)	1=yes; 0=otherwise	0.49	0.50	0	1
Acquired more dryland area (planned)	1=yes; 0=otherwise	0.38	0.49	0	1
Increased livestock (planned)	1=yes; 0=otherwise	0.63	0.48	0	1
Diversified crops for risk and labour purposes (planned)	1=yes; 0=otherwise	0.57	0.50	0	1
Decreased irrigated area (planned)	1=yes; 0=otherwise	0.12	0.33	0	1
Disposed dryland area (planned)	1=yes; 0=otherwise	0.11	0.31	0	1
Decreased livestock (planned)	1=yes; 0=otherwise	0.19	0.39	0	1
Dependent variables: Actual individual farm adaptation practices (using 2017 survey data responses for the period 2014-2017)					
Increased irrigated area (actual)	1=yes; 0=otherwise	0.67	0.47	0	1
Acquired more dryland area (actual)	1=yes; 0=otherwise	0.57	0.50	0	1
Increased livestock (actual)	1=yes; 0=otherwise	0.64	0.48	0	1
Diversified crops for risk and labour purposes (actual)	1=yes; 0=otherwise	0.73	0.44	0	1
Decreased irrigated area (actual)	1=yes; 0=otherwise	0.30	0.46	0	1
Disposed dryland area (actual)	1=yes; 0=otherwise	0.31	0.46	0	1
Decreased livestock (actual)	1=yes; 0=otherwise	0.30	0.46	0	1
Independent variables (using 2014 survey data responses for 2014-2017)					
Male	1=male; 0= otherwise	0.71	0.46	0	1
Age	Age of household head in years	51.37	16.44	18	92
Primary school	1=attended primary school; 0= otherwise	0.65	0.48	0	1

Table C.16 (continued)

Definition of variables	*Unit of measurements*	*Mean*	*Std. Dev.*	*Min*	*Max*
Secondary school or above	1=attended secondary school or above; 0=otherwise	0.20	0.40	0	1
Household size	Number of persons	5.59	2.24	1	10
Farming experience	Dryland farming experience in years	24.93	16.03	0	70
Car/motorbike/bicycle	1=own car, motorbike or bicycle; 0=otherwise	0.62	0.49	0	1
Ox/donkey cart	1=own ox/donkey cart; 0=otherwise	0.27	0.44	0	1
Livestock holding	Tropical livestock units (TLU)	3.38	5.35	0	23.94
On-farm income	Income from crop sale and animal product sale in USD (in 2014 prices)	891.51	1441.29	0	9073.15
Off-farm income	Income from off-farm activities in USD (in 2014 prices)	551.21	976.39	0	5708.85
Total land	Hectares of total farmland	1.66	1.37	0.2	7.28
Source of advice	1=extension officer; 0=otherwise	0.68	0.47	0	1
Credit access	1=accessed loan from financial institutions/other institutions/individuals; 0=otherwise	0.13	0.33	0	1
Climate perception	1=temperature has increased/become more unpredictable over the past 10 years; 0=otherwise	0.71	0.45	0	1
Increased irrigated area (past 3 years)	1=yes; 0=otherwise	0.28	0.45	0	1
Acquired more dryland area (past 3 years)	1=yes; 0=otherwise	0.19	0.39	0	1
Increased livestock (past 3 years)	1=yes; 0=otherwise	0.46	0.50	0	1
Diversified crops for risk and labour purposes (past 3 years)	1=yes; 0=otherwise	0.33	0.47	0	1
Decreased irrigated area (past 3 years)	1=yes; 0=otherwise	0.10	0.29	0	1
Disposed dryland area (past 3 years)	1=yes; 0=otherwise	0.09	0.29	0	1
Decreased livestock (past 3 years)	1=yes; 0=otherwise	0.26	0.44	0	1
Country dummy: Tanzania	1=Tanzania; 0=otherwise	0.18	0.39	0	1

Table C.17 Summary of the full binary probit regression results of the comparison of planned and actual individual farm practices for the period 2014-2017 (n=263)

Variables	*Increase irrigated area*	*Acquire more dryland area*	*Increase livestock*	*Diversify crops for risk and labour purposes*	*Decrease irrigated area*	*Disposed dryland area*	*Decrease livestock*	*Increased irrigated area*	*Acquire d more dryland area*	*Increased livestock*	*Diversified crops for risk and labour purposes*	*Decreased irrigated area*	*Disposed dryland area*	*Decreased livestock*
Male	-0.08	0.34	-0.34	0.09	0.29	-0.21	-0.80***	0.74***	0.61***	-0.29	0.57**	-0.66**	-0.60***	0.17
	(0.24)	(0.27)	(0.23)	(0.24)	(0.43)	(0.37)	(0.30)	(0.25)	(0.21)	(0.21)	(0.23)	(0.29)	(0.23)	(0.22)
Age	-0.02**	0.00	-0.00	-0.02*	-0.01	0.01	-0.02	-0.01	-0.01*	-0.00	0.00	0.00	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Primary school	0.71**	0.68**	0.77***	0.89***	-0.00	0.47	0.06	-0.04	-0.18	-0.22	0.21	0.26	-0.09	0.40
	(0.31)	(0.28)	(0.27)	(0.27)	(0.50)	(0.47)	(0.31)	(0.28)	(0.23)	(0.25)	(0.25)	(0.35)	(0.24)	(0.27)
Secondary school or	0.15	0.27	0.34	-0.19	-1.04	0.41	0.18	-0.11	-0.62**	-0.31	0.03	0.61	0.22	0.59*
above	(0.35)	(0.36)	(0.31)	(0.32)	(0.68)	(0.56)	(0.41)	(0.35)	(0.30)	(0.31)	(0.33)	(0.43)	(0.31)	(0.32)
Household size	0.02	-0.08*	-0.00	0.01	-0.00	0.00	-0.00	-0.01	-0.11***	0.02	0.01	0.03	0.11***	-0.02
	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Farming experience	-0.00	-0.02**	0.00	0.01	-0.00	-0.03**	-0.00	-0.01	0.01**	-0.01**	-0.00	-0.00	-0.01	0.01*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Car/motorbike/bicycle	0.45*	0.08	-0.11	0.55**	-0.54*	-0.12	-0.08	0.30	0.11	0.43**	0.50**	-0.46**	0.01	-0.40*
	(0.24)	(0.23)	(0.21)	(0.24)	(0.30)	(0.30)	(0.27)	(0.22)	(0.19)	(0.20)	(0.20)	(0.24)	(0.21)	(0.21)
Ox/donkey cart	-0.39	0.10	0.43	0.16	0.42	0.67	0.51	-0.31	-0.08	-0.11	0.16	0.63	0.08	0.20
	(0.33)	(0.35)	(0.28)	(0.30)	(0.65)	(0.41)	(0.45)	(0.31)	(0.26)	(0.25)	(0.32)	(0.38)	(0.28)	(0.26)
Livestock	-0.03	0.02	-0.03	-0.02	0.06*	0.01	-0.00	0.00	0.00	-0.00	0.00	-0.01	-0.00	0.01
	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
On-farm income	-0.00	0.00	0.00*	0.00	-0.00	-0.00	-0.00	0.00	0.00	-0.00***	-0.00	-0.00	-0.00	0.00**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Off-farm income	0.00	-0.00	0.00	0.00	0.00	0.00	0.00	-0.00	-0.00	-0.00*	-0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Total land	0.06	-0.06	0.09	0.08	0.15	0.34***	0.15*	-0.17**	-0.34***	0.20**	-0.14*	0.23**	0.45***	-0.17**
	(0.09)	(0.07)	(0.09)	(0.10)	(0.10)	(0.10)	(0.08)	(0.08)	(0.08)	(0.08)	(0.07)	(0.09)	(0.09)	(0.07)
Source of advice	0.64*	0.64**	0.42	0.55*	0.55*	0.32	0.01	0.42*	0.01	-0.16	0.31	-0.13	0.54**	0.53**
	(0.33)	(0.26)	(0.32)	(0.33)	(0.31)	(0.30)	(0.25)	(0.23)	(0.23)	(0.23)	(0.25)	(0.23)	(0.24)	(0.25)
Credit access	0.59	-0.05	0.91**	1.22***	0.33	0.62*	0.67**	0.38	0.34	0.28	0.10	-0.17	-0.31	-0.50*
	(0.38)	(0.27)	(0.37)	(0.43)	(0.37)	(0.38)	(0.28)	(0.27)	(0.27)	(0.26)	(0.28)	(0.27)	(0.34)	(0.29)
Climate perception	-0.37	0.03	-0.12	-0.70***	0.11	-0.58**	0.27	0.15	-0.27	0.36**	0.27	-0.14	0.47**	-0.29
	(0.24)	(0.24)	(0.25)	(0.25)	(0.30)	(0.28)	(0.23)	(0.19)	(0.20)	(0.18)	(0.20)	(0.21)	(0.22)	(0.19)
Past adaptation practice	1.86***	0.84***	2.27***	2.00***	2.10***	1.50***	0.95***	0.13	0.15	-0.22	-0.09	-0.18	-1.04**	-0.16
	(0.32)	(0.29)	(0.28)	(0.28)	(0.37)	(0.33)	(0.22)	(0.21)	(0.23)	(0.18)	(0.21)	(0.30)	(0.47)	(0.21)

Table C.17 (continued)

Variables	*Increase irrigated area*	*Acquire more dryland area*	*Increase livestock*	*Diversify crops for risk and labour purposes*	*Decrease irrigated area*	*Disposed dryland area*	*Decrease livestock*	*Increased irrigated area*	*Acquire d more dryland area*	*Increased livestock*	*Diversified crops for risk and labour purposes*	*Decreased irrigated area*	*Disposed dryland area*	*Decreased livestock*
Country: Tanzania[a]	1.15***	1.82***	0.86**	0.45	2.53***	2.50***	1.78***	-1.88***	-0.50*	-0.33	-0.44	2.63***	0.46	0.58*
	(0.35)	(0.37)	(0.36)	(0.35)	(0.62)	(0.51)	(0.42)	(0.33)	(0.30)	(0.29)	(0.33)	(0.38)	(0.32)	(0.32)
Constant	-0.72	-1.83***	-1.64**	-1.01*	-3.62***	-4.04***	-1.63**	1.22**	1.83***	1.01*	0.06	-2.17***	-2.61***	-1.83***
	(0.64)	(0.67)	(0.68)	(0.61)	(1.11)	(0.87)	(0.65)	(0.61)	(0.55)	(0.57)	(0.59)	(0.66)	(0.56)	(0.61)
Observations	263	263	263	263	263	263	263	263	263	263	263	263	263	263
Pseudo R^2	0.55	0.44	0.49	0.46	0.45	0.41	0.29	0.23	0.14	0.09	0.10	0.33	0.22	0.11
Wald χ^2	115.35***	113.92***	101.57***	93.22***	81.77***	81.40***	72.39***	69.22***	48.08***	27.95**	26.32*	79.88***	62.76***	30.63**
Log pseudo likelihood	-81.91	97.69	-88.76	-94.36	-53.47	-53.89	-91.14	-129.60	-154.98	-155.61	-121.96	-107.74	-127.07	-142.66

Notes: ***p≤0.01; **p≤0.05; *p≤0.1

[a] Since all irrigators in some irrigation schemes did not plan to and actually implement some individual farm adaptation practices (e.g., *'acquire more dryland area'*, *'decrease irrigated area'* and *'disposed dryland area'* by 25 de Setembro scheme irrigators, *'disposed dryland area'* by Silalatshani and Magozi schemes irrigators), it was difficult to include scheme dummies in the modelling. Therefore, country dummy was used in the two waves of data analysis. Robust standard errors in parentheses.

Appendix D Household Survey Questionnaires

Appendix D.1 The baseline (first) project survey questionnaire

Farm household survey for ACIAR funded project: increasing irrigation water productivity in Mozambique, Tanzania and Zimbabwe through on farm monitoring, adaptive management and agricultural innovation platforms

Introductory statement

This survey is carried out by Ardhi university, Government of Tanzania, in collaboration with the University of South Australia and the Australian National University as part of the project 'Increasing Irrigation Water Productivity in Mozambique, Tanzania and Zimbabwe through on farm monitoring, adaptive management and agricultural innovation platforms' funded by the Australian International Centre for Agricultural Research. The purpose of the survey is to establish farm and household characteristics of irrigator households as well as how you perceive a number of issues related to your irrigation scheme and your community. We will at least conduct one survey at the beginning of this project and one at the end so that we can identify any changes taking place during the process of implementing the Agricultural Innovation Platform. Your responses to these questions will remain anonymous but you will be given a household ID which is only known to the researchers on the project. This ID will allow us to contact you later and to compare your answers from the first and subsequent surveys. Information will be treated as strictly confidential.

All the questions in this survey are about your farm and household situation during the 2013/14 season. We would like to interview a member of the HH who is either a key decision maker or is actively involved in farming activities within the HH.

Thanks you for your co-operation in this survey and we are looking forward to talk to you again over the coming years.

Name of Irrigation Scheme: ____________________ Scheme code: ________________Household Head Name: __________________________

Common Household Name: ___________________________Respondent/Interviewee: _____________________________

Relation to HH Head: ___________________________Interviewer/Enumerator: ________________________Date:______________________

1 Questions about your household

1. Who are the members of your household? *(First, ask about the head of household, then list the members of the household as each person relates to the head of household. Then fill out the rest of the table using the below keys)*

HH No	Name of HH member	Relation to HH Head	*Marital Status*	*Gender*	*Age*	*Education*	*Children Edu. exp.*	*Children not at school*	*Working on farm (%)*	*Working off farm (%)*	*Working away 1=Yes; 2=No*	*How long working away*	*Health*
1													
2													
3													
4													
5													
6													
7													
8													
9													
10													
11													

Answer Key:

Marital status: 1=never married; 2=Married/de facto; 3=married but not living with partner; 4=divorced; 5=Separated; 6=Widowed

Relation to HH Head:1=Head; 2=Husband; 3=wife; 4=Son; 5=Daughter; 6=Parent; 7=Grandchild; 8=Other(specify)

Gender:1=male; 2=female

Age: Please record actual or estimated age in years

Education: 1=no formal schooling; 2=some primary school; 3=completed primary school; 4=some secondary school; 5=completed secondary school; 6=some university or college; 7=Professional College/trade certificate; 8=still at school; 9=not started school yet; 10=other, specify

Children Edu. Exp. (Educational expectations): For each child not yet started school or still attending school, ask: after which year/level do you expect them to finish school?

Children not at school: For children not at school and not having finished high school: Why did they stop going to school? 1=Had to contribute to work on the farm; 2=Had to work off-farm to contribute to the family income; 3=We could not afford to pay the cost of keeping him/her in school; 4=We do not think he/she needs any further schooling; 5=Not yet started schooling 6=Child did not want anymore, 7=Other, specify

Working on farm: % of time spend working on the farm (includes selling or transport produce at the market or processing produce)

Working off-farm: % of time spend working off-farm

Working away: seasonal work away from home: which household members work away from home

How long working away: On average how long time do they spend away from home (1=days, 2=weeks or 3=months)? Please explore: how many month, week, days etc. to reach percentage **Healt**h: How do you consider each household's members' health: 1=Good (<5 days); 2=infrequently sick (6-10 days); 3=Frequently/regularly sick (>10 days); 4=Bed ridden

2. Was the head of household born in this village 1=Yes ☐; 2=No ☐

   b=If the answer is no to the above question: How many years have you lived in this village? ☐

   c=And, why did you move to this village? ☐

   d=What is the main language spoken in your household?

   1=Ndebele; 2=Shona; 3=Other Zim (specify); 4=Shangana; 5=Ronga; 6=Portuguese; 7=Other Moz (specify)

3. How many years has the household been farming? Years: Dry land farming _________ Irrigation farming ______ Irrigation scheme_______

Let's discuss the food security situation of your household

4. Have you faced food shortage (i.e., not sufficient food from your own production) over the last 5 years (2009-2014)? 1=Yes ☐ 2=No ☐ *(If No, go to Q9)*
5. On average, during which months do you face food shortage in a given year? (*Please circle the months mentioned*): J F M A M JJ A S O N D
6. If you did not have access to an irrigated plot during which months would you face food shortage? (*Please circle the months mentioned):*

   J F M A M JJ A S O N D

7. Out of the last five years, how many years were you faced with food shortages? Number of years? ☐
8. What is the main cause of food shortage in your household?

   1=Drought ☐; 2=Poor harvest ☐; 3=Lost job ☐; 4=Death in the family ☐; 5=Unreliable income ☐; 6=Inflation ☐; 7=Theft ☐;

   8=family size ☐; 9=Irrigation scheme not functional ☐; 10=Other (specify) ☐

9. Have you received food aid in any form over the last five years? 1=Yes ☐; 2=No ☐ If yes, how many times? Number of years: ☐

10. Have you sold produce from the irrigation scheme to overcome your food shortage? 1=Yes; 2=No

    If yes, 1=During a normal year? ☐; 2=During a drought year? ☐

11. If you did not have access to the irrigation scheme, how would you have secured your food needs?

    Describe: ☐

12. Nutrition and food access; please indicate how often you access the following food items: *(see answer key below table)*

How often does your household	milk	sugar	Meat	fish	beans	other vegetables	fruits
a. eat/drink							
b. purchase							
Codes frequency: 1=daily, 2=weekly, 3=monthly, 4=seasonally/occasionally, 5=yearly, 6 =never 7=other (specify)							

13. Which of the following assets does the household or somebody in your household own?*(Tick all applicable boxes)*

Household assets:

1=Generator	☐	2=Car	☐	3=Motorbike/scooter	☐	4=Bicycle	☐
5=Fridge	☐	6=Sewing machine	☐	7=Radio	☐	8=TV	☐
9=Solar panel	☐	10=Borehole/water pump	☐	11=Mobile phone	☐	12=others specify	☐

Type of dwelling: 1=Brick ☐ 2=mud, grass ☐

Type of roofing: 1=Timber ☐ 2=Thatched roof ☐ 3=metal or other solid roof ☐

Farm assets:
1=Tractor ☐; 2=Tractor-driven tools ☐; 3=Hand tools ☐; 4=Animal-driven tools ☐; 5=Wheel Barrow ☐; 6=☐Ox/donkey cart ☐; 7=Other (specify) ☐; 8=Disc plough ☐; 9=Harrow Plough ☐

14. Which of the following financial arrangements do you have? *(Tick all applicable boxes)*

1=Functional bank account	☐	2=Savings account	☐
3=Traditional savings schemes at local community level	☐	4=Traditional burial schemes at local community level	☐
5=Loan from a financial institution	☐	6=Loan from an individual (*specify e.g. uncle, neighbour, trader etc)*	☐
7=Loan from other institution (*please specify e.g. church, government)*	☐	8=*Don't know*	☐
9=No account	☐	10=other (*please specify)*	

15. Do you think your participation in the irrigation scheme will provide you with a better life in the future? *(Tick one box only)*

1=Much worse	☐	3=Better	☐	5=About the same	☐
2=Worse	☐	4=Much better	☐	6=Don't Know	☐

7=No, I think we need to opt out of agriculture to achieve a better life in the future ☐

2 Questions about your Farm

16a. Next, we would like to draw a map that outlines your fields and homestead. Start by showing your homestead compound. Then draw the fields closest and furthest in a picture on the ground. Our enumerator will transcribe this onto this page. Show any major landmarks near your homestead/fields like roads, school, and borehole. (Draw map and crops grown in the 2013/14 season here).

16b. Please tell us about the land you and your household cultivates, who controls it and how (own/lease/share-farm): (*use keys below to fill out the form) (this should be similar to the areas and crops you have indicated on the map drawn in 16a)*

	Area	*Unit of measurement 1=ha; 2=acres; 3=m^2*	*Who owns*	*Type of ownership*	*Soil type*	*Soil fertility*	*Slope*	*Erosion*
Land which can be irrigated:								
Irrigated plot (IP) 1								
Irrigated Plot 2								
Uncultivated during 13/14								
Farmed without irrigation in 13/14								
Rainfed Land:								
Rainfed Plot 1								
Rainfed Plot 2								
Uncultivated during 13/14								
Home garden (HG)								
Total land area			NA	NA	NA	NA	NA	NA

Interviewer: add up and make sure that the area for irrigated +rain-fed +uncultivated ads up to the total area. If not ask questions until the numbers add up.

Answer Keys:

Who owns: note the person(s) who controls the land using the number(s) from question 1 i.e.1=Head; 2=Husband; 3=wife; 4=Son; 5=Daughter; 6=Parent; 7=Grandchild; 8=husband and wife 9=Other(Specify)

Type of ownership/access: 1=private title and use; 2=Government tenure; 3=Community tenure (no written lease); 4=Leased in (used others land and paid); 5=leased out (others use my land and pay); 6=borrowed land without paying; 7=share cropping in; 8=share cropping out; 9=other specify, 10=used land <10 years, 11=used land>10 years, 12=others use my land without paying
Soil type:1=Sandy, 2=clay, 3=black soil, 4=red soil
Soil fertility: 1=Very fertile, 2=moderately fertile; 3=infertile
Slope: 1=flat; 2=slight slope (up to 20%), 3=steep
Erosion: 1=no erosion; 2=moderate erosion; 3=severe erosion

17. If rain fed land or irrigated land is uncultivated: Why are you not cultivating all your rain fed/irrigated land? *Please provide the answers here: (specify rain-fed/irrigated land)*

18. **Crop production –** (please fill out the following table, and check area sizes with question 16, note that the cultivated land should sum up)

Plot (refer to the map)									
crop name									
type/variety									
area size									
Unit of area (1=ha; 2=acres 3=m^2)									
tillage implement									
tillage passes (no)									
Date sown									
seed [unit]									
Farm yard manure									
Other manure. ________									
fertiliser 1, top dress									
fertiliser 2, basal									
fertiliser 3 _________									

fertiliser 4 ________									
total fertl expenses mt(US)									
herbicide expenses (US)									
fungi/pesticideexp (US)									
% of irrigation water used									
Type of harvest									
water expenses (US/MT/sh)									
Cost of non-family labour									
Date harvested									
Output									

Answer Key:

Plot number: for each of plots of crop grown ask which of the plots in question 16 the crops was grown on (e.g., IP1 or RF 2)

Crop: 1=Maize; 2=Sorghum; 3=Ground nut; 4=Tobacco; 5=Cotton; 6=Cow pea; 7=Pigeon pea; 8=Irish potato; 9=Sweet potato; 10=Tomato; 11=Finger Millet; 12=Bambara nut; 13=Sugar beans; 14=Sun flower; 15=Soya bean; 16=rice; 17=Other cereal crops; 18=Other legume crops; 19=Other vegetables; 20=Fruits; 21=Feed crop, 22=cabbage, 23=onion, 24=lettuce, 25=carrots, 26=green beans, 27=peppers, 28=chillies

Tillage implement: 1=harrow; 2=disk; 3=rotavator, 4=plough, 5=other, please specify

Type of harvest: 1=manual; 2=mechanical

Months: 1=Jan; 2=Feb; 3=Mar; 4=Apr; 5=May; 6=Jun; 7=Jul; 8=Aug; 9=Sep; 10=Oct; 11=Nov; 12=Dec

19. What is your use of your main crop products (SHELLED or NOT):

Crop name (use code)	*% eaten*	*% seed*	*% feed*	*% sold/barter*	*If sold, specify market channel (code)*	*Main months of sale*	*Average price per kg (and range)*

Answer Key:
crops 1=Maize, 2=Sorghum, 3=Ground nut, 4=Tobacco, 5=Cotton, 6=Cow pea, 7=Pigeon pea, 8=Irish potato, 9=Sweet potato, 10=Tomato, 11=Finger Millet,12=Bambara nut, 13=Sugar beans, 14=Sun flower, 15=Soya bean, 16=rice, 17=Other cereal crops, 18=Other legume crops, 19=Other vegetables, 20=Fruits, 21=Feed crops, 22=cabbage, 23=onion, 24=lettuce, 25=carrots, 26=green beans, 27=peppers, 28 chillies
Market channel: 1=farm gate, 2=village market, 3=local collection point, 4=cooperative for bulk sales, 5=regular trader, 6=contract with buyer, 7=regional city, 8=wholesaler
Prices: provide average price, and range if prices differed substantially by time of sales
Months: 1=Jan; 2=Feb; 3=Mar; 4=Apr; 5=May; 6=Jun; 7=Jul; 8=Aug; 9=Sep; 10=Oct; 11=Nov; 12=Dec

20. Which crops have you not yet grown, but would like to adopt?

Crop (use code)	*For what purpose?*	*What prevents you from adoption?*

Answer key: Crops 1=Maize; 2=Sorghum; 3=Ground nut; 4=Tobacco; 5=Cotton; 6=Cow pea; 7=Pigeon pea; 8=Irish potato; 9=Sweet potato;10=Tomato; 11=Finger Millet; 12=Bambara nut; 13=Sugar beans;14=Sun flower; 15=Soya bean; 16=rice; 17=Other cereal crops;18=Other legume crops;19=Other vegetables; 20=Fruits; 21=Feed crops; other, specify, 22=cabbage, 23=onion, 24=lettuce, 25=carrots, 26=green beans, 27=peppers, 28=chillies

21. Do you think you got the best possible price for your commodities or do you think there are other buyers/market channels that would pay a better price?

    1=Yes, there are other buyers that would pay a better price ☐; 2=No, this is the best price I can get ☐; 3=Don't know ☐

22. If yes in the question above: Why do you not sell to that buyer/market channel?

    Please provide the answer here: ☐

23. Did you buy any fertiliser and/or farm chemicals during the 2013/14 season? *(Tick all that apply)*

    1=Yes 2=No, If your answer to the above is Yes, tell us more on how these were bought

    1=Seller came to the village ☐; 2=I bought it from a wholesale business in a nearby town ☐; 3=Through irrigation association ☐

    4=I bought it on the nearest local market ☐ 5=Other, specify ☐

24. Do you think you could get it cheaper somewhere else? *(Tick one box only)*

    1=Yes, there are other sellers that would be cheaper ☐; 2=No, it was the best possible price ☐; 3=Don't know ☐

24.1 Do you get subsidised/free inputs (seed, fertiliser)? 1=From government? ☐; 2=From NGOs ☐; 3=No, I don't get those ☐

25. If yes to the above question, why did you not buy it there?

    Please provide the answer here: ☐

26. Do you commonly need farm equipment that you do not own? 1=Yes ☐; 2=No ☐

If yes, how do you commonly get access to equipment? *(Tick all that apply)*

1=Rent it from your irrigation association/cooperative ☐
5=Other ☐
2=Rent it from a private contractor ☐
6=Have no ability to access ☐
3=Rent it from a neighbouring farmer for cash or in-kind ☐
7=*Don't know (do not read out only record if no answer)* ☐
4=Borrow it from a neighbouring farmer without payment ☐

27. Would better ability to access farm equipment significantly improve the viability/profitability of your land?

1=Yes ☐; 2=No ☐; 3=Don't know ☐

28. What are the main constraints to improving the viability/profitability of your land? (rank 1-3)

1=Inputs (seeds fertilisers) ☐
2=Implements and tools ☐
3=Knowledge and information ☐
4=Access to functional markets ☐
5=Access to land/Tenure ☐
6=Access to water ☐
7=Quality of water ☐
8=Salinity ☐
9=Other - specify ☐

3 Questions about your Livestock

29. Please tell us the details of your livestock production in the 2013/14 *(please use the answer key below to fill out the form)*

	Number currently owned	*Who own/ Control*	*How many are used as Draft animals*	*Main dry season feed (rank, see codes)*			*Main rainy season feed (rank, see codes)*			*Main dry season water source (rank, see codes)*			*Main rainy season water source(rank, see codes)*			*Costs inputs (MT)*
				1	*2*	*3*	*1*	*2*	*3*	*1*	*2*	*3*	*1*	*2*	*3*	
Cattle																
Donkeys																

Pigs																
Sheep																
Goats																
Chicken																
Ducks																
Other																

Answer key: Number: please provide the number of each category

Who own/control: Who in the Household control land make most decisions regarding these animals: provide number from table in Q1 If more than one provide all person numbers (*1=Head; 2=Husband; 3=wife; 4=Son; 5=Daughter; 6=Parent; 7=Grandchild; 8=husband and wife , 9=Other(specify)*

Feed, in order of importance rank the three most important feed types: 1=rangelands, 2=crop residues grazed in rain fed fields, 3=crop residues collected in rain fed fields, 4=forage planted in rain fed fields, 5=crop residues grazed in irrigation fields, 6=crop residues collected in irrigation fields, 7=forages planted in irrigation fields, 8=purchased stock feed, 9=other (specify)

Water Source, in order of importance rant the three most important water sources: 1=surface water, 2=wells, 3=river, 4=irrigation scheme, 5=borehole, 6=others (specify)

30. Please tell us the details of your livestock marketing during the 2013/14 season: *(please use the keys below to fill out the form)*

	How many were lost/died (specify)	*How many consumed*	*How many sold*	*If sold, specify market channel (code)*	*When did you sell: 1=Jan; 2=Feb; 3=Mar; 4=Apr; 5=May; 6=Jun; 7=Jul; 8=Aug; 9=Sep; 10=Oct; 11=Nov; 12=Dec*	*Average price per animal (range)*
Donkeys						
Cattle						
Pigs						
Sheep						
Goats						
Chicken						
Ducks						
Other						

Answer Key: Who sold to: 1=Farm gate; 2=village market; 3=local business centre, 4=collection point, 5=sale pen; 6=regional auction, 7=regional town, 8=others (specify)

Prices: provide average price, and range if prices differed substantially across animals and time of sales

31. Do you think there are other buyers that would pay a better price?
1=Yes, there are other buyers that would pay a better price ☐; 2=No, it was the best possible price ☐; 3=Don't know ☐

32. If yes to the question above, why did you not sell to that buyer/market channel?
Please provide the answer here:

33. Who makes the major decisions in the household over the following crops and livestock? *(If joint decision by several note all relevant* (i.e.1=Head; 2=Husband; 3=wife; 4=Son; 5=Daughter; 6=Parent; 7=Grandchild; 8=Husband and wife; 9=Other (specify)

	Rain fed crops	*Irrigated crops*	*Cattle*	*Small stock*
What crops/feed to grow				
Use of farm implements				
Buying of inputs				
When to carry out the work				
When and where to sell the products				
How to use the income from sale				

34. When making decisions about your farm (what to grow, where to sell, when to irrigate etc.), where do you seek advice from? *(tick all relevant)*

	Rain fed crops		*Irrigated crops*		*Livestock*	
	Source of information	*Relevance*	*Source of information*	*Relevance*	*Source of information*	*Relevance*
What crops/feed to grow						
How to manage the crops/livestock						
Where to sell the outputs						

Answer key:
Sources of information: 1=Buyers of my crop/livestock; 2=Sellers of farm input; 3=Extension officer; 4=Farmer group/cooperative; 5=Irrigation association; 6=Research; 7=NGOs; 8=Other farmers; 9=Others (specify)
Relevance: 1=Yes, relevant I follow the advice; 2=Sometimes I follow the advice; 3=No, not relevant, I don't follow the advice.

35. If the answer above was 2 or 3 (sometimes or not relevant), why is it not relevant? *Please provide the answer here:*

36. Have you over the last three years, or do you intend to over the next three years:*(Tick all that apply)*

	Last 3 years 1=Yes; 2=No	Next 3 years 1=Yes; 2=No
a. Increased your irrigated area on an annual basis (that is taking multiple cropping into account)	☐	☐
b. Acquired additional irrigated land (either purchased, leased or share farmed)	☐	☐
c. Acquired additional dry farm land (either purchased, leased or share farmed)	☐	☐
d. Acquired any implements to improve the productivity of your land	☐	☐
e. Diversified your crops to better deal with risk	☐	☐
f. Intensified crop production to increase your profit	☐	☐
g. Specialised on certain crops you are growing to increase your income	☐	☐
h. Increased the proportion of your production that you are selling rather than consuming	☐	☐
i. Decreased your irrigated area on an annual basis (that is taking multiple cropping into account)	☐	☐
j. Disposed of any of your irrigated land (either sold, leased out or share farmed out)	☐	☐
k. Disposed of any of your dry farm land (either sold, leased out or share farmed out)	☐	☐
l. Disposed of any implements used to increase the productivity of your land	☐	☐
m. Changes to the crops you are growing to reduce your workload from farming and accepting a lower farm income	☐	☐
n. Increased the proportion of your production that you and your family are consuming	☐	☐
o. Reduced the size of your holding of livestock	☐	☐
p. Increased the size of your holding of livestock	☐	☐

37. Have you used any of these practices on your farm, if so when did you start doing it and are you still doing it?*(Fill all relevant columns)*

Practice	*1=Yes; 2=No*	*When Adopted (years ago)*	*Do you do this every year? 1=Yes; 2=No*	*Why not Used*
Pumping directly from river independently of scheme				
Establish ground water pump				
Carry water in buckets or other devices from local water source				
Growing cover crop				
Run-off harvesting				
Mulching				
Crop rotation				
Accessing other natural resources such as wood, charcoal, fish etc.				
Planting leguminous crops (e.g. cowpea) to utilise remaining soil moisture after harvest of main crop				
Grow crops or varieties which require less water or have a shorter growing season				

38. Do you think that the temperature in your area has generally changed over the past ten years? *(tick one box only)*1=Yes ☐; 2=No ☐

If yes, did it: 1=increase ☐; 2=decrease ☐; 3=became more unpredictable ☐; 4=pattern changed ☐

39. Do you think that rainfall in your area has generally changed over the past ten years? 1=Yes ☐; 2=No ☐*(tick one box only)*

If yes, did it:1=increase ☐; 2=decrease ☐; 3=became more unpredictable ☐; 4=pattern changed ☐

4 Questions about your irrigation

40. How would you define your right to receive water? E.g.: is it to a certain number of irrigation events, a certain flow rate during a certain period of time? *Please provide the answer here:* ☐

41. What do you need to do to receive water? *(Tick all that apply)*

1=I have to order it a certain number of days in advance ☐; 2=Irrigation management committee tells me when I will get the water ☐;

3=Set Irrigation Roster (A certain day per week etc.) ☐; 4=Other (*please specify in box):* ☐

42. Do you always get all the water you need when you order it? *(Tick one box only)*

1=Never ☐; 2=Rarely ☐; 3=Mostly ☐; 4=Always ☐

43. How much do you pay for water? ☐ Price per ha/acres or other**:** ☐

44. Do you think that is a reasonable rate for water? (Tick one box only if the farmer does pay for the water)

1=Far too expensive ☐; 2=Expensive ☐; 3=Fair ☐; 4=Cheap ☐; 5=Very cheap ☐; 6=Not applicable

45. Apart from paying this amount, do you also have to do some work maintaining the irrigation system? (Tick one box only)

1=Yes ☐; 2=No ☐

46. If yes to the question above, what and how much? ☐

47. From which type of canal do you receive your water? *(Write the plot number)*

1=Primary ☐; 2=Secondary ☐; 3=Tertiary ☐; 4=Overflow from neighbouring plot ☐; 5=Don't know ☐

48. Is it lined or earthen? *(Tick one box only)*

1=Lined ☐; 2=Earthen ☐; 3=Don't know ☐; 4=Pipe ☐

49. Is it a permanent canal or temporary furrow/canal? *(Tick one box only)*

1=Permanent ☐; 2=Temporary ☐; 3=Don't know ☐

50. Where on that canal are your plots located: *(Write where the specific plots are)*

1=Beginning ☐; 2=Middle ☐; 3=End ☐; 4=Don't know ☐

51. Overall how satisfied are you with your supply of irrigation water? *(Tick one box only)*

1=Very dissatisfied ☐; 2=Dissatisfied ☐; 3=Neutral ☐; 4=Satisfied ☐; 5=Very satisfied ☐; 6=Don't know ☐

52. Do you think water is equitably distributed among the irrigators in your irrigation system? *(Tick one box only)*

1=Totally disagree ☐; 2=Disagree ☐; 3=Neutral ☐; 4=Agree ☐; 5=Strongly agree ☐; 6=Don't know ☐

53. How do you determine when to irrigate and how much water to apply? *Please write the answer here:*

54. Do you think you could improve the way crops are irrigated? *(Tick one box only)*

1=Yes ☐; 2=No ☐; 3=Don't know ☐

55. If yes to the previous question, please explain how? *(Please provide the answer here):*

57. Over the next five years, how do you expect the adequacy, quality and timing of your water supply to change? *(Tick one box only)*

1=Become much worse ☐; 2=Become worse ☐; 3=Stay the same ☐; 4=Improve ☐; 5=Improve greatly ☐; 6=Don't know ☐

5 Questions about your community

58. How satisfied are you with the support you receive from your local community? *(Tick one box only)*

1=Very dissatisfied ☐; 2=Dissatisfied ☐; 3=Neutral ☐; 4=Satisfied ☐; 5=Very satisfied ☐; 6=Don't know ☐

58.1 Are you member of any group or association? (*Tick*)

1=AIP ☐; 2=Farm producer association ☐; 3=Irrigation scheme association ☐; 4=Church group ☐; 5=Others, specify ☐

59. Thinking about your local community, its wellbeing and the support you receive from it, in five years how good do you think it will be? *(Tick one box only)*

1=Much worse ☐; 2=Worse ☐; 3=About the same ☐; 4=Better ☐; 5=Much better ☐; 6=*Don't know* ☐

60. Within your irrigation district, do you think there is a significant gap between the poorest and wealthiest families? 1=Yes ☐; 2=No ☐

61. If yes, over the past ten years, has this gap: 1=diminished ☐; 2=about the same ☐; 3=Increased ☐; 4=don't know ☐

62. In the future, do you expect this gap to: 1=diminish; ☐ 2=remain the same ☐; 3=Increase ☐; 4=don't know ☐

6 Questions about your Values and Attitudes

63. In the following sections we would like to explore the values you hold in general terms. Please use a seven-point scale to measure the importance of each value "as a guiding principle in my life": extremely important (7); strongly important (6); important (5); neutral (4); unimportant (3); strongly unimportant; opposed to my values.

Value List	*Rating (1 to 7)*	*Value that is Most Important (tick one only)*	*Value that is least important (tick one only)*
Honoring of parents and elders (show respect)			
Capable (competent, effective, efficient)			
Unity with nature (fitting into nature)			
Choosing own goals (selecting own purposes)			
Wealth(material possessions, money)			
Broad-minded (tolerant of different ideas and beliefs)			
Daring (seeking adventure, risk)			
Healthy (not being sick physically or mentally)			
A spiritual life (emphasis on spiritual not material matters)			
Ambitious (hard working, aspiring)			
Successful (achieving goals)			
Responsible (dependable, reliable)			
Social recognition (respect, approval by others)			
Social justice (correcting injustice, care for the weak)			
Self-respect (belief in one's own worth)			
Social order (stability of society)			
Loyal (faithful to my friends, group)			
Freedom (freedom of action and thought)			
Independent (self-reliant, self-sufficient)			
Meaning in life (a purpose in life)			

64. Please rate your level of agreement with the following statements (*Please tick the answer agreed with)*

	1=Extremely disagree	*2=Strongly disagree*	*3=Disagree*	*4=Neutral*	*5=Agree*	*6=Strongly agree*	*7=Extremely agree*
Habits and initiatives							
When I work on the farm, I Do it the way it has always been							
When I work on the farm, it is something I do without thinking.							
To change the way I am managing my farm would require a big							
I am ready to take risks in order to develop new strategies on my farm, e.g. produce new crops and sell them at a new market							
Balance between economic, social and environmental issues							
Decisions about investments at my farm are more about immediate livelihood benefits/solving problems, rather than about long term environmental benefits							
I am more concerned about ensuring immediate livelihood benefits/solving problems than attending to traditional/cultural/social activities or lifestyle							
Investing in long term environmental benefits is more important than attending to traditional/cultural/social activities or lifestyle							
Common property and community engagement							
Land is the most important heritage of the family, more than livestock or other assets							
My neighbors' farming practices affect me and my farming							
The cooperation with other community members helps me in							
I am interested, active and motivated to undertake activities in							
Engagement with external actors							
I invested more in my farm because of the knowledge that I gained from other farmers							

I have started new collaborations with organizations/partners outside the community that help me to engage in new value chains							
Leadership, communication, information sharing							
I have a clear understanding of my role and responsibility within							
I trust the leaders in my community							
We have structures that help us to communicate and share information effectively in our community.							
If I bring in good new ideas, I know that they will be supported by the leaders and my community							

65. **Households expenditures and income:**

Household expenditure 2013/14, in USD/shilling/Meticais

	Expenses	*Trend, shr, 5 y*			*Expenses*	*Trend, shr, 5 y*
crop inputs		↑ = ↓		Household food		↑ = ↓
harvesting/transp		↑ = ↓		education		↑ = ↓
livestock inputs		↑ = ↓		health		↑ = ↓
hired labour		↑ = ↓		social events/leisure		↑ = ↓
irrigation expenses		↑ = ↓		personal transport		↑ = ↓
others____________		↑ = ↓		housing		↑ = ↓
				others____________		↑ = ↓
total agric expenditure 2013/14				total non agric- expenditure		

Household income for 2013/14

Activity	*Revenue*	*Trend, shr, 5 y*			*Revenue*	*Trend, shr, 5 y*
crops, rain-fed		↑ = ↓		agricultural labour		↑ = ↓
crops, irrigated		↑ = ↓		other non-agric. lab		↑ = ↓
livestock sales		↑ = ↓		regular employment		↑ = ↓

milk sales		↑ = ↓		business/self-employed		↑ = ↓
other_		↑ = ↓		remittances		↑ = ↓
other_________________		↑ = ↓		others_____________		↑ = ↓
				Seasonal work away from home		↑ = ↓
total on-farm income				Total off-farm income		

Thank you very much for your time and do you have any questions, suggestions, comments or issues we should know?

Appendix D.2 The end of the project (second) survey questionnaire

Increasing Irrigation Water Productivity in Mozambique, Tanzania and Zimbabwe through on farm monitoring, adaptive management and agricultural innovation platforms

Project survey

Introductory statement

This survey is carried out by ICRISAT in collaboration with the University of South Australia and the Australian National University as part of the project 'Increasing Irrigation Water Productivity in Mozambique, Tanzania and Zimbabwe. This is a follow up survey to the one carried out in 2013/14 and we would like to target the same households we interviewed then. The purpose of the survey is to identify changes that have taken place within the scheme over the last four years with respect to issues such as irrigation, crop production, decision-making within households etc.

Your responses to these questions will remain anonymous but you will be given a household ID which is only known to the researchers on the project. This ID will allow us to contact you later and to compare your answers from the first and subsequent surveys. Information will be treated as strictly confidential. We would like to interview a member of the HH who is either a key decision maker or is actively involved in farming activities within the HH. If husband and wife jointly manage the farm, both should be interviewed together. Participation of the wife should be encouraged. **Link to new project…**

<u>Please note that this data will not influence whether you will be selected for any relief assistance.</u>

Thanks you for your co-operation in this survey.

1. Name of irrigation scheme:______________________________
2. Date: ____
3. Scheme code: _______________________________________
4. Block/Section: ______________________________________

5. Plot number: ____

6. Name of respondents: ____________________________________; phone number:________________

7. Common household name: _________________________________

8. If name of respondent is different from the initial survey, why? ___________________________

9. Interviewer: _______________________

10. Start time of interview: _______________; 10a. Finish time of interview:_______________

Questions about your household

12. Relation of the respondent to the HH: 1=HH; 2=husband; 3=wife; 4=Son; 5=Daughter; 6=Parent; 7=Grandchild; 8=Other, specify______	
13. How many years have the HH been dryland farming?	
14. How many years have the HH been farming within this irrigation scheme?	
15. Have the head of household changed since four years ago 1=Yes, go to 16; 2=No, go to Q18?	
16. What has changed?: 1=was male now female; 2=was female now male; 3=was male and is still male	
17. Why did it change 1=spouse died, 2=parent died, HH alive but passed HH decision making to 4=son or 5=daughter	
18. Are you affiliated to any farmer group or community based organisation? 1=Yes; 2=No; If Yes, which:____________	

We would like to review the size and membership of this household. This includes all the people living in your household.

19. Household member Name	*Relationship to HH*[A]	*Gender*[B]	*Age*[C]	*Marital status*[D]	*Health*[E]	*Education*[F]	*Working on farm*[G]
19.1							
19.2							
19.3							
19.4							
19.5							
19.6							
19.7							
19.8							

19.9							
19.10							
19.11							

A: 1=HH, 2=spouse, 3=child, 4=brother/sister; 5=parent of HH/Spouse; 6=uncle/aunt; 7=other, specify
B: 1=male; 2 = female;
C: actual age;
D: 1=Never Married; 2=Married or de facto; 3=married but not living with partner; 4=divorced; 5=separated; 6=widowed);
E: 1=good (<5 days sick per year); 2=infrequently sick (6-10 days); 3=frequently sick (10+ days); 4=bedridden;
F: 1=no formal schooling; 2=some primary school; 3=completed primary school; 4=some secondary school; 5=completed secondary school; 6=some university or college, trade certificate; 7=still at school; 8=not started school yet; 9=other, specify;
G: % of time spend working on the farm (includes selling or transport produce at the market or processing produce

Next, we would like to ask some questions about how your situation has changed over the last four years

20. On a scale from 1 to 5 with 1 being much worse and 5 much better, how would you rate the following statements (please tick the appropriate box)	*1=much worse*	*2=worse*	*3=same*	*4=better*	*5=much better*
20.1 Compared to four years ago, what is your capacity to pay for your children's education?					
20.2 Compared to four years ago, how do you consider your household's food security?					
20.3 Compared to four years ago, how is the health of your family members?					
20.4 Compared to four years ago, how would you rate your off-farm income:					
20.5 Compared to four years ago, how would you rate your farm income:					

If 20.4 and/or 20.5 was 4 or 5, go to Q20.6, if not go to Q21

20.6 How did you spend the extra income (1=food; 2=education; 3=health; 4=farm input; 5=investment in home; 6=investment in farm (multiple choices)

20.7 Who decided what it was spent on (1=husband; 2=wife; 3=Joint husband and wife; 4=joint HH and other, gender____; 5=Child, gender_____; 6=Other, gender :____)

20.8 If answer to Q20.6 was 4 or 6 whose farming activity was the money spent on (1=husband; 2=wife; 3=Joint husband and wife; 4=joint HH and other, gender____; 5=Child, gender: _____; 6=Other, gender :____) ☐

21. Have your income sources changed over the last four years? Yes ☐ go to Q21.1; no ☐ go to Q22

21.1 What new income sources have you had (1=farm labour; 2=small business; 3=work in nearby town; 4=remittances; 5=other) ☐; if other please specify:____

Next, we would like to ask some questions about how you spent your money and time and how it has changed over the last four years

22. On a scale from 1 to 5 with 1 being much less and 5 much more, compared to 4 years ago, how much are you now spending on:	*1= Much less*	*2= Less*	*3= About the same*	*4= more*	*5= Much more*	*Rank from 1 to 6 in order of importance where you spend your income now.1 being the most important*
22.1 Irrigation/Farm input						
22.2 Irrigation/ Scheme maintenance						
22.3 Education						
22.4 Food						
22.5 Farm implements						
22.6 Home (buildings, appliances, transport etc)						

23. On a scale from 1 to 5, with 1 being much less and 5 much more, compared to 4 years ago, what proportion of your time are you now spending on:	*1= Much Less*	*2= Less*	*3= About the same*	*4= More*	*5= Much More*	*Rank from 1 to 6 in order of importance where you spend your time now*
23.1 Irrigation plot						
23.2 Irrigation scheme maintenance						
23.3 Dry land farming						
23.4 Livestock						
23.5 Home improvements (buildings, thatching, roofing etc.						
23.6 Not working on the household farm						

Next, we would like to know who participates in various community activities.

24. Who in your household participates in the following activities:	*0=Nobody; 1=husband; 2=wife; 3=Joint husband and wife; 4=joint HH and other, note gender, 5=Child, note gender; 6=Other, note gender*
24.1 Irrigation management committee	
24.2 Farming groups	
24.3 Market groups	
24.4 AIP meetings	
24.5 Other community based organizations	

Next, we would like to know about your accesses to information.

25. How do you think your information needs have changed over the last 4 years? (1=Gone up; 2=Stayed the same; 3=Decreased):

26. How do you think your range of information sources has changed over the last 4 years? (1=Gone up; 2=the same; 3=Decreased):

27. Who in your household accesses the following information services:	*0=Nobody; 1=husband; 2=wife; 3=Joint husband and wife, 4=joint HH and other, note gender; 5=Children, note gender; 6=Other, note gender*	*Rank from 1 to 12 in order of importance*	*Which of these are new the last 4 years? Tick relevant*
27.1 Farm/field days			
27.2 Training sessions by NGOs			
27.3 Extension officers from the Government, District or irrigation scheme			
27.4 AIP meetings			
27.5 Input suppliers			
27.6 Output buyers			
27.7 Other farmers			
27.8 Marketing platforms			
27.9 Shows (e.g. Trade Fairs)			

27.10 Researchers			
27.11 Media			
27.12 Other (specify)			

28. Compared to four years ago, are you now getting more or better agricultural advice? Yes ☐; No ☐

29. What information do you find that male and female farmers need most?

Information	*Rank from 1-6 in order of importance for female farmers*	*Rank from 1-6 in order of importance for male farmers*
29.1 Inputs		
29.2 Crop choices		
29.3 Markets		
29.4 Water use		
29.5 Nutrients		
29.6 Other, what:		

We would like to understand who makes which decisions within your household

30. Who makes decisions about production and marketing of crop and livestock? 1=husband; 2=wife; 3=Joint husband and wife; 4=joint HH and other, note gender; 5=child, note gender; 6=person controlling the enterprise; note gender; 7=Other, note gender	*Do not have this activity*	*Production*	*Marketing*	*where/how is income spent?*
30.1 Irrigated cereal crops				
30.2 Irrigated legume crops				
30.3 Irrigated horticultural crops				
30.4 Dryland cereal crops				
30.5 Dryland legume crops				
30.6 Large livestock				
30.7 Small livestock (sheep, goats)				

30.8 Micro livestock (poultry)				

31. Who makes decisions about how to use resources? 1=husband; 2=wife; 3=Joint husband and wife; 4=joint HH and other, note gender; 5=child, note gender; 6=person controlling the enterprise, note gender; 7=Other, note gender	*Now*	*Four years ago*
31.1 Use of farm implements (including 2 wheel tractors, draft power)		
31.2 Land allocation for dryland crops?		
31.3 Land allocation for irrigated crops?		
31.4 Buying of inputs		
31.5 When to carry out the work		
31.6 Proportion of total income to invest		
31.7 Proportion of total time to invest		
31.8 When and where to irrigate		

32. Who makes decision about income from: 1=husband; 2=wife; 3=Joint husband and wife; 4=joint HH and other, note gender; 5=child, note gender; 6=person controlling the enterprise, note gender; 7=Other, note gender	*Now*	*Four years ago*
32.1 Small business (specify this)		
32.2 Off-farm work (specify this)		
32.3 Remittance		
32.4 Other, type		

33. Who makes decision about other issues within the household: 1=husband; 2=wife; 3=Joint husband and wife, 4=joint HH and other, note gender; 5=child, note gender; 6=Other, note gender	*Now*	*four years ago*
33.1 Investment in household items (modes of transport, television, improvement to building)		
33.2 Purchases of staple food (for food security purposes)		
33.3 Health related expenses		

33.4 Education		
33.5 Purchase of smaller household items (cloth, school material)		

34. Have you observed any changes in gender roles more generally within the community: Yes ☐ go to Q34.1; No ☐ go to Q35

34.1 Please describe which general changes you have observed: ____

Next, we would like to understand who does the various activities within irrigated agriculture:

35. Whose main role is it to do the following activities in irrigated agriculture?	*1=main; 2=support; 3=no role*				
	HH	*spouse*	*Children*	*Hired labour*	*Other family members*
35.1 Ploughing/Land preparation					
35.2 Planting					
35.3 Fertiliser application					
35.4 Weeding					
35.5. Irrigation					
35.6 Application of pesticides					
35.7 Harvesting					
35.8 Post-harvest work for sale					
35.9 Processing for home consumption					

We would like to understand how your food security situation has changed over the last four years (2013-17)
The next set of questions is about your rain-fed and irrigated crops and the reason why you grow it:

36. Reasons for growing	*Rank the reasons for undertaking rain-fed agriculture in order of importance with 1 being least important and 3 most important*	*Rank the reasons for undertaking irrigated agriculture in order of importance with 1 being least important and 3 most important*
36.1 Household food		
36.2 Cash income		
36.3 Risk management		

37. Do you have access to staple food markets where you can buy it if you do not produce it yourself? Yes ; No
38. Do you think it is cheaper to grow your own staple food or buy it: 1=Cheaper; 2=More or less the same; 3=more expensive

39. Over the last four years normally how did you secured your stale food

	Tick	*Jan*	*Feb*	*March*	*April*	*May*	*June*	*July*	*August*	*Sept*	*Oct*	*Nov*	*Dec*
39.1 Maize green													
39.2 Maize grain													
39.3 Rice													
39.4 Beans													
39.5 Wheat													
1=self-supply; 2=buy; 3=food aid; 4=could not obtain; 5=don't need													

40. If you did not have access to an irrigated plot how many months in a year do you think you would have faced food shortages?

41. In the last 4 years, what were the 3 main causes of food shortages in your household? (please probe, not just drought)

42. Have you sold irrigated produce to buy staple food to overcome food shortage? Yes ; No

Next, we would like to understand your farming activities and how they have changed over the last four years

43. Four years ago did you have irrigated land that you did not farm: yes go to Q43.1; No go to Q44

43.1 Do you farm this land now: Yes go to Q43.2; No go to Q44

43.2 Why did you decide to start irrigating the plot____

43.3 What are you producing on the plot____

44. Are you now growing irrigated crops that you did not grow four years ago? Yes go to Q44.1; No go to Q45

44.1 What new irrigated crops did you decide to grow? ____

44.2 Why did you decide to grow these crops? ____

45. For the three main irrigated crops, what are the yields and how has it changed?	*Area (ha)*	*production in 2016/17*	*Proportion sold*	*On a scale from 1-6, compared to four years ago, how would you rate your production for 2016-17 (Tick appropriate box)*					
				1= Less	*2= The same*	*3= 25% more*	*4= 50% more*	*5= 75% more*	*6= Double or more*
45.1									
45.2									
45.3									
Crop: 1=Grain maize; 2=Green maize; 3=Sorghum; 4=Ground nut; 5=Tobacco; 6=Cotton; 7=Cow pea; 8=Pigeon pea; 9=Irish potato; 10=Sweet potato; 11=Tomato; 12=Finger millet; 13=Bambara nut; 14=Sugar beans; 15=Sun flower; 16=Soya bean; 17=rice; 18=Other cereal crops; 19=Other legume crops; 20=Other vegetables; 21=Fruits; 22=Feed crop; 23=onions									

46. I answer to Q45 is not 2, why has the production changed? ____

47. For your three main irrigated crops, what are the prices and how have they changed?	*Price in 2016/17 kg*	*On a scale from 1-6, compared to four years ago how would you rate the price you received during 2016-17 (Tick appropriate box)*					
		1= less	*2= The same*	*3= 25% more*	*4= 50% more*	*5= 75% more*	*6= Double or more*
47.1							
47.2							
47.3							
Crop: 1=Grain maize; 2=Green maize; 3=Sorghum; 4=Ground nut; 5=Tobacco; 6=Cotton; 7=Cow pea; 8=Pigeon pea; 9=Irish potato; 10=Sweet potato; 11=Tomato; 12=Finger millet; 13=Bambara nut; 14=Sugar beans; 15=Sun flower; 16=Soya bean; 17=rice; 18=Other cereal crops; 19=Other legume crops; 20=Other vegetables; 21=Fruits; 22=Feed crop; 23=onions							

48. Why has the price changed in the past 4 years?____

49. How much dryland did you farm four years ago: ☐ ☐ ha; and 50 how much do you farm today: ☐ ☐ ha

51. If 50 is bigger than 49; why did you increase? ____

52. If 49 is bigger than 50; why did you reduce? ____

53. *What is the production and income of your three main dryland crops*	*Typical dry-land production*			*Typical income from production*
	Area in crop (ha)	*Total production in units*	*Proportion sold*	
53.1				
53.2				
53.3				
Crop: 1=Grain Maize; 2=Green Maize; 3=Sorghum; 4=Ground nut; 5=Tobacco; 6Cotton; 7=Cow pea; 8=Pigeon pea; 9=Irish potato; 10=Sweet potato; 11=Tomato; 12=Finger Millet; 13=Bambara nut; 14=Sugar beans; 15=Sun flower; 16=Soya bean; 17=rice; 18=Other cereal crops; 19=Other legume crops; 20=Other vegetables; 21=Fruits; 22=Feed crop				

We would now like to know about your post-harvest management

54. *In which of your crops do you have the major post-harvest losses*[A]	*Extent of losses %*	*What are the major causes of the losses*[B]*:*	*How do you try to minimise these losses?*	*What would allow you to prevent or minimise these losses*[C]*:*
54.1				
54.2				
54.3				
A: Crop: 1=Grain Maize; 2=Green Maize; 3=Sorghum; 4=Ground nut; 5=Tobacco; 6=Cotton; 7=Cow pea; 8=Pigeon pea; 9=Irish potato; 10=Sweet potato; 11=Tomato; 12=Finger Millet; 13=Bambara nut; 14=Sugar beans; 15=Sun flower; 16=Soya bean; 17=rice; 18=Other cereal crops; 19=Other legume crops; 20=Other vegetables; 21=Fruits; 22=Feed crop; **B**: 1=insects, 2=fungi, 3=rodents, 4=rotting, 5=other, specify **C**: 1=access to pesticides; 2=access to storage facilities; 3=training; 4 other, specify; 5=Integrated pest management				

We would now like to understand how your spending on farm inputs has changed in the last four years.

55. *Compared to four years ago how much are you now spending on farm inputs*	*Spending in 2016/17 ($)*	*On a scale from 1-6, compared to four years ago how would you rate your spending during 2016-17 (please tick appropriate box)*					
		1= less	*2= The same*	*3= 25% more*	*4= 50% more*	*5= 75% more*	*6= Double or more*
55.1 Chemical fertiliser							

55.2 Insecticide							
55.3 Herbicide							
55.4 Manure (if this is bought)							
55.5 Water fees in irrigation schemes							
55.6 Labour (non-family)							
55.7 Equipment							
55.8 Seeds							
55.9 Post harvest management costs							

We would like to know about your fertiliser use and how it has changed over the last four years

56. *Method of fertilisation*	*Use 4 years ago*[A]	*Today/Current*[A]	*Magnitude of change*[B]	*Why has it changed?*
56.1 Manure				
56.2 Chemical fertiliser				
A: 1=None; 2=Principal/main; 3=Secondary; **B:** 1=Decreased a lot; 2=Decreased; 3=Stable; 4=increased; 5=Increased a lot				

The next set of questions is about your livestock and the reason why you keep it:

57. Please tell us the details of your livestock enterprise during 2016 and how it has changed over the last 4 years:

	Current herd (n)	*How many lost/died*	*How many consumed*	*How many sold*	*If sold, market*[A]	*Average price per animal*[B]	*Change over the last 4 years*[C]	*Why has it changed*	*Main reasons for keeping it*[D]
57.1 Cattle									
57.2 Donkeys									
57.3 Pigs									
57.4 Sheep									
57.5 Goats									
57.6 Chicken									

57.7 Ducks									
57.8 Other									

A: 1=Farm gate; 2=village market; 3=local business centre; 4=collection point, 5=sale pen; 6=regional auction; 7=regional town; 8=others (specify):__
B: provide average price, and range if prices differed substantially across animals and time of sales;
C: 1=Decreased a lot; 2= Decreased; 3=Stable; 4=increased; 5=Increased a lot
D: 1=consumption; 2=cash income; 3=savings; 4=draft power; 5=Other (specify):_______

58. Do you see an opportunity to integrate livestock and feed production into your irrigation production? Yes ☐ go to Q58.1; No ☐ go to Q59

58.1 How do you think this could be done? 1=Growing fodder crops? 2=Making better use of crop residues?; 3=using the income from livestock to purchase input for crop production; 4=other (multiple answers if applicable) ☐ ☐ ☐, if other specify:______________________

What changes have taken place over the last 4 years to the input and output markets you use for irrigated crops.

59. How has the range of input markets changed? 1=Decreased a lot; 2=Decreased; 3=Stable; 4=increased; 5=Increased a lot ☐

59.1 How has this changed the buying process? 1=Much easier; 2=easier; 3=About the same; 4=More difficult; 5=Much more difficult: ☐

59.2 How would you rate the price you pay for inputs today compared to 4 years ago? 1=Decreased a lot; 2=Decreased; 3=Stable; 4=Increased; 5=Increased a lot ☐

60. How do you think the range of buyers has changed? 1=Decreased a lot; 2=Decreased; 3=Stable; 4=increased; 5=Increased a lot

60.1 How has this change influenced the selling process? 1=Much easier; 2=Easier; 3=About the same; 4=More difficult; 5=Much more difficult: ☐

60.2 How would you rate the price you get for your product? 1=Decreased a lot; 2=Decreased; 3=Stable; 4=Increased; 5=Increased a lot ☐

Monitoring tools and their influence on farming practices within irrigated agriculture

60. Have you changed how often or for how long you irrigate during the last 4 years? Yes ☐ go to Q60.1; No☐ go to Q61

60.1 Why did you do that? ____

61. Are you aware that some farmers in your scheme have some monitoring tools installed in their fields? Yes ☐ go to Q61.1; No ☐ go to Q61.40

61.1 Do you know what other people within your scheme have done based on the results from these tools? Yes ☐ go to Q61.2; No ☐ go to Q61.3

61.2 What has it meant for these people? ____

61.3 Do you think you can maintain or increase crop production using less water through the application of the tools? Yes ☐; No ☐

61.4 Do you have a monitoring tools? Yes ☐; No ☐

61.5 When did you first hear about these monitoring tools? __________________from____________________________________

61.6 Do you know what these tools measure and what they are used for? Yes ☐ go to Q61.7; No ☐ go to Q61.9

61.7 Please explain what the Chameleon measures: Easier for plant to access water ☐; wet or dry ☐; blue=wet ☐; green=wet but dry ☐; red=dry irrigate ☐; different depths relative to plant ☐; consist or reader an sensor array ☐

61.8 Please explain what the full stop measures: rate of nutrients losses ☐; buried in two depths ☐; used together with the chameleon ☐; pops up when full ☐; measure amount of solute in the water ☐; EC meter and nitrate strips ☐

61.9 Have you made any changes to your farming practices as a result of what you learned from the chameleon? Yes ☐ go to Q61.10; No ☐ go to Q61.12

61.10 When did you make the first change? ____

61.11 What did you change? ____

61.12 Have you made any changes to your farming practices as a result of what you learned from the Full Stop? Yes ☐ go to Q61.13 No ☐ go to Q61.15; if no to both Q61.9 and Q61.12 go to Q61.35

61.13 When did you make the first change? ____

61.14 What did you change? ____

Why did you change?	*Please rank in order of importance from 1 to 5*	
	Chameleon	*Full Stop*
61.15 Save water		
61.16 Save labour		
61.17 Save money on water charges or fuel		
61.18 Save fertiliser		
61.19 Increase yield		

61.20 Have you changed the frequency of your irrigation based on the monitoring tools? Yes ☐ go to Q61.21 No ☐ go to Q61.25

61.21 How frequently did you irrigate before; number of days between irrigation events ☐ ☐

61.22 How frequently do you irrigate now, number of days between irrigation events ☐ ☐

61.23 How much time do you saved per irrigation cycle (incl. time spend walking to the plot, collecting the pipes, blocking the canal etc.) (hours)? ☐ ☐

61.24 What are you now using this time for? ____

61.25 Have you changed the number of hours you irrigate each time based on the monitoring tools? Yes ☐ go to Q61.26; No ☐ go to Q61.30

61.26 How many hours did it take to irrigate your plot in the past (how long time was the water running)? ☐; 61.27 how many pipes did you use in the past ☐

61.28 How many hours does it take to irrigate your plot now? ☐; 61.29 how many pipes are you using now ☐

61.30 Have you changed your fertiliser application based on the monitoring tools? Yes ☐ go to Q61.31; No ☐ got to Q61.33

61.31 What changes have you made? ____

61.32 What have been the impacts from these changes____

61.33 How have these changes in irrigation scheduling and fertiliser application influenced your yield?	1-6
On a scale from 1-6, with 1=reduced; 2=the same; 3=25% more; 4=50% more; 5=75% more and 6 more than double, how would you say these changes in irrigation scheduling and fertiliser application have influenced your yield	

61.34 How have these changes in irrigation scheduling and fertiliser application changed your income?	1-6
On a scale from 1-6, with 1=reduced; 2=the same; 3=25% more; 4=50% more; 5=75% more and 6 more than double, how would you say these changes in irrigation scheduling and fertiliser application have influenced your yield	

61.35 Where is the nearest tool installed: 1=I have; 2=My neighbour; 3=Two plots away; 4=Three plots away; 5=on the same canal as me; 6=on a different canal: ☐

If a community organization (e.g. IMC) or a farm group purchases a reader?	
61.36 How much would you be willing to pay for a sensor array? (show payment card to respondent)	1=US75; 2=US$50; 3=US$40; 4=US30; 5=US$20; 6=10; 7=5; 8=0
61.37 How much would you be willing to pay (as a one-off payment) to have weekly access to a reader? (show payment card to respondent)	1=$50; 2=$45; 3=$40; 4=$35; 5=30; 6=25; 7=20; 8=10; 9=0

61.38 Why are you willing to pay that much:____

61.39 With the use of the "Tools" do you think you can make better use of rainfall and therefore make better irrigation decisions? Yes ☐; No ☐ go to Q61.41

61.40 To those who did not make any change; why have you not made any changes?___________________________________

61.41 What would convince you to further reduce water use at the plot level?

1=social pressure; 2=Provision of more information; 3=Having a tool within same canal/block; 4=If my neighbour has the tools; 5=If I had the tool installed on my plot; 6=If water was measured and priced ☐ ☐ ☐ (multiple choices)

Irrigation scheme management and the community

Lastly, we would like to understand how the scheme is managed and whether there have been any changes in the management since 2013

62. Where within the scheme is your plot located: 1=upstream; 2=middle; 3=downstream

63. Does this location of your plot within the scheme affect your access to water, Yes, No, I Yes how: ___________________________

64. In your experience have your access to water changed over the last four years? Yes ☐ go to Q64.1; No ☐ Q65

64.1 Please explain how it has changed: ____

64.2 What has this meant to you and other farmers within the scheme? ____

65. In your opinion who has the responsibility for maintaining the following parts of your scheme?	*Who*
65.1 The night storage dam/pump	
65.2 The main canal	
65.3 The secondary canal	
65.4 The immediate canal that brings water to your plot	

66. Do you now participate more in scheme maintenance than you did four years ago? Yes ☐; No ☐

67. Are you now more willing/prepared to pay for water within the scheme than you were 4 years ago?

68. Compared to four years ago are you now more able to pay for water Yes ☐; No ☐

69. Do you think the process of water allocation and use is fairer now than 4 years ago? Yes ☐; No ☐

70. Tell us how conflict within the scheme have changes over the last four years	*1=Decreased; 2=Same; 3=Increased*
70.1 Within the household	
70.2 Between farmers in the section/block	
70.3 Between different sections/blocks	
70.4 Between the scheme and other water users	

71. Thinking about the changes that has happened over the last four years, which one would you say is the single most important change and why:____

Thank you very much for your time

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