

Adoption of modern irrigation water management practices by smallholder farmers in Bushbuckridge Local Municipality, Mpumalanga

Tiisetso Christain Mashego

201877341



orcid.org/ 0000-0002-7186-2690

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Supervisor: Dr. J. NDORO

Co-supervisor: Prof. V. Mlambo

School of Agricultural Sciences
Faculty of Agriculture and Natural Sciences

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**UNIVERSITY OF
MPUMALANGA**

DECLARATION

I, the undersigned, declare that this research project report titled, ‘Adoption of modern irrigation water management practices by smallholder farmers in Bushbuckridge Local Municipality, Mpumalanga’ submitted to the University of Mpumalanga for the degree of Master of Science in Agriculture in the Faculty of Agriculture and Natural Sciences, School of Agricultural Sciences, and the work contained herein is my original work with exemption to the citations and that this work has not been submitted to any other University in partial or entirely for the award of any degree.

Name: Tiisetso Christain Mashego

Signature: 

Date: May 2025

Supervisor: Dr. J. NDORO

Signature: 

Co-supervisor: Prof. V. Mlambo

Signature: 

DEDICATION

I dedicate this work to my wonderful parents, Ronel Mapaseka Mashego and Amos Modipane, my lovely sisters, Trustee Ntebogeng Mashego and Baatlegi Rhandzani Mashego. This research is also dedicated to the Bushbuckridge community at large.

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ABSTRACT

Water is a scarce natural resource that threatens food security as there is limited water available for agricultural production. This has resulted in the agricultural industry seeking alternative ways for enhancing the efficiency of water utilization while maintaining high production yields. One of the ways that smallholder farmers can adapt to low water availability and quality is by adopting modern irrigation water management practices. While research has been undertaken on the adoption of several agricultural practices, there is limited information on the adoption of modern irrigation water management practices.

This study sought to investigate the adoption of modern irrigation water management practices by smallholder farmers in Bushbuckridge Local Municipality. Convenience sampling was employed to collect data from 296 smallholder farmers in Bushbuckridge Local Municipality using structured questionnaires. Descriptive and inferential statistics were employed for data analysis. Under descriptive statistics, frequency tables were used to determine the number of smallholder farmers that had adopted modern irrigation water management practices. The results indicate that most of the smallholder farmers used crop based (59.1%) and soil based (79.4%) irrigation scheduling, and the feel method (27.4%) for soil moisture monitoring. Hand hoes (94.3%) and tractors (77%) were used by most smallholder farmers for land levelling; whereas, a majority of the smallholder farmers had not adopted any of the methods or tools for tail-water recovery. Most smallholder farmers used drums (59.1%) and tanks (58.4%) to collect and store rainwater (rainwater harvesting).

Inferential statistics was employed to examine the relationship between drivers and the adoption of modern irrigation water management practices using binary logistic regression. The socio-economic drivers: gender, education level, household size, farm size, off-farm employment status, and group membership had a significant influence ($p < .05$) on the adoption of some of the modern irrigation water management practices. Under socio-psychological drivers, intention, attitude, personal efficacy, and social capital had a significant influence on the adoption of at least one of the modern irrigation water management practices. Several constraints hindered smallholder farmers from adopting modern irrigation water management practices. The constraints included inadequate extension services, lack of information, lack of financial capital, farm distance from adopters and training programmes, as well as lack of technical expertise.

Priority should be given to the training and motivation of extension officers to disseminate modern irrigation water management practices to smallholder farmers. More extension officers should be hired by the Department of Agriculture to meet the demand from smallholder farmers for regular visits. The Department of Agriculture should also fund campaigns that raise awareness on the adoption of modern irrigation water management practices to smallholder farmers. Policymakers should implement policies that allow smallholder farmers to gain access to financial capital to encourage them to adopt modern irrigation water management practices. Other sampling methods such as random sampling should be used to get a general representation of the population of smallholder farmers. Questionnaires should be translated to participants' native language for better understanding of survey questions.

Keywords: modern irrigation water management practices, adoption, smallholder farmers

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CHAPTER ONE: INTRODUCTION

This is the introductory chapter to the study. In Section 1.1 the background of the study is given, which includes the orientation to the topic. Section 1.2 explains the research problem, the study gap identified, and what will be done in this study to meet the research gap. The research questions are outlined in Section 1.3, while the research objectives are outlined in Section 1.4. The importance of this study, its contribution, and impact to the research field is revealed in Section 1.5. Important key terms are defined in Section 1.6.

1.1 Background of Study

Agriculture is a major source of employment and aids in the development of rural areas (Lekhuleni, 2020). However, this sector has been impacted by the adverse effects of climate change, leading to most smallholder farmers exiting the sector (Lekhuleni, 2020). Successful crop production is constrained by a shortage of water globally which has led to major economic yield losses of most crops (Yohannes *et al.*, 2017). Smallholder farmers in sub-Saharan Africa face challenges as far as access and management of water is concerned (Jordán & Speelman, 2020; Martey *et al.*, 2023). Over 70% of total water consumption globally is attributed to agriculture (Grafton *et al.*, 2018; Siebert *et al.*, 2010). Irrigation consumes more water than any other sector, water availability for irrigation remains a problem globally (Bjornlund *et al.*, 2009; Danso *et al.*, 2021; Yohannes *et al.*, 2017). The lack of success of most irrigation schemes led by smallholder farmers is attributable to poor irrigation water management combined with water shortages (Yohannes *et al.*, 2017). There has been requests for the agricultural industry to use less water to meet the demands of other industries (Schaible & Aillery, 2006).

The agricultural industry is compelled to optimize water usage due to the expanding global population and anticipated climatic scenarios (Fernández, 2017). This has resulted in governments and researchers searching for strategies to promote water use efficiency to save water for other sectors (Bjornlund *et al.*, 2009). Improved agricultural water use efficiency increases availability of water for other users (Bjornlund *et al.*, 2009). Indeed, irrigation water use efficiency is low, ranging from 25 to 50% globally (Tiwari & Dinar, 2001). However, Levidow *et al.* (2014) and Oyarzún *et al.* (2008) argued that irrigation is a necessary climate adaptation strategy for farming. To mitigate the negative effects of water scarcity amid climate

change, smallholder farmers need to adopt modern irrigation water management practices (Sani & Chalchisa, 2016).

The adoption of modern irrigation water management practices can enable smallholder farmers to minimize the effects of recurrent droughts (Huang *et al.*, 2017; Schaible & Aillery, 2006). Modern irrigation water management practices refer to new and improved ways to monitor and control irrigating water application and water use efficiency using different irrigation systems (Schaible & Aillery, 2006). The main goal of modern irrigation water management practices is to ensure that crops receive enough water for higher yields at the same time enhancing the efficiency of water utilization in irrigation (Bryant *et al.*, 2017). The advantages of adopting modern irrigation water management practices include: improved efficiency of water utilization and supply for other uses, increased crop yields and quality, water scarcity adaptation, reduced irrigation runoff, reduced energy and labour costs, reduced loss of fertilizer or pesticides by runoff, prevention of soil erosion, and less time required to irrigate (Bryant *et al.*, 2017; ICDC, 2017; Mpanga & Idowu, 2020; Schaible & Aillery, 2012; Senzanje, 2007; Stevens, 2007).

Smallholder farmers can adapt to low water availability and quality by modifying their irrigation water management practices (Dinar *et al.*, 2017). However, the implementation of modern irrigation water management practices is mostly prevalent at research level but less so among irrigating smallholder farmers (Taghvaeian *et al.*, 2020). This may be attributed to high installation costs, sophistication, and maintenance requirements of modern irrigation water management practices which smallholder farmers may not be equipped for (Mpanga & Idowu, 2020; Yohannes *et al.*, 2019). Most smallholder farmers still use intuition based on experience and indigenous knowledge for irrigation as opposed to modern irrigation water management practices (Martey *et al.*, 2023). Other constraints such as lack of information, irrigation support tools and resources were reported to be responsible for the low adoption of modern irrigation water management practices to some extent (Martey *et al.*, 2023).

The low rate of adoption of improved agricultural practices among smallholder farmers has evoked research as to which practices smallholder farmers have adopted or planning to adopt, and different drivers that influence adoption (Taghvaeian *et al.*, 2020). Furthermore, understanding the various drivers influencing the adoption of agricultural technologies is necessary to prepare for the future and strategically implement those technologies (Mariano,

Villano & Fleming, 2012). This will enable decision-makers and water resource managers to determine the scope of policy measures (Wang *et al.*, 2016).

1.2 Problem statement

Even with increased investment and countless attempts to improve irrigation water management, the effectiveness of most smallholder irrigation schemes is still not ideal (IFAD, 2005). Although most small-scale irrigation systems function poorly, relevant stakeholders pay little attention to them (Yohannes *et al.*, 2017). The agricultural industry tends to overlook the low sustainability of most irrigation schemes (Yohannes *et al.*, 2017). Jordán and Speelman (2020) stated that about 98% of smallholder farmers neither know what the overall irrigation requirement of their crops is, nor how much water is irrigated to crops each time. Total irrigation water application is based on experience and personal preferences of each smallholder farmer and not on the specific crop's water requirements, resulting in over-irrigation (Pardossi & Incrocci, 2011; Yohannes *et al.*, 2017). This is attributed to the lack of awareness, inability to distribute water evenly, and failure to consider the effects of water wastage (Yohannes *et al.*, 2017).

Irrigation water management practices are designed to promote the application of the most appropriate quantity of water precisely timed to maintain high production yields (Virginia Cooperative Extension, 2000). Improved irrigation water management can maintain long-term sustainability of the agricultural industry (Schaible & Aillery, 2006). The need to adopt more efficient and improved management practices cannot be overemphasized (Bjornlund *et al.*, 2009). Smallholder farmers' awareness, knowledge, and adaptive capability to the important aspects in irrigated agriculture must all be improved (Yohannes *et al.*, 2017). There is still a lot of room to improve agricultural water conservation (Schaible & Aillery, 2006). How much can be accomplished depends on how well water-conserving methods and irrigation systems are integrated (Schaible, 2004; USDA, 2004). Previous studies have investigated smallholder farmers' intention to adopt soil and water conservation practices (Asfaw & Neka, 2017; Belachew *et al.*, 2020; Mango *et al.*, 2017). There is limited literature on smallholder farmers' intention to adopt modern irrigation water management practices (Focus, 2015). Therefore, it is crucial to study and comprehend the actual drivers and constraints toward adoption of modern irrigation water management practices. This study seeks to analyse smallholder

farmers' adoption of modern irrigation water management practices in Bushbuckridge Local Municipality.

1.3 Research questions

- What are the modern irrigation water management practices adopted by smallholder farmers?
- What are the socio-economic and socio-psychological drivers toward adoption of modern irrigation water management practices?
- What are the constraints faced by smallholder farmers towards adoption of modern irrigation water management practices?

1.4 Main objectives

- To investigate the adoption of modern irrigation water management practices by smallholder farmers
- To identify the socio-economic and socio-psychological drivers toward the adoption of modern irrigation water management practices
- To examine the constraints faced by smallholder farmers toward the adoption of modern irrigation water management practices

1.5 Significance of the study

One of the Bushbuckridge Local Municipality's main economic sectors is agriculture, but limited research has been conducted on the different irrigation water management practices smallholder farmers in the region undertake to make agriculture a success (Integrated Development Planning (IDP), 2022). This study will be one of the first to be conducted in Bushbuckridge Local Municipality, investigating smallholder farmers' adoption of modern irrigation water management practices and the constraints they are faced with. The pressing need to improve irrigation practices among smallholder farmers will be addressed in this study. Smallholder farmers' current practices will be identified, the drivers toward adoption explored, as well as the constraints preventing the adoption of modern irrigation water management practices. Overall, this study will add to limited literature on the adoption of modern irrigation water management practices and general agricultural research conducted in Bushbuckridge Local Municipality. The results of this study will have significant implications for improving

agricultural productivity, ensuring water use efficiency, and promoting economic and social development in farming communities.

1.6 Operational definitions of key terms

Modern irrigation water management practices: new and improved ways to observe and regulate irrigating water application and water use efficiency by smallholder farmers using different irrigation systems (Schaible & Aillery, 2006). Examples of modern irrigation water management practices in this study include; irrigation scheduling, soil moisture monitoring, land levelling, tail-water recovery and rainwater harvesting.

Adoption: implementation and utilization of practices to manage irrigation water by smallholder farmers (Adesope *et al.*, 2012).

Smallholder farmers: farmers who own and manage small-scale farms mainly to feed their families and sell the produce locally (Moyo, 2016).

CHAPTER TWO: LITERATURE REVIEW

The adoption of modern irrigation water management practices by smallholder farmers varies across regions and farmers. While some have adopted affordable technologies, others are still considering improvements. Modern irrigation water management practices include irrigation scheduling, land levelling, soil moisture monitoring, tail-water recovery systems, and rainwater harvesting, all of which improve water management and boost the efficiency of irrigation systems. Even though enhanced irrigation systems can increase water efficiency, crop yields, and reduce costs, these benefits alone may not always drive adoption. Several factors influence smallholder farmers' decisions to adopt new practices, including socio-economic and socio-psychological drivers, which vary across different innovations. The constraints experienced by smallholder farmers include: inadequate extension services, financial constraints, lack of information, access to water, farm location, lack of technical expertise, and agricultural policies.

In this chapter findings from previous studies on related topics are reviewed. An introduction to the literature review can be found in section 2.1. Section 2.2 explains what the adoption of modern irrigation water management practices entails. Section 2.3 reviews the modern irrigation water management practices as discussed in other studies. In Section 2.4 the socio-economic and socio-psychological drivers toward the adoption of modern irrigation water management practices are studied. Lastly, Section 2.5 includes a review of several constraints that hinder the adoption of modern irrigation water management practices.

2.1 Introduction

Water is a natural renewable resource that is available in short supply (Magar, 2006). As a vital resource sustaining agriculture, water is essential in ensuring global food security (Focus, 2015). Smallholder farmers depend on water for economic well-being as agriculture is a major contributor to most countries' economy (Yohannes *et al.*, 2017). Water use in agriculture is excessive which threatens available water bodies of depletion (Panagopoulos *et al.*, 2014). In most regions, crop irrigation is the largest consumer of agricultural water and has exceeded stable levels in some cases (Bjornlund *et al.*, 2009; Panagopoulos *et al.*, 2014). Population growth and urbanization are expected to cause a 55% increase in global water demand by 2050 (Focus, 2015). Therefore, water resource conservation is of vital importance and encouraged (Agholor & Nkosi, 2020). Development of agriculture through irrigation is being prioritized

worldwide (Yohannes *et al.*, 2017). The agricultural industry is advised to use less water in order to save some for other industries (Schaible & Aillery, 2006). Enhanced irrigation water management practices could potentially lessen the impact of irrigated agriculture on offsite water quantity and quality, allowing more water to be saved for non-agricultural uses (Schaible & Aillery, 2006).

Irrigation water management entails the controlled distribution of water and associated inputs in irrigated agricultural production to maximize financial return while ensuring environmental sustainability (Schaible & Aillery, 2006). Irrigating too much water or less water than required may stress the crop or cause diseases which will increase the crop production costs and decrease crop yields (Irrigation Crop Diversification Corporation (ICDC), 2017). Improved irrigation water management reduces the accumulation of compounds from irrigation runoff to surface water and prevents leaching of chemicals into groundwater sources (Schaible & Aillery, 2006). Smallholder farmers will keep relying on new technologies and water management strategies to reduce water consumption as water becomes scarcer (Schaible & Aillery, 2006). With the current and predicted climatic and environmental challenges, smallholder farmers should start adopting modern technologies and practices to enhance farm production efficiency (Panuska, Sanford & Newenhouse, 2015).

Modern irrigation water management practices can improve the efficiency of water utilization and meet the ever-increasing need for water (Bjornlund *et al.*, 2009). However, English, Solomon and Hoffman (2002) and Whittlesey (2003) argued that improved water use efficiency does not necessarily reduce total water use. Improved irrigation technologies may increase water utilization (Danso *et al.*, 2021). Similarly, Schaible and Aillery (2006) stated that smallholder farmers update irrigation systems to promote environmental sustainability, and increased farm profits are likely to be the primary motivators. English *et al.* (2002) and Whittlesey (2003) and added that improved irrigation technologies are adopted to increase production yields and that these technologies increase total water consumption and not reduce it.

Irrigation technologies provide several advantages, including enhanced agricultural and water management, improved water use efficiency, increased yields, and allow for easy change to better crops (Levidow *et al.*, 2014). Smallholder farmers can improve their fields' productivity by using updated irrigation methods to boost profitability, grow high-value crops and expand irrigated areas (Danso *et al.*, 2021). Irrigation technologies are regarded critical in dealing with

water scarcity and generating long-term climate change adaptation methods (Jordán & Speelman, 2020). McCrea and Rivers (2003) reported that modern irrigation water management practices reduce water requirement, while enhancing the water quality from drained irrigated areas to the most vulnerable areas. Hussain and Hanjra (2004) added that irrigation technologies allow smallholder farmers to diversify their production.

Different irrigation systems are adopted according to the impact they have on production, ability to cope with climate change, input costs, and overall irrigation efficiency (Jordán & Speelman, 2020). There is potential for enhancing irrigation by the introduction of modern irrigation water management practices (Bjornlund *et al.*, 2009). Furthermore, these practices require less financial investment than improved technologies (Bjornlund *et al.*, 2009). Therefore, it is crucial to study and comprehend the actual drivers and constraints toward adoption of modern irrigation water management practices.

2.2 Adoption of modern irrigation water management practices by smallholder farmers

Adoption is the implementation and use of modern irrigation water management practices by smallholder farmers (Adesope *et al.*, 2012). However, improved technologies and management practices have varying adoption rates (Bjornlund *et al.*, 2009). The knowledge about the degree to which smallholder farmers adopt water conservation practices is limited (Bagheri & Teymouri, 2021). Bjornlund *et al.* (2009) reported that some smallholder farmers are still planning on adopting better management practices in future.

Even though a few irrigators are still planning on adopting new technologies, most irrigators had already adopted practices they could afford (Bjornlund *et al.*, 2009). Danso *et al.* (2021) found that smallholder farmers' adoption behaviour is likely to change in favour of better irrigation technology if the projected net returns are higher than the expected net returns from continuing to use the current irrigation method. Similarly, Schaible and Aillery (2006) reported that smallholder farmers often invest in enhanced irrigation systems when the perceived advantages outweigh the net production costs. Although there are certain benefits to adopting efficient irrigation systems, these benefits may not be sufficient to promote adoption (Danso *et al.*, 2021).

In other regions with low water costs, the adoption of irrigation water management practices is less common (McCrea & Rivers, 2003). However, adoption of online or external support for

irrigation is decreasing (Bjornlund *et al.*, 2009). Most smallholder farmers depend on traditional practices for production in their farms which decreases productivity (Mwangi & Kariuki, 2015; Schaible & Aillery, 2012). Adopting improved irrigation technology at the farm level could increase the efficiency of water utilization and crop yields while lowering production and energy costs, potentially saving water for other purposes (Danso *et al.*, 2021; Bjornlund *et al.*, 2009).

2.3 Modern irrigation water management practices

Modern irrigation water management practices are defined as improved management practices and technologies that promote the efficient use of irrigation water (Mpanga & Idowu, 2020; Schaible & Aillery, 2012). The most common practices and technologies involved in modern irrigation water management currently are irrigation scheduling, land levelling, soil moisture monitoring, tail-water recovery system, and rainwater harvesting which improve water management and enhances the overall efficiency of most irrigation systems (Huang *et al.*, 2017; Montoro, López-Fuster & Fereres, 2011; Mpanga & Idowu, 2020; Schaible & Aillery, 2012; Stevens, 2007; Zhang *et al.*, 2019).

2.3.1. Irrigation Scheduling

Irrigation scheduling focuses on determining the appropriate timing and the correct quantity of water required to irrigate a field (Bureau of Reclamation, 2000; Gu *et al.*, 2020; Schaible & Aillery, 2012; Senzanje, 2007). It involves managing water to make certain that the right amount is applied to meet the crop's water requirements when it is necessary to irrigate (ICDC, 2017). This ultimately saves water, reduces the high costs of crop production, increase crop yields, and conserves water (ICDC, 2017; Senzanje, 2007). ICDC (2017) stated that it is important to consider the type of soil, its water holding capacity, moisture content, type of irrigation system used, and crop water requirements when scheduling irrigation.

Irrigation scheduling that is not aligned with crop water requirements or soil type results in less effective irrigation schemes (Yohannes *et al.*, 2017). The type of irrigation scheduling method used can be determined by the type of plant, soil characteristics, and crop water use (ICDC, 2017). Bureau of Reclamation (2000) also outlined that irrigation scheduling can be determined by the appearance and feel of the crop and soil, availability of water, and acceptable moisture depletion in the soil. Schaible and Aillery (2012) reported that smallholder farmers rely mostly

on traditional methods to decide when and the quantity of water to irrigate, such as irrigating based on the condition of the crop, a calendar schedule determined by the availability of labour or a fixed rotation schedule.

Scientific irrigation scheduling methods decrease the frequency of irrigation while reducing the amount of water used (Bryant *et al.*, 2017). Schaible and Aillery (2006) reported that smallholder farmers can match water supplied to crop requirements with proper irrigation schedule and accurate water flow monitoring. However, Senzanje (2007) reported that smallholder farmers may not adopt irrigation scheduling with assumptions that applying more water is better for their crops or that irrigation scheduling is a complicated process. This may be because smallholder farmers do not know their crop's water requirements or do not know the benefits that come with irrigation scheduling (Senzanje, 2007). Despite the advances in irrigation scheduling techniques, the adoption rate is low, smallholder farmers depend on personal preferences to schedule irrigation (Christian, Obi & Agbugba, 2019; Pardossi & Incrocci, 2011).

Irrigation scheduling techniques have a low adoption rate even in water scarce regions (Bryant *et al.*, 2017; Frisvold & Deva, 2012). Bjornlund *et al.* (2009) and Danso *et al.* (2021) found that irrigating smallholder farmers intend to change their systems by implementing low pressure centre pivots and buying computer panels to control irrigation water. Jordán and Speelman (2020) reported a very low adoption of irrigation scheduling, which was only practiced in fruit production. However, Engler *et al.* (2016) found that the chances of adopting irrigation scheduling increase with the implementation of effective irrigation methods like drip irrigation. Less than 10% of smallholder farmers adopted irrigation scheduling in the Western States of America (Schaible & Aillery, 2012). Between 2000 and 2004, only 18% irrigators adopted irrigation scheduling in South Africa, whereas all other irrigators use their traditional knowledge and methods to schedule irrigation (Christian, Obi & Agbugba, 2019; Stevens, 2007).

2.3.2. Soil moisture monitoring

Soil moisture monitoring is the measure of the quantity of water that is readily accessible to crops (Gu *et al.*, 2020; ICDC, 2017; Panuska *et al.*, 2015). It is also critical to monitor the amount of water a crop consumes which can vary with crops, varieties, the crop's growth stage, state of the crop, crop management practices, and weather conditions (Bureau of Reclamation,

2000; Earth Sciences, 2018; ICDC, 2017). Soil moisture monitoring tools have become more sophisticated over time (Panuska *et al.*, 2015). It can be done by testing soil samples from different soil depths that the roots may reach using the traditional feel method, soil moisture monitoring tools such as moisture sensors, or computer-based models (ICDC, 2017). The use of soil moisture monitoring is encouraged especially in areas with varying soil types.

Soil moisture monitoring aids in irrigation scheduling and managing the soil moisture content to promote optimum plant growth, increase yields and not stress the crop (Earth Sciences, 2018; Panuska *et al.*, 2015). It is important to know the amount of moisture available in the soil as this may have an influence on a crop's water requirements (Senzanje, 2007). It can also aid in determining the soil water holding capacity (Earth Sciences, 2018). The adoption of monitoring tools and use of electronic devices has increased over the years (Bjornlund *et al.*, 2009). Smallholder farmers can use tools such as soil sensors to track and control the moisture levels in the soil on irrigated farms (Panuska *et al.*, 2015; Schaible & Aillery, 2012). Panuska *et al.* (2015) also argued that improved soil moisture monitoring equipment are worth the cost as they are risk management tools. However, Bjornlund *et al.* (2009) found that improved practices such as use of soil monitoring tools were not common among smallholder farmers.

The feel method is the most common among smallholder farmers as it is easy and cheaper, whereas moisture sensors and computer systems are sophisticated and costly to implement (ICDC, 2017). Schaible and Aillery (2012) also reported that monitoring the moisture level of the soil using the feel method is one of the most used practices among smallholder farmers. Less than 10% adopted soil or plant moisture sensing devices and less than 2% adopted computer-based models to monitor water requirements based on a crop's growth stage and weather conditions (Schaible & Aillery, 2012). Mpanga and Idowu (2020) found that between 2007 and 2017, the adoption of soil moisture sensors increased by 55% in the United States.

2.3.3. Land levelling

Land levelling involves restructuring the land to promote better flow and penetration of water and making it easy for machinery to navigate through the farm (Bureau of Reclamation, 2000). It is the preparation of the irrigation plot to maintain an even field to prevent irregular application of irrigation water (Schaible & Aillery, 2012). Land levelling is usually done for surface irrigation systems, especially where basin and furrow irrigation is applied. Land levelling was first practiced using draft animals, then tractors with a conventional wooden

leveller, and now tractors with laser beams are used by more advanced farmers (Weber, 2005). However, Weber (2005) further reported that most smallholder farmers prefer using the simple tractors for land levelling over those with laser beams. For sustainable agricultural production in dry regions, efficient water utilization and productivity should be prioritized by land levelling, drainage, and use of improved irrigation technologies (Ali, 2010; World Bank, 2007).

Land that is not even can result in crops receiving too much or not enough water consequently affecting crop yield (Weber, 2005). Land levelling helps to prevent soil erosion and improves water drainage through canals after heavy rainfalls (Hoffman, 2018). Water is evenly distributed in levelled fields ensuring uniform growth of crops, saving time and water required to cultivate the land (Hoffman, 2018). The type and condition of the soil and the irrigation system used can influence how land levelling is done, the land can either be prepared to be straight or to a specific slope (Weber, 2005). Smallholder farmers can practice intercropping and combined harvesting of row crops on levelled land (Weber, 2005). Mahmood *et al.* (2015) found that all the study participants had adopted laser land levelling and over 90% of the participants had also adopted scraper land levelling. In contrast, Schaible and Aillery (2012) found that the adoption of laser land levelling decreased from 27% to 16% between 1998 and 2008. Kumar *et al.* (2022) reported that laser land levelling was adopted by farmers of all sizes without favouring large-scale farmers, it reduced irrigation costs for 97% of farmers.

2.3.4. Tail-water recovery system

Tail-water recovery is the process of reusing irrigation water from the farm that is intended for release into receiving streams (Amankwaa-Yeboah *et al.*, 2023; Bouldin *et al.*, 2004). Natural Resources Conservation Service (NRCS) (2007) defined the tail-water recovery system as a properly installed irrigation system that facilitates the collection and storage of irrigation runoff as well as runoff from rainfall. Huang *et al.* (2017) reported that tail-water pits increase the amount of water available and stored on-farm. Irrigation runoff can be collected using different techniques and stored in reservoirs to be reused for irrigation (Bouldin *et al.*, 2004). When groundwater is used, tail-water reduces power consumption from irrigation (Broner, 2003). During run-off from flooded fields, irrigation water is collected and transferred to a reservoir for future use (Bouldin *et al.*, 2004). Tail-water recovery can also be applicable for irrigation systems such as sprinkler irrigation which may have runoff problems (Broner, 2003).

The tail-water recovery system encourages water use efficiency as water is recycled to reduce wastage as much as possible (Bouldin *et al.*, 2004; Broner, 2003). As part of a water management practice, this system preserves irrigation water resources concurrently improving offsite water quality (NRCS, 2007). Similarly, Bouldin *et al.* (2004) reported that an advantage of using the tail-water recovery system for surface runoff is the conservation of groundwater since less water is pumped for irrigation. However, the disadvantage of the tail-water recovery system is the space required for a reuse pit and the regular need to maintain the pump, storage and return facilities (Broner, 2003).

Notwithstanding the environmental benefits, Bouldin *et al.* (2004) pointed out that the tail-water recovery system may not be applicable for some irrigation systems. Furthermore, Bouldin *et al.* (2004) reported that the cost of using tail-water recovery systems is greatly outweighed by the economic benefits of using the system. NRCS (2007) stated that tail-water recovery system is applicable in lands that have been well prepared, with irrigation systems properly installed, in which runoff from irrigation or rainfall can be expected. Earlier, Broner (2003) had indicated that tail-water recovery can be adopted by smallholder farmers with irrigation system with runoff problems such as sprinkler and furrow irrigation systems. However, Adusumilli and Wang (2018) found that the tail-water recovery was only adopted by 4.76% of smallholder farmers.

2.3.5. Rainwater Harvesting

About 97% of cultivated land in sub-Saharan Africa is under rain-fed agriculture (Lamprey, 2022). Rainwater harvesting involves collecting and storing rainwater from roofs for irrigation of fields (Aliabadi *et al.*, 2020; Liaw & Chiang, 2014). Tradition ways of collecting rainwater directly from the roof are through the use of basins, and drums. Whereas modern ways of collecting rainwater involve the use of roof gutters and pipes that deliver the rainwater into tanks or cisterns (Aliabadi *et al.*, 2020; Medina, 2016). Metal roofs are recommended for rainwater harvesting as they are easy to keep clean to ensure that clean water is delivered into the storage (Medina, 2016). The benefits of rainwater harvesting include reduced water use from other sources and the recycling and reuse of water (Medina, 2016). Liaw and Chiang (2014) indicated that the cost of implementing domestic rainwater harvesting systems is relatively cheaper than the cost of treating wastewater for reuse. Mango *et al.* (2017) reported that rainwater harvesting was only adopted by 5.22% of smallholder farmers in Chinyanja

Triangle, Southern Africa. To understand the adoption patterns of modern irrigation water management practices, the driving factors towards adoption are studied.

2.4 Drivers toward adoption of modern irrigation water management practices

The reasons behind the low adoption of improved agricultural practices are not clearly explained (Syan *et al.*, 2019). Drivers toward adoption are possible factors that may influence smallholder farmers considering adopting improved practices (Scheierling, Young & Cardon, 2006). There are many factors that influence smallholder farmers' production decisions (Bjornlund *et al.*, 2009). Furthermore, the socio-economic and socio-psychological drivers that influence smallholder farmers' adoption decisions are not the same for different innovations (Bjornlund *et al.*, 2009; Smithers & Furman, 2003). Each smallholder farmer's individual characteristics are crucial determinants of whether they will adopt an innovation or not (Bagheri & Teymouri, 2021). To comprehend smallholder farmers' adoption behaviour toward different agricultural practices, more focus needs to be paid to the drivers that influence them (Bagheri & Teymouri, 2021).

2.4.1. Socio-economic drivers

Socio-economic drivers are made up of smallholder farmers' demographic characteristics (Antolini, Scare & Dias, 2015). Understanding the socio-economic drivers that influence the adoption of modern irrigation water management practices is important for proper dissemination of the practices (Terano *et al.*, 2015). The following socio-economic drivers will be discussed in this section: farmer's age, gender, education level, farm size, off-farm employment, household size, and group membership.

2.4.1.1 Farmer's age

Age determines the adoption of newly introduced technologies by smallholder farmers (Mwangi & Kariuki, 2015). The age of smallholder farmers was a positive driver toward the adoption of water conservation practices (Agholor & Nkosi, 2020). Early adopters of technological innovations are generally younger farmers (García *et al.*, 2020; Stephenson, 2003). Similarly, Alexander and Van Mellor (2005) reported that the use of genetically engineered maize increased among younger farmers than elderly farmers. Under the study of the adoption of sustainable water conservation practices, Agholor and Nkosi (2020) demonstrated that 50% of farmers were between the age of 18 and 35 years, 47% were from the middle age group between

36 and 49 years, and 36% were between the age of 50 and 60 years. A different view was provided by Mzoughi (2009) who reported a lower likelihood of younger farmers adopting integrated crop protection or organic farming practices compared to older farmers.

Kariyasa and Dewi (2011) and Mignouna *et al.* (2011) reported that the older the farmer, the more experienced and knowledgeable they are of most practices, and they can process information on new practices better than younger farmers. Agholor and Nkosi (2020) also found that elder farmers with considerable farming experience are naturally motivated and ready to acquire knowledge from a range of sources. As a result, older smallholder farmers are generally more aware of improvements in agricultural practices than younger farmers (Agholor & Nkosi, 2020). Mango *et al.* (2017) found that each year a farmer gets older, the likelihood of that particular farmer adopting a water conservation practice increases by 3%. The average age of irrigators was revealed to be between 56 and 63 years of age (Moyo, 2016). The average age of participants was reported to be 41 and 51 years by Belachw *et al.* (2020) and Terano *et al.* (2015), respectively. Aliabadi *et al.* (2020) also found that participants older than 50 years made up only 20% of the total participants, where the majority (43%) were between 40 to 50 years old in a study of the intended adoption of sustainable water management practices through rainwater harvesting by rural people. Annor-Frempong (2013) reported an insignificant variation between age groups and adoption behaviour. In the study by Annor-Frempong (2013), age did not appear to correlate with the adoption of introduced seed practices.

2.4.1.2 Gender

Farmers may have different roles and responsibilities according to their gender in different cultures (Annor-Frempong, 2013; Scott, Oates & Young, 2015). Females have limited access to extension services in some areas as they are not allowed to engage with extension officers of the opposite gender because of their culture (Annor-Frempong, 2013). Mignouna *et al.* (2011) and Scott *et al.* (2015) explained that males, as the household heads, make most decision regarding farming and have access and control over production resources than females because of social norms. Furthermore, Annor-Frempong (2013) reported that more males had a higher production efficiency than females. Lavison (2013) also found that more males adopted organic fertilizer than females. Agholor and Nkosi (2020) reported that water conservation practices were adopted more by males (39%) than females (21%). Moyo (2016) found that scheme irrigators had the highest number of male (93.3%) household heads. However, Agholor and

Nkosi (2020) reported that most females like being involved and in control, they tend to initiate more innovative projects than males.

Quisumbing *et al.* (2014) reported that women who are determined and responsible for decision-making of farm inputs were more successful in running farms than men. On the other hand, gender was not significantly correlated to adoption behavior toward recommended seed practices (Annor-Frempong, 2013). Whereas Mzoughi (2009) reported mixed results for gender, which had a significant influence on the adoption of integrated crop protection practices but not for the adoption of organic farming practices. Gender had a significant influence on the production of improved cassava in Nigeria (Obisesan, 2014). Agholor and Nkosi (2020) reported that the gender of the smallholder farmers had a positive influence on the adoption of water conservation practices. Gender had a negative but significant influence on the use of solid waste management services (Alhassan *et al.*, 2017). Therefore, the influence of gender on the adoption of modern irrigation water management practices may vary across different cultures and social norms.

2.4.1.3 Education level

Education is important for behavioral change as it aids in improving agricultural sustainability (Agholor & Nkosi, 2020). Moyo (2016) emphasized that education can influence how smallholder farmers make marketing decisions and adopt modern technologies. Educated smallholder farmers are open to new practices (Moyo, 2016). It is much easier to introduce an innovation to smallholder farmers with higher levels of education as it increases their chances of adopting it (Adebiyi & Okunlola, 2010). Smallholder farmers that have acquired higher levels of education have more access to information and increased capability of adopting new technologies (Agholor & Nkosi, 2020; Jordán & Speelman, 2020; Mignouna *et al.*, 2011). The education level of the farmers positively influenced the decision-making process to adopt improved technologies and practices (Mwangi & Kariuki, 2015; Okunlola *et al.*, 2011; Ajewole, 2010). Agholor and Nkosi (2020) found that the level of education had a significant influence on the adoption of water conservation practices.

Education level significantly influenced the adoption of introduced seed practices (Annor-Frempong, 2013). The adoption of organic farming was also significantly influenced by farmers' level of education (Mzoughi, 2009). Another study reported that formal education negatively influenced the use of genetically modified crops (Uematsu & Mishra, 2010).

Contrary to other studies, Ishak and Afrizon (2011) and Samiee *et al.* (2009) found an insignificant influence of smallholder farmers' education level on the adoption of technology.

2.4.1.4 Years of farming experience

The years of farming experience refers to the duration a smallholder farmer has been practicing farming and acquiring experience (Li *et al.*, 2019). Increase in farming experience increases the likelihood of technology adoption (Li *et al.*, 2019). The more years spent practicing farming the more the experience and knowledge in production (Adejo & Opeyemi, 2019; Alam, 2015; Obisesan, 2014). Studying the drivers affecting the adoption of pressurized irrigation technology, Nejadrezaei *et al.* (2018) found that 46.2% of the participants' experience was between 11 and 20 years. Similarly, Aliabadi *et al.* (2020) reported that 46% of the farmers had 10 to 20 years of farming experience in a study of rural people's intention to adopt sustainable water management practices. Li *et al.* (2019) also found that the mean experience was 22 years with 66.84% of the participants having more than 20 years farming experience.

Smallholder farmers that had many years of farming experience were most likely to adopt improved practices (Alam, 2015). Longer years of farming experience increased the likelihood of practicing crop diversification by 5% (Alam, 2015). Li *et al.* (2019) found that increase in farming experience influenced the adoption of top grafting by 1%. Longer years of farming experience score increased technology adoption by 0.0506 (Obisesan, 2014). In contrast, Amengor *et al.* (2018) reported that experienced smallholder farmers were less likely to adopt enhanced varieties. The least experienced smallholder farmers were the most likely to adopt improved sweet potato varieties than the experienced (Amengor *et al.*, 2018).

2.4.1.5 Household size

Household size is used to determine available farm labour (Moyo, 2016; Mwangi & Kariuki, 2015; Zeweld *et al.*, 2017). Larger households have the ability to alleviate the labour constraints associated with the implementation of new technology (Mignouna *et al.*, 2011; Zeweld *et al.*, 2017). An average of 5.7 members were reported among the households that participated in the study of smallholder farmer irrigation farming (Moyo, 2016). Zeweld *et al.* (2018) found that on average less than 4 adult household members made up the farm labour pool. Increase in full-time farm working household members increases the farm labour pool which results in a higher likelihood to adopt labour-intensive technologies (Moyo, 2016). Household size positively influenced adoption (Darkwah *et al.*, 2019). Smallholder farmers with larger household sizes

adopted technology more than smallholder farmers with small household sizes (Darkwah *et al.*, 2019). Larger households can carry out the labour and maintain soil and water conservation practices (Asfaw & Neka, 2017; Mwangi & Kariuki, 2015). However, Mango *et al.* (2017) found no notable distinction among adopters and non-adopters with respect to household sizes.

2.4.1.6 Source of income

Sources of income may include farming, remittances, social grant, pension, informal trading, and private businesses (Antolini *et al.*, 2015; Ragie *et al.*, 2020). Source of income can influence decisions about farm improvements (Ntai, 2011). It was found that 58% of households depended on farming as their source of income, 20% on informal businesses, 14% on social grant or pension, and 8% on wages from formal employment (Ntai, 2011). Annor-Frempong (2013) reported that 59% of the respondents indicated that they had no other job apart from farming. Zeweld *et al.* (2017) discovered that agriculture is the primary sector providing livelihoods for approximately 67% of farmers. Ragie *et al.* (2020) reported that crop production was a common source of income in Bushbuckridge. However, 84.2% households depended on social grants, while 82.0% depended on savings and loans (Ragie *et al.*, 2020). Other farmers have predominantly involved themselves in small-scale commerce, running small enterprises, trading charcoal and firewood, and taking on occasional employment (Zeweld *et al.*, 2017). Antolini *et al.* (2015) reported that smallholder farmers who have additional sources of income besides farming were more likely to adopt precision agricultural technologies. Moyo (2016) found that 48.1% scheme irrigators and 57.1% independent irrigators depended on agriculture as their primary means of income.

2.4.1.7 Land ownership

Smallholder farmers practice farming on land they had bought themselves, inherited, renting, or permitted to occupy by the relevant tribal authority (Mugure, Oino & Sorre, 2013; Lawin & Tamini, 2019; Séogo & Zohonogo, 2019; Zeng *et al.*, 2018). Land ownership encourages the use of agricultural technologies while not having land ownership prevents it (Zeng *et al.*, 2018). It was observed that farmers tend to handle their own land more favourably than those who rent it which increases the chances of adopting precision agricultural technologies (Antolini *et al.*, 2015). Individual land ownership rights positively influenced the adoption of agroforestry systems (Mugure *et al.*, 2013). Having ownership of the farm plot provides the smallholder

farmers with assurance of long-term farming (Lawin & Tamini, 2019; Séogo & Zahonogo, 2019).

However, most of the smallholder farmers did not have formal land rights which resulted in low technology adoption (Séogo & Zahonogo, 2019). Mugure *et al.* (2013) also found that smallholder farmers who were renting or had borrowed land were constrained from adopting agroforestry systems. Furthermore, Lawin & Tamini (2019) found that renting of land discouraged the adoption of agri-environmental practices. This is because smallholder farmers who are not farming on their own land face the possibility of being evicted which may prevent them from taking advantage of future technology-induced benefits (Mugure *et al.*, 2013; Zeng *et al.*, 2018).

2.4.1.8 Irrigation method

Irrigation methods include the use of sprinkler irrigation, drip irrigation, furrow irrigation, and pressurized systems (Fan & McCann, 2017; Gunarathna *et al.*, 2018; Huang *et al.*, 2017; Mpanga & Idowu, 2020; Ntai, 2011; Yohannes *et al.*, 2017). Sprinkler irrigation systems are commonly used during cool seasons when there is less occurrence of evapotranspiration (Huang *et al.*, 2017). Ntai (2011) also reported that most of the smallholder farmers used sprinkler irrigation. Fan and McCann (2017) found that only 12% of the participants used drip irrigation, while 45% employed sprinkler irrigation. However, Mpanga and Idowu (2020) discovered that the use of drip irrigation increased by 71% between 2007 and 2017. However, Gunarathna *et al.* (2018) reported that furrow irrigation had low adoption rates because it is labour intensive and has low water use efficiency than sprinkler and drip irrigation. This is in contradiction to the earlier study of Yohannes *et al.* (2017) who reported that surface irrigation (furrow) was the most applied irrigation method.

2.4.1.9 Farm size

Farm size plays an important role when adopting new technologies as some technologies are scale dependent (Mwangi & Kariuki, 2015). In regions where irrigation is a small part of the farm operation, smallholder farmers do not see the need to invest in irrigation technology (Bjornlund *et al.*, 2009). However, smallholder farmers with larger farm sizes tend to adopt new technologies as their large farms enable them to try the new practice on just a piece of their land (Uaiene *et al.*, 2009). The ability to test the technology on a small portion of the farm before implementing it on a larger scale increases the likelihood of adoption since smallholder

farmers can assess benefits or impact of the technology (Antolini *et al.*, 2015). Smallholder farmers in irrigation schemes have a greater proportion of farm size and grow a variety of crops compared to community gardeners who focus mostly on vegetables (Moyo, 2016). Mignouna *et al.* (2011) and Uaiene *et al.* (2009) found a correlation indicating that farm size influenced the adoption of improved agricultural technologies.

Farm size and the total area cultivated influenced the adoption of maize agronomic practices (Annor-Frempong, 2013). Dinar *et al.* (2017) reported that farm size had a significant influence on the adoption of conservation practices. Farm size had a significant influence on the adoption of irrigation technology (Jordán & Speelman, 2020). Mango *et al.* (2017) reported that large farm size increased the likelihood of adopting conservation practices by 29%. Asfaw and Neka (2017) reported that an increase in farm size lowered the probability of adopting soil and water management practices. However, Asfaw and Neka (2017) found that the larger the farm size, the lower the probability of adopting soil and water management practices. The typical farm size for smallholder farmers in irrigation schemes was 0.2 ha, whereas independent irrigators had larger farms of up to 20 ha (Moyo, 2016).

2.4.1.10 Off-farm employment

It is believed that off-farm employment has a positive effect on adoption behaviour as they provide ready and available source of finance for farm inputs (Annor-Frempong, 2013). Off-farm income play a crucial role in enhancing the economic capacity of rural households and tackling issues related to food security (Mengistie & Kidane 2016). Decision-making, adopting and maintenance of improved practices can be influenced by off-farm employment (Shiferaw *et al.*, 2009). Income earned outside of farming has been demonstrated to favourably influence the adoption of technology (Mwangi & Kariuki, 2015). Agholor and Nkosi (2020) reported that 41% of the study participants had off-farm employment, whereas 34% were self-employed, and only 24% had no employment. Annor-Frempong (2013) reported that 41% of the respondents indicated that they were engaged in other activities in addition to farming. The study also found no significant differences or relationships between the adoption of the recommended seed practices and off-farm employment (Annor-Frempong, 2013). Ragie *et al.* (2020) found that 73.1% of smallholder farmers were employed off-farm.

2.4.1.11 Group membership

Smallholder farmers in cooperative groups have similar socio-economic and infrastructural elements shared reservoir or water sources, they may even be in the same environmental setting (Chaudhry, 2018). It is recommended that smallholder farmers take part in group engagements at scheme level for better irrigation management (Muchara *et al.*, 2014). Annor-Frempong (2013) found that 70.3% of smallholder farmers in farmers' associations had higher production efficiencies than those who were not part of farmers' associations. However, it was found that close friends had no influence on the adoption decision of recommended maize practices (Annor-Frempong, 2013). Farmers in formal farmer organizations were 6% more likely to adopt two or more sustainable land management practices (Zeweld *et al.*, 2018). Antolini *et al.* (2015) postulated that adoption practices were influenced by the sharing of information and experiences between the smallholder farmers in farmer associations.

2.4.2. Socio-psychological drivers

Smallholder farmers' socio-psychological issues should be considered to encourage the adoption of modern irrigation water management practices (Zeweld *et al.*, 2017). The socio-psychological drivers include adoption intention, attitude, personal efficacy, and social capital (Zeweld *et al.*, 2019).

2.4.2.1 Adoption intention

Smallholder farmers' decision to adopt improved practices is derived from having an intention to adopt those practices (Antolini *et al.*, 2015). Ajzen's Theory of Planned Behaviour has been applied by several researchers in the study of the socio-psychological factors influencing the adoption intention of improved agricultural practices and technologies (Aliabadi *et al.*, 2020; Buyinza *et al.*, 2020; Pino *et al.*, 2017; Terano *et al.*, 2015; Zeweld *et al.*, 2017). The Theory of Planned Behaviour constitutes of the constructs attitude, perceived behavioural control (personal efficacy), and subjective norms (social capital) (Ajzen, 2011). Positive attitudes influence the intention to adopt new practices (Aliabadi *et al.*, 2020; Pino *et al.*, 2017; Terano *et al.*, 2015; Zeweld *et al.*, 2017). In particular, the intention to adopt improved practices positively influenced the adoption of precision agricultural technologies (Antolini *et al.*, 2015).

2.4.2.2 Attitude

The attitude of smallholder farmers is an important determinant of the successful implementation of irrigated agriculture (Stevens, 2012). According to the Technology Acceptance Model (TAM), attitude is made of two components, perceived usefulness and perceived ease of use, which determine the acceptance and use of an information-based technology (Bagheri & Teymouri, 2021). Zeweld *et al.* (2017) stated that smallholder farmers' attitudes are formed based on observed statements regarding perceived ease, perceived usefulness and perceived compatibility of agricultural practices. Extension agents have difficulties in changing smallholder farmers' attitudes towards different agricultural practices (Stevens, 2012). Attitudes towards the end results of a new practice represents personal beliefs of the benefits of the practice and the individual's evaluations of those beliefs (Scott *et al.*, 2015). Where favourable beliefs represent positive attitudes that give a motive to adopt practices (Scott *et al.*, 2015).

Smallholder farmers' attitudes should be considered in all stages of technology diffusion and implementation to encourage adoption (Waheed *et al.*, 2015). However, Waheed *et al.* (2015) argued that a positive attitude is not enough to determine long-term commitment to the product. The attitude of smallholder farmers toward new practices can influence their adoption, whereby such attitudes are either positive or negative (Terano *et al.*, 2015). Smallholder farmers who have positive attitudes have perceived those practices as beneficial to them; easy to comprehend, adopt and integrate into their existing farming values and traditions (Zeweld *et al.*, 2017). Positive attitudes towards practices increase the likelihood of adoption (Zeweld *et al.*, 2017).

Individuals with positive attitudes toward water management were more likely to participate in it instead of participating in general and unsustainable approaches (Aliabadi *et al.*, 2020). Positive attitudes increased the chances of adopting two or more land management practices by about 10% (Zeweld *et al.*, 2018). Positive attitudes also influenced the adoption of minimum tillage and row planting among smallholder farmers (Zeweld *et al.*, 2017). Syan *et al.* (2019) and Terano *et al.* (2015) also found that attitude had a positive influence on adoption intention, smallholder farmers with positive attitudes about certain practices had a high intention of adopting them. Similarly, Adusumilli and Wang (2018) reported that conservation practices are adopted mostly by smallholder farmers who felt that land conservation and changes to existing agricultural practices could protect water quality in streams and rivers. Furthermore,

Waheed *et al.* (2015) reported a significant influence of attitudes towards eBook reader adoption. However, Mahmood *et al.* (2015) found that farmers had positive, negative and mixed attitudes on the adoption of different practices.

Attitude significantly influenced the adoption of crop rotation with legumes and compost application but was not related to the adoption of agroforestry systems (Zeweld *et al.*, 2018). However, smallholder farmers with negative attitudes were not willing or interested in adopting sustainable practices (Zeweld *et al.*, 2017). Attitude did not have a significant influence on conversions to organic agriculture (Zeweld *et al.*, 2017).

i. Perceived usefulness

Perceived usefulness of the application of new technology, is the extent to which a person believes using a particular technology will improve their productivity (Syan *et al.*, 2019). When smallholder farmers do not perceive new innovations useful, they are hesitant to adopt them even if they are expected to improve performance (Allahyari, 2009; David & Ardiansyah, 2018). Smallholder farmer's intention to adopt new practices is motivated by the perceived gains which may at times be overestimated (Barrett, 2005; Halima *et al.*, 2018; Venkatesh, Thong & Xu, 2012). The intention to adopt sustainable agricultural practices was significantly influenced by how useful the practices were perceived to be (Syan *et al.*, 2019). Similarly, Wauters and Mathijs (2014) reported that the perceived usefulness of sustainable agricultural practices and the information regarding their implementation significantly influence the adoption of the practices.

ii. Perceived compatibility

The type of technology plays a crucial role in the decision-making process for adoption (Mignouna *et al.*, 2011). The likelihood of adopting new technology is higher when smallholder farmers perceive the technology aligning with their needs, values, past experiences, and fitting well to their environment as they view it as a beneficial investment (Adebayo *et al.*, 2018; KardanMoghaddam, Rajaei & Jafari, 2022; Mignouna *et al.*, 2011; Syan *et al.*, 2019). The intention of smallholder farmers to adopt technology is influenced by how they perceive the performance of that technology (Mwangi & Kariuki, 2015). Hence, it is important that smallholder farmers participate in evaluating any new technology to assess its suitability for their specific circumstances (Mwangi & Kariuki, 2015). The more compatible the innovation is with the needs and values of the individual, the greater the chance of adoption

(Waheed *et al.*, 2015). Wauters and Mathijs (2014) stated that when smallholder farmers perceive that sustainable agriculture aligns with their existing practices, they will consider it advantageous to them.

2.4.2.3 Personal efficacy

Personal efficacy, also referred to as self-efficacy represents how much a farmer believes in their capabilities to implement an improved practice (Heslin & Klehe, 2006; Waheed *et al.*, 2015; Zeweld *et al.*, 2017). Personal efficacy is a construct of perceived behavioural control which reflects the capability and ability of a smallholder farmer to take control and implement improved practices (Annor-Frempong, 2013). High personal efficacy can change a farmer's perspective to being strategic in implementing new technologies and practices rather than focusing on the constraints they face (Heslin & Klehe, 2006). Personal efficacy has to do with self-esteem and self-confidence of the smallholder farmer, the belief they have in themselves to adopt improved practices based on their knowledge and experience (Zeweld *et al.*, 2017). Smallholder farmers with a low personal efficacy do not see the value of their own actions and do not believe they can make a difference (Scott *et al.*, 2015), whereas smallholder farmers with a high personal efficacy believe in the importance of the actions they make (Scott *et al.*, 2015).

Personal efficacy was found to play an important role in smallholder farmers' decision-making process and adoption intention towards sustainable agricultural practices (Buyinza *et al.*, 2020; Syan *et al.*, 2019; Zeweld *et al.*, 2017). Aliabadi *et al.* (2020) reported a significant influence of personal efficacy on rural people's intention to participate in sustainable water resource management. Jung *et al.* (2012) found that personal efficacy influences the adoption of media technology innovations. Personal efficacy also influenced the intention and adoption of organic practices for avocado production (Zeweld *et al.*, 2018). Buyinza *et al.* (2015), Tama *et al.* (2021) and Terano *et al.* (2015) found a significant influence of perceived behavioural control on behavioural intention. Tosakana *et al.* (2010) reported personal efficacy as the main determinant of the implementation of most sustainable practices. Of interest are the reports by Aliabadi *et al.* (2020) and Pino *et al.* (2017) who found that personal efficacy had no significant influence on the intention to adopt new technologies.

2.4.2.4 Social capital

Social capital includes networks, social relations, and associations that smallholder farmers can draw information and obtain support with matters relating to their production (Moyo, 2016). According to Jordán and Speelman (2020) decisions about irrigation management are sometimes made collectively or influenced by peers and fellow farmers regarding irrigation systems, infrastructure, and transportation. Smallholder farmers in corporative groups have similar socio-economic and infrastructural elements shared reservoir or water sources, they may even be in the same environmental setting (Chaudhry, 2018). It is feasible that smallholder farmers may make decisions based on the reasonable adoption presumptions when selecting how to use water trading gains to adopt efficient irrigation systems (Danso *et al.*, 2021). Smallholder farmers usually adopt practices that are used by people in their social groups and those they look up to (Bagheri & Teymouri, 2021). Smallholder farmers are less influenced by external sources of information when it comes to decision-making (Bagheri & Teymouri, 2021).

Social capital had a positive influence on the adoption of agroforestry systems, crop rotation and compost (Zeweld *et al.*, 2018). David and Ardiansyah (2018) reported that social capital has a significant influence on technology adoption. Alhassan *et al.* (2017) found a positive influence of social capital on willingness to pay for solid waste management practices, significant at 1%. Social capital influenced the intention to adopt sustainable forest management practices (Ofoegbu & Speranza, 2017). Others, however, demonstrated that social capital had an insignificant relationship with farmers' intention to adopt sustainable agricultural practices (Syan *et al.*, 2019). Buyinza *et al.* (2020) also found no significant influence of social capital on the intentions to integrate trees to coffee plantations.

2.5. Constraints faced by smallholder farmers towards adoption of modern irrigation water management practices

Regardless of differences in production among smallholder farmers, similar issues are faced by all in maintaining their productive farms (Bjornlund *et al.*, 2009). The following factors affect a smallholder farmers' decision regarding the adoption of efficient irrigation technologies. The constraints experienced by smallholder farmers include: inadequate extension services, financial constraints, lack of information, access to water, farm location, lack of technical expertise, and agricultural policies.

2.5.1. Inadequate extension service

Agricultural extension officers have a key role to play in the flow of information, networking, and adoption of new technologies and sustainable practices (Agholor & Nkosi, 2020; Baig & Straquadine, 2014). Danso *et al.* (2021) argued that farmers are frequently confronted with a variety of irrigation technologies and crop options, and selecting the most efficient technology to produce profitable crops is not an easy task.

2.5.1.1 New practices not introduced to smallholder farmers

Extension officers should be informing smallholder farmers of new and improved practices, their benefits and how to use them effectively (Mwangi & Kariuki, 2015). The introduction of modern irrigation water management practices for adoption by smallholder farmers could improve irrigated crop production and climate change adaptation (Taghvaeian *et al.*, 2020). Alarming, Ntai (2011) reported that 60% of smallholder farmers did not receive advice on irrigation water management from extension officers. This may be due to the shortage of extension officers in Lesotho resulting in less smallholder farmers receiving extension services (Mojaki & Keregero, 2019).

2.5.1.2 Lack of training

Smallholder farmers received little to no training on irrigation water management by extension services personnel (Yohannes *et al.*, 2017). Furthermore, it was discovered that smallholder farmers had not received training on irrigation water management (Yohannes *et al.*, 2017). As a result, smallholder farmers have not been irrigating their plots correctly to meet soil and crop water requirements (Yohannes *et al.*, 2017). Asfaw *et al.* (2012) argued that smallholder farmers who had access to adequate extension services were more likely to adopt sustainable practices than farmers who had no access to extension services.

2.5.1.3 No access to extension services

It is important for smallholder farmers to have regular access to extension officers for effective technology transfer and agricultural development (Ntai, 2011). However, some smallholder farmers reside in isolated rural locations where extension workers are unable to reach them, and therefore do not obtain the information they require to adopt methods for improving their farming practices (Zeweld *et al.*, 2019). Smallholder farmers' access to extension services was

reported to have an impact on the adoption of sustainable agricultural practices (Kumari, 2018; Wauters & Mathijs, 2014). Asfaw *et al.* (2012) reported that smallholder farmers who were more curious and had access to adequate extension services were more likely to adopt sustainable practices than farmers who had no access to extension services.

2.5.2. Financial constraints

A major reason as to why smallholder farmers do not adopt improved water use efficiency practices is their poor financial status, which hinders their adoption of improved farming practices (Bjornlund *et al.*, 2009). Financial constraints are common in most irrigated farms which limit the adoption of new methods in farming (Caswell & Zilberman, 1985; Schaible & Aillery, 2006). Financial capital impends the adoption of innovations that can be implemented easily with demonstrable benefits (Morrison, 2005). Lack of access to funding also hinders the intention to adopt technology and sustainable practices (Adebayo *et al.*, 2018; Venkatesh, Thong & Xu, 2012). Whilst Jordán and Speelman (2020) reported that financial capital encourages the adoption of irrigation technologies. Belachew *et al.* (2020) reported that farmers with financial capital invested more in off-farm activities as opposed to adopting or improving their practices.

2.5.2.1 Lack of funding to purchase equipment

Financial constraints hindered smallholder farmers from implementing changes and improving their practices (Bjornlund *et al.*, 2009). Bagheri and Teymouri (2021) stated that smallholder farmers lack the financial capital needed to invest in new practices. Schaible and Aillery (2012) found that 28.4% of irrigators could not finance improvements, whereas 25.6% found high installation cost of improvements as a constraint toward adoption. Jordán and Speelman (2020) reported that access to financial resources could encourage adoption of irrigation technologies.

2.5.2.2 Access to credit

Access to credit enables smallholder farmers to invest in improved practices, buy new equipment, and improve maintenance (Obisesan, 2014). However, the process of credit application is complicated, and most smallholder farmers are unable to provide the supporting documents required (Maheswari, Ashok & Prahadeeswaran, 2008). Lack of access to credit limited the adoption of practices in irrigated farms (Caswell & Zilberman, 1985; Schaible & Aillery, 2006). Access to credit had an influence on the adoption of soil and water conservation

practices (Belachew *et al.*, 2020; Darkwah *et al.*, 2019). Obisesan (2014) found that smallholder farmers with access to credit were 15.82% more likely to adopt improved technology compared to those without access to credit.

2.5.2.3 Lack of money to maintain practices

Smallholder farmers prefer adopting practices that are affordable and can be applied with already acquired knowledge and skills rather than sophisticated and expensive innovations (Bjornlund *et al.*, 2009). Bagheri and Teymouri (2021) reported that smallholder farmers were open to adopting soil and water conservation practices that cost less and could easily be implemented with available resources.

2.5.3. Lack of information

The availability of appropriate information is important in providing smallholder farmers with an awareness of new technologies and practices and how to implement them (Mwangi & Kariuki, 2015). Accurate information about the effectiveness of the advanced techniques can promote the adoption of technologies and new innovations (García *et al.*, 2020). Mahmood *et al.* (2015) found that 3.3% of the participants thought that the lack of information hindered the adoption of water saving interventions. Since there is a long delay between a technology's introduction to the market and its widespread use by smallholder farmers, adoption is not quick (Antolini *et al.*, 2015).

2.5.3.1 No access to information

Without relevant information decisions are undertaken in states of uncertainty due to a lack of information, education, and skills, which implies that cultural influences and cognitive biases could result in the adoption of ineffective practices or no adoption at all (García *et al.*, 2020). Lack of information about the advantages of improved systems is a key constraint that prevents smallholder farmers from improving their systems (Schaible & Aillery, 2006). Mwangi and Kariuki (2015) stated that farmers should be made aware of the existence of technology, its benefits, and its usage for them to adopt it. It is believed that smallholder farmers who have greater access to technology information sources adopt new technologies since they are more aware of the effects of technology adoption on farm enterprises (Antolini *et al.*, 2015).

2.5.3.2 Lack of awareness

A lack of awareness refers to the extent to which the decision maker is unaware of the recommended practices (Annor-Frempong, 2013). It is the in-depth knowledge a farmer has about a particular recommendation beyond just knowing about the practice (Annor-Frempong, 2013). A lack of awareness of alternative management strategies leads to practices not being adopted (Bagheri & Teymouri, 2021; Zeweld *et al.*, 2019). Farmers will only adopt the technology they are aware of or have been informed about it (Mwangi & Kariuki, 2015). A significant variation was found between farmers' awareness of recommended practices and their adoption behaviour towards those practices (Annor-Frempong, 2013). Annor-Frempong (2013) found that 80% of the smallholder farmers who were aware of recommended maize practices adopted them. The study revealed that farmers who do not use irrigation systems are unable to harness the benefits of small-scale irrigation due to their lack of awareness about it (Mengistie & Kidane 2016).

2.5.3.3. Misunderstanding of the information provided

Bagheri and Teymouri (2021) and Zeweld *et al.* (2019) reported that there is a lot of confusion and doubt among smallholder farmers about certain practices due to the lack of appropriate knowledge. Maheswari *et al.* (2008) found that the lack of knowledge hindered smallholder farmers from adopting precision farming technology as it made it difficult for the smallholder farmers to understand and adopt new technologies.

2.5.4. Farm location

The physical location of the farm affects agricultural productivity (Annor-Frempong, 2013). Pokhrel, Paudel and Segarra (2018) reported that farm location was one of the factors that affected drip irrigation technology adoption. Distance from a farmer's home to the farm has a negative influence on the adoption of soil and water conservation practices, the probability of adopting the practices decreases with longer farm distance from the farmer's home (Asfaw & Neka, 2017; Belachew *et al.*, 2020). Whereas Annor-Frempong (2013) found no noticeable variation between the farm location and the adoption of introduced seed practices, but a close correlation between the two. Chirwa (2005) found a negative relationship between farm distance and the adoption of maize technologies.

2.5.4.1 Distance from water source

The distance from farm to water source can be a determining factor for the adoption of technology. Shallo, Ayele and Sime (2020) reported that distance to water source had a negative impact on the adoption of biogas technology. A minute increase in time spent walking to the water sources decreased the likelihood of biogas technology adoption by a factor of 0.97 (Shallo *et al.*, 2020).

2.5.4.2 Distance from training programmes

Isgin *et al.* (2008) stated that the farm location determines which agricultural services are easily accessible to the farmers, which ultimately influences the decision-making process toward adoption. Ransom, Paudyal and Adikharil (2003) reported a positive correlation between the farmers' closeness to agricultural research stations and adoption, which is attributed to the exposure that farmers have and the easy access to agricultural information.

2.5.4.3 Distance from other adopters

Farm distance from an adopter of an innovation and the ability of the farmer to visit the adopter frequently could influence the adoption of agricultural innovation (Ghadim & Pannell, 1999). This is because the farmer may easily access information on the innovation, learn valuable skills and have less doubts about the innovation (Ghadim & Pannell, 1999). Taghvaeian *et al.* (2020) reported that the adoption of improved practices such as irrigation scheduling is more likely among smallholder farmers who have witnessed the demonstration of that improved practices in their area than those had witnessed the practice demonstrated.

2.5.5. Access to water

Inadequate water supply and irregular water availability hinder the successful irrigation of most smallholder farms (Marques *et al.*, 2005; Moyo, 2016; Schaible & Aillery, 2012). This may be caused by prevalent droughts, irregular rainfall, and water shortages in most areas (Taghvaeian *et al.*, 2020). Access to water has an impact on the adoption of irrigation technologies (Taylor & Zilberman, 2017). Smallholder farmers are more likely to adopt modern irrigation water management practices to reduce the amount of water required to irrigate large farms (Jordán & Speelman, 2020).

2.5.5.1 Inadequate water supply

Inadequate access to water posed a major constraint for gardening (Moyo, 2016). Unlimited water supply improves adoption by about 50%, allowing people to fully exercise their water rights and, as a result, make investments aimed at improved management (Jordán & Speelman, 2020). The excess amounts of surface water, on the other hand, discourages smallholder farmers from investing in and adopting irrigation technologies, as well as reducing water consumption (Mendelsohn & Dinar, 2003). Under no scarcity conditions, if a significant level of subsidy is provided, smallholder farmers will be motivated to convert to a better irrigation technology (Danso *et al.*, 2021). However, Danso *et al.* (2021) reported that the probability of changing to efficient irrigation technologies is low even under full water access.

2.5.5.2 Irregular water availability

The reliability of water supply influences adoption of irrigation technologies (Marques *et al.*, 2005). Council of Australian Governments (COAG) (2003) found that smallholder farmers are hesitant to invest in irrigation due to the lack of assurance of access to water in the long-term. Adekunle, Oladipo and Busari (2015) reported that smallholder farmers were discouraged from participating in irrigation schemes because irregular water availability. Senzanje (2007) also reported irregular water supply hindered proper irrigation scheduling. Lack of water availability was also reported to hinder the adoption of precision farming technology (Maheswari *et al.*, 2008).

2.5.6. Lack of technical expertise

Technical expertise and abilities are required for adopting and controlling the most appropriate technology level (García *et al.*, 2020). However, smallholder farmers prefer technologies that are not sophisticated (Antolini *et al.*, 2015). Some modern irrigation water management practices may be too sophisticated for smallholder farmers to implement (ICDC, 2017). Yohannes *et al.* (2017) reported that the main constraints hindering the adoption of irrigation water management by smallholder farmers are lack of technical knowledge. Maheswari *et al.* (2008) also found that the lack of technical skills hindered the adoption of precision technology. Antolini *et al.* (2015) reported that challenges in adopting specific technologies had a negative impact on smallholder farmers' adoption of new technologies. Smallholder farmers without technical knowledge were less likely to adopt modern agricultural technologies (Lima *et al.*, 2018). In keeping with the adoption of technology, Antolini *et al.* (2015) reported that

smallholder farmers who had some form of mechanization technology or had already adopted some technologies were more likely to adopt precision agricultural technologies.

2.5.7. Agricultural policies

Irrigation technology adoption has been found to be constrained by agricultural policies (Zhang *et al.*, 2019). Similarly, Jordán and Speelman (2020) reported that the adoption of irrigation technologies has been shown to be limited by institutional and policy considerations. Furthermore, poor government support as well as top-down approaches undertaken by policymakers and extension officers, constraint smallholder farmers from adopting modern irrigation water management practices (Yohannes *et al.*, 2017). Danso *et al.* (2021) added that policies that focus on tackling water management issues can aid in long-term decimation of water scarcity challenges, and therefore aiding to climate change adaptation. Policies that encourage controlled water use and increase in irrigated acreage should be implemented (Berbel *et al.*, 2015).

2.6. Conceptual framework

Figure 1 below is an illustration of the relationship between the adoption of modern irrigation water management practices by smallholder farmers, the socio-economic and socio-psychological drivers toward adoption, and the constraints hindering the adoption. The blue boxes at the top represents the determining factors and constraints toward adoption. The table in the middle are the modern irrigation water management practices which includes different methods of irrigation scheduling, soil moisture monitoring, land levelling, tail-water recovery, and rainwater harvesting. The green box at the bottom represents the adoption of the modern irrigation water management practices. The black arrows indicate the relationship between the socio-economic drivers, socio-psychological drivers and the constraints. The blue arrows represent the influence of the socio-economic and socio-psychological drivers and the constraints toward the adoption of the different modern irrigation water management practices.

The socio-economic drivers included in the framework are farmer's age, gender, education level, farm size, off-farm employment, household size, and group membership. These socio-economic drivers may influence the adoption of modern irrigation water management practices such as the different methods used for irrigation scheduling, soil moisture monitoring, land levelling, tail-water recovery, and rainwater harvesting (Terano *et al.*, 2015). The black arrow

between the socio-economic and socio-psychological drivers indicates that the drivers may influence each other, which may in turn influence smallholder farmer's adoption modern irrigation water management practices. For example, education level may influence smallholder farmers' personal efficacy as those with low levels of education and experience may not be confident in their capability to adopt modern irrigation water management practices (Zeweld *et al.*, 2017). Therefore, there is some relationship between socio-economic drivers and socio-psychological drivers.

Socio-psychological drivers may influence how smallholder farmers perceive the different modern irrigation water management practices which ultimately determines the adoption of those practices. The socio-psychological drivers included in this study are adoption intention, attitude, personal efficacy, and social capital. The influence of socio-psychological drivers on the adoption of improved practices and agricultural technologies has been studied by several researchers using the Theory of Planned behaviour (Aliabadi *et al.*, 2020; Buyinza *et al.*, 2020; Pino *et al.*, 2017; Terano *et al.*, 2015; Zeweld *et al.*, 2017). Regardless of whether smallholder farmers have high intentions, attitudes, personal efficacy or social capital, different constraints could hinder the adoption modern irrigation water management practices.

The constraints include but are not limited to inadequate extension services, financial constraint, lack of information, access to water, farm location, and lack of technical expertise (Annor-Frempong, 2013; Bjornlund *et al.*, 2009; Schaible & Aillery, 2006; Zeweld *et al.*, 2019). These factors could hinder the adoption of the different methods used for irrigation scheduling, soil moisture monitoring, land levelling, tail-water recovery, and rainwater harvesting. The constraints may also have a determining effect on the socio-economic and socio-psychological drivers that influence smallholder farmers' adoption of modern irrigation water management practices. For example, the adoption of modern irrigation water management practices by smallholder farmers with higher education levels can be hindered by the lack of financial capital. Constraints such as lack of information and technical expertise may also determine smallholder farmer's perceived compatibility of the modern irrigation water management practices to their current practices. The blue arrows represent the adoption of the different methods in modern irrigation water management practices as determined by the socio-economic drivers, socio-psychological drivers, and the constraints encountered.

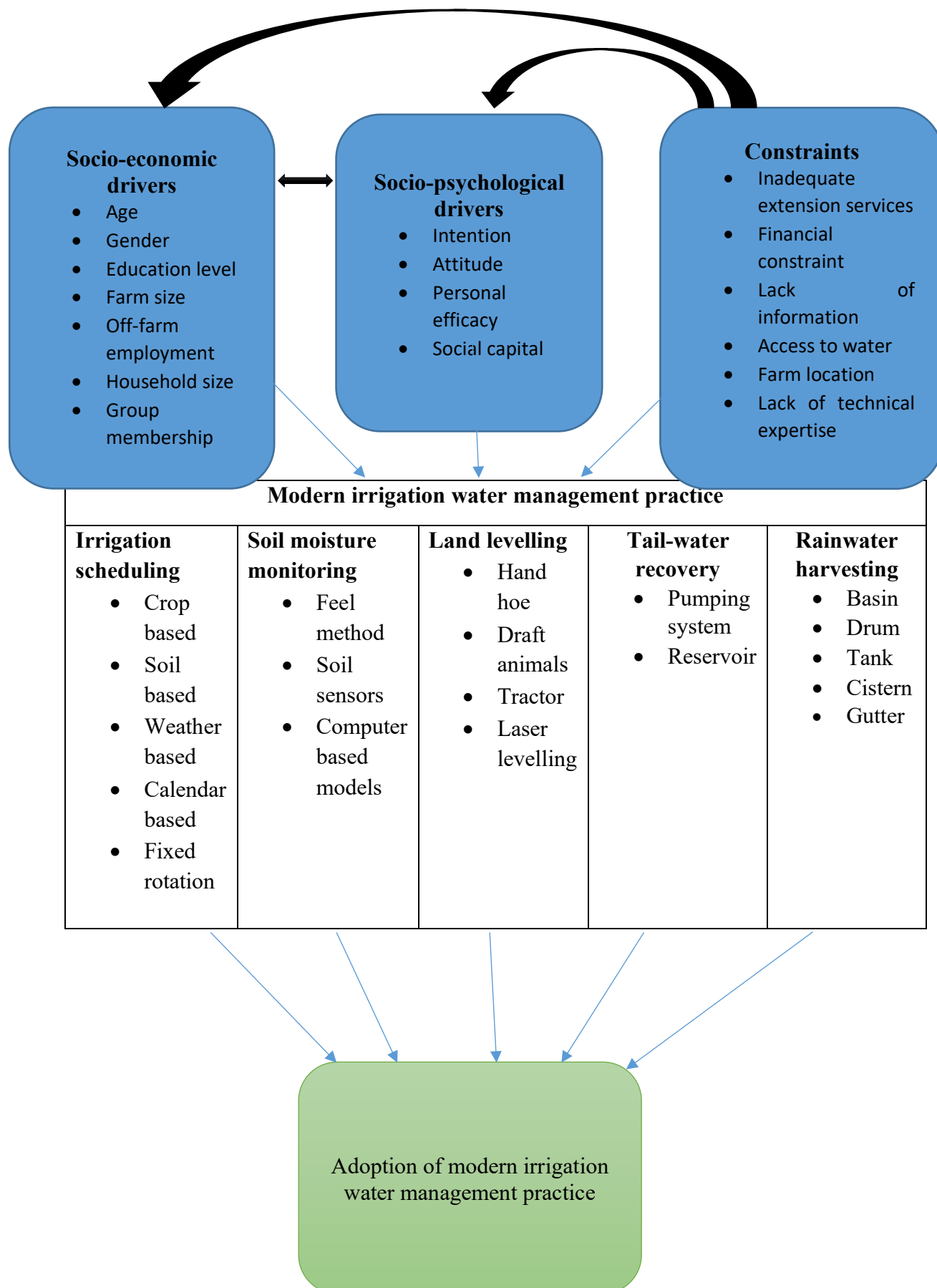


Figure 1: Conceptual framework on the adoption of modern irrigation water management practices by smallholder farmers

CHAPTER THREE: MATERIALS AND METHODS

The study methodology is explained in this chapter. Section 3.1 describes the area where the study was conducted. In Section 3.2 the research design employed in this study is explained. The target population, sampling method, and sample size that was used for data collection are detailed in Section 3.3. The method used for data collection is provided in Section 3.4. The type of data analysis is explained in Section 3.5, including the type of statistics and analytical tools employed. Lastly, Section 3.6 outlines the ethical guidelines the study adhere to.

3.1 Description of the study area

The research was conducted in Bushbuckridge Local Municipality. Bushbuckridge is a category B municipality in the Mpumalanga province, South Africa (IDP, 2022). Bushbuckridge Local Municipality is one of the four local municipalities within Ehlanzeni District, and the largest of all, covering over a third of the geographic area (Municipalities of South Africa, 2022). Bushbuckridge Local Municipality has the coordinates -24.8398° S, 31.0464° E, and covers an area of 10 248 square kilometers (Distancesto.com, 2022; Municipalities of South Africa, 2022). From the Community Survey in 2016, the population size was 548 760 people, with a growth rate of 0.3% annually, it makes up 34% of the Ehlanzeni District Municipality accounting for 14% of the overall population of the Mpumalanga province (IDP, 2022).

The population age structure in Bushbuckridge Local Municipality is characterized by children aged between 0- and 14-years accounting for 218 954 of the total population, youth (15 to 34) 188 500, adults (35 to 65) 102 465, and the elderly over 65 making up 38 841 of the total population (IDP, 2022). This indicates that over half of the population of Bushbuckridge Local Municipality is in the working-age group. However, the dependency ratio for the age group between 15 to 64 years is 73.4 per 100 people (Municipalities of South Africa, 2022). There were 83.3 males per 100 females recorded in 2011, and 52.1% women and 49.7% men in 2016 (IDP, 2022; Municipalities of South Africa, 2022). IDP (2022) reported that 99.55% of the population group is made up of black Africans, 0.19% are Whites, Coloured and Indian/Asian groups make up 0.10% of the population.

From the census, the highest level of education achieved by most of the respondents was matric at 34%, 13% have been to primary school, whereas 16% had no schooling (Wazimap, 2016).

There was a total of 137 419 households recorded, whereby 53% of the households were female headed, with an average household size of 4 people. (IDP, 2022; Municipalities of South Africa, 2022). Low employment rates and poverty are major development concerns in Bushbuckridge Local Municipality; as most of the residents in the municipality are not employed, limiting the municipality's development economically (IDP, 2022).

The study area is characterized by an annual average rainfall of 600mm during summer (De Mendiguren, 2004). Rainfall is lower in the eastern part of the municipality with reported drought occurrences (De Mendiguren., 2004). Agriculture is one of the primary economic sectors in Bushbuckridge Local Municipality, hence the study area was chosen. Below is a picture of the study area map, showing some of the communities in Bushbuckridge Local Municipality. The blue stickers in Figure 2 represent the smallholder farmers' communities included in the study.

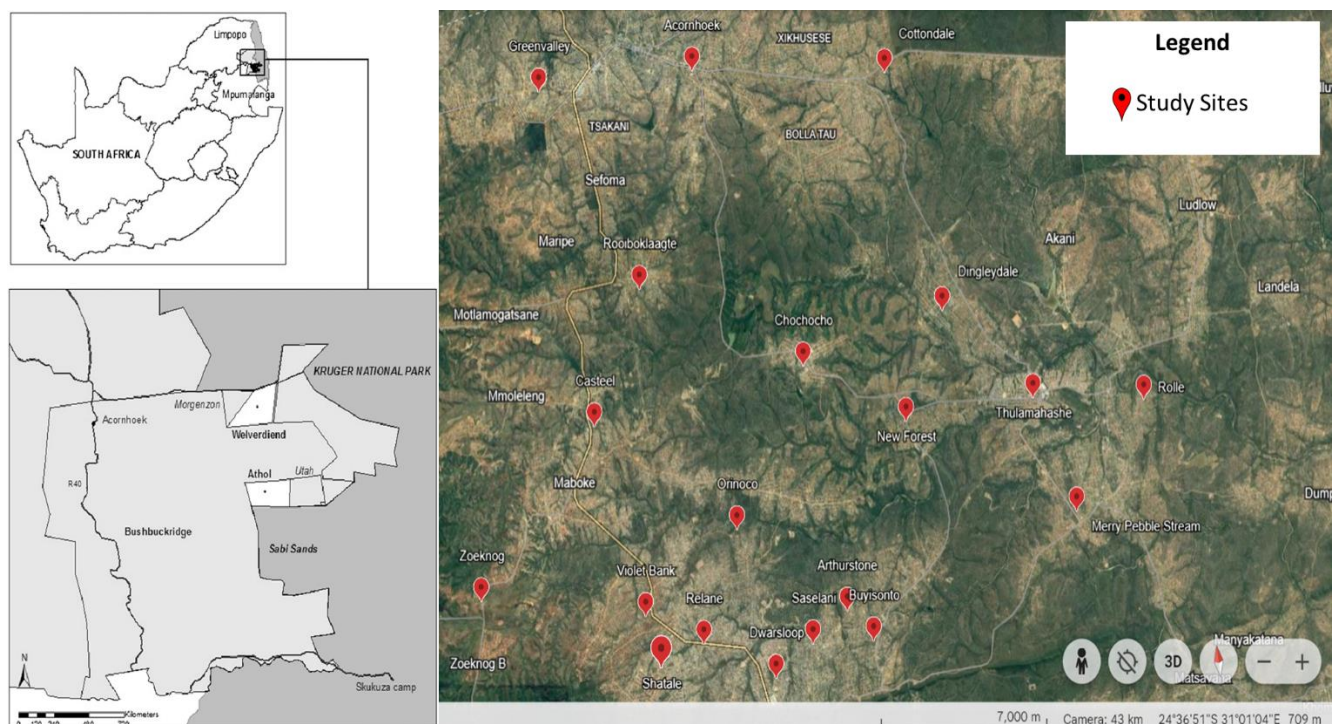


Figure 2: Study area map

(Matsika, Erasmus & Twine, 2012; Google Earth).

3.2 Research design

A quantitative research design was used to conduct this research. Relationships between independent and dependent variables are established in quantitative research (USC Libraries,

2021). The study seeks to classify separate different variables, identifying relationships, determining factors and ensuring that external variables not related to the study do not influence the results (USC Libraries, 2021). A few principles used in quantitative research include measurement, causality, and generalization (Harding, 2019). The aim of the quantitative research is to ascertain if what is identified as effective factors for the participants in the study, may be generalized to farmers in the area. When data cannot be collected from the whole population, a specific sample is chosen from the population from which statistical inferences are drawn about the population (Harding, 2019).

A quantitative research design was used to get numerical measurements of the study variables to quantify smallholder farmers' behavior toward the adoption of modern irrigation water management practices based on socio-economic and socio-psychological drivers, as well as the constraints. This approach allows for findings to be generalized to the population and data can be compared with previous studies or replicated.

3.3 Sampling

3.3.1. Target population

The target population refers to the intended participants of the study (Fritz & Morgan, 2012). From the total population of 548 760 people residing in Bushbuckridge Local Municipality, the target population are the 1400 smallholder farmers participating in irrigation schemes. The specific target group were the smallholder farmers practicing crop production in the area.

3.3.2. Sampling method

The selection of the sample from the target population was done using convenience sampling. Convenience sampling is a form of non-probability sampling whereby participants are chosen based on their availability (Farmer & Farmer, 2022a; Salkind, 2012). This sampling strategy entailed gathering people wherever they could be found, which was wherever was most convenient. Convenience sampling is the simplest method of sampling compared to other methods (Salkind, 2012). Convenience sampling is very useful during the exploratory stage of a research project, as well as when collecting pilot data to uncover and address questionnaire design errors (Salkind, 2012). This sampling approach allowed us to examine smallholder farmers' behaviors, attitudes, and opinions on various irrigation management practices in the most effective way feasible (Farmer & Farmer, 2022a). The convenience sampling method has

several advantages, including quick data collecting, low costs, simplicity, and the accessibility of participants (Farmer & Farmer, 2022a; Salkind, 2012; Takwi, 2021). Although this sampling approach may result in sampling bias, it was a practical method for this research.

3.3.3 Sample size

The recorded number of smallholder farmers in irrigation schemes in Bushbuckridge Local Municipality was 1400 in 2016 (Post-Harvest Innovation Programme, 2016). With 1400 as the population size (since the target group are smallholder farmers), Cochran's Formula was used to calculate the sample size with a 95% confidence level and 5% precision (Agholor & Nkosi, 2020; Bagheri & Teymouri, 2021). With 385 as the recommended sample size from Cochran's Formula, N as the population size of smallholder farmers, a new sample size (n) was calculated for this study (Statistics How To, 2022).

$$n = \frac{n_0}{1 + (n_0 - 1)/N}$$

$$n = 385 / (1 + (384/1400)) = 302$$

The sample size for this study was 302 smallholder farmers. However, from the calculated sample size, only 296 smallholder farmers participated in the study during data collection. Time constraints due to inadequate funding to cover transportation and accommodation costs, as well as payment of enumerators to assist with data collection, hindered the achievement of the intended sample size.

3.4 Data collection

A structured questionnaire was employed for data collection. The questionnaire consisted of close-ended questions; this approach is ideal for saving time when conducting a large-scale research (Farmer & Farmer, 2022b). Furthermore, this approach was convenient since the participants scaled their responses, making it clear where they stood regarding particular issues addressed in the study (Farmer & Farmer, 2022b). For a proper and relevant questionnaire to be developed, general characteristics of the population were studied using previous literature, and thoroughly conducting a pilot study to understand what was relevant to the smallholder farmers. A face-to-face administration of the questionnaire was undertaken with the targeted smallholder farmers in Bushbuckridge Local Municipality.

3.5 Data analysis

Descriptive and inferential statistics were applied for data analysis. Descriptive statistics is a type of quantitative data analysis used to summarize and present captured data (Farmer & Farmer, 2022c). Inferential statistics is a type of quantitative data analysis used to determine the relationship between variables (Farmer & Farmer, 2022c). Statistical Package for Social Sciences (SPSS) software was used as an analytical tool.

3.5.1. Objective 1- To investigate adoption of modern irrigation water management practices by smallholder farmers

Descriptive statistics were used to measure the adoption of modern irrigation water management practices by smallholder farmers. Frequency results on the adoption of modern irrigation water management practices were presented on tables.

3.5.2. Objective 2- To identify the socio-economic and socio-psychological drivers toward adoption of modern irrigation water management practices

To identify the main drivers toward the adoption of modern irrigation water management practices, inferential statistics was used for data analysis. Regression analysis, a form of inferential statistics, is a procedure conducted to examine the influence of various independent variables on a dependent variable (Harding, 2019). In this study, binary logistic regression was employed to dictate the correlation between the socio-economic and socio-psychological factors (independent variables) and the adoption of the modern irrigation water management practices (dependent variables). The Logistic regression analyses were used separately on the dependent variables: Crop based, Soil based, Weather based, Calendar based, and Fixed rotation under irrigation scheduling practices. For soil moisture monitoring practices, the Logistic regression analyses were ran for the Feel method, Moisture sensors, and Computer based models. Hand hoe, Draft animals, Tractor, and Laser levelling were the dependent variables under land levelling practices. Pumping system and Reservoir were the dependent variables for the tail-water recover system. Finally, Logistic regression analyses were used for the dependent variables: Basin, Drum, Tank, Cistern, and Gutter for rainwater harvesting.

The socio-economic variables included age, gender, education level, household size, farm size, off-farm employment status, and group membership. The socio-psychological variables were intention, attitude, personal efficacy, and social capital. The socio-psychological drivers were

transformed to scale items before running the regression. The transformation was done by calculating the mean of the variables under each socio-psychological driver. The mean was used to get new variables representing each socio-psychological driver (Obumneke, 2021). The new variables were labelled INT (intention), ATT (attitude), PEFF (personal efficacy), and SCAPT (social capital). Higher mean scores on these variables meant that the smallholder farmers had higher intention, attitude, personal efficacy, and social capital.

The following model specification for the binary logistic regression was used:

$$\log \frac{Y}{(1-Y)} = B_0 + B_1X_1 + B_2X_2 + B_3X_3 + \dots + B_nX_n$$

Where:

- Y is the dependant variable – which determines the probability of adopting modern irrigation water management practices
- X is a set of independent fixed effect variables summarising the socio-economic and socio-psychological drivers toward adoption
- B is the regression coefficient, where B_0 is the constant Y intercept

3.5.3. Objective 3- To examine the constraints faced by smallholder farmers towards adoption of modern irrigation water management practices

Descriptive statistics was employed to analyse the constraints that smallholder farmers are faced with to assess the adoption of modern irrigation water management practices. Frequencies were used to present the Likert scale results.

3.6 Ethical considerations

3.6.1. Honesty

Transparency was adhered to in this study, the goal and objectives of the study were explained to the participants. Furthermore, what was expected from the participants was clearly stated from the beginning. Participants in the study were fully informed about the method or components of the study, as well as any potential risks (Orb, Eisenhauer, Wynaden, 2000).

3.6.2. Autonomy

The researcher took the responsibility to respect and support people's choices (Pallipedia, 2021). This included respecting participants' privacy and keeping them anonymous to maintain confidentiality. Privacy was not only with regards to information but also not prying on participants' personal lives if it was not related to the study. Adhering to autonomy involves informed consent from participants (Pallipedia, 2021). A consent form was handed to the participants to sign, acknowledging their participation. Participants had the option of participating in the study or not, and they could withdraw at any time during the study (Orb *et al*, 2000).

3.6.3. Beneficence

Involves doing what is right by the participants and avoiding possible harm (Orb *et al*, 2000; Pallipedia, 2021). Participants' identities remain confidential to avoid criticism of one's opinion. This research was undertaken in such a manner that the participants were all respected, treated equally, and without posing any harm to them.

CHAPTER FOUR: RESULTS

This chapter presents the study results from the collected data. Section 4.1 outlines the descriptive statistics results for the demographic variables. Descriptive statistics results are also outlined for the modern irrigation water management practices adopted by smallholder farmers in Section 4.2. The results for the Logistic regression analyses are outlined in detail in Section 4.3. Lastly, the descriptive statistics results for the constraints hindering the adoption of modern irrigation water management practices are presented on Section 4.4.

4.1 Demographics

Table 1: Descriptive statistics results for categorical variables

Variables	Categories	Frequency	Percentage
Age	20-29	3	1.0
	30-39	13	4.4
	40-49	109	36.8
	50-59	107	36.1
	60+	64	21.6
Gender	Female	160	54.1
	Male	136	45.9
Education level	No school	25	8.4
	Primary	59	19.9
	Secondary	54	18.2
	Matriculated	112	37.8
	ABET	19	6.4
	Diploma	20	6.8
	Degree	7	2.4
Source of income	Own business (registered)	14	4.7
	Social grant (child/disability)	16	5.4
	Informal trader	37	12.5
	Pension	38	12.8
	Remittance	44	14.9
	Farming	147	49.7
Land ownership	Yes	268	90.5
	No	12	4.1
	Renting	3	1.0
	Permission to occupy	13	4.4

Water source	Borehole	107	36.1
	River	134	45.3
	Dam	6	2.0
	Tapwater	32	10.8
	Rain water	17	5.7
Irrigation method	Drip irrigation	124	41.9
	Sprinkler irrigation	80	27.0
	Furrow irrigation	56	18.9
	Other	36	12.2
Physical irrigation assets	Tank	174	58.8
	Water pump	65	22.0
	Generator	7	2.4
	None	50	16.9
Type of farming	Crop	257	86.8
	Mixed	39	13.2
Off-farm employment status	Employed	115	38.9
	Unemployed	181	61.1
Group membership	Yes	96	32.4
	No	200	67.6

Table 1 above outlines the descriptive statistics results for categorical demographic variables. The total number of participants was 296 smallholder farmers.

4.1.1. Age, gender, education level and source of income

The results indicate that most of the smallholder farmers (36.8%) were between the ages of 40 and 49 years. Females made up 54.1% of the smallholder farmers that took part in this study. Most of the smallholder farmers (37.8%) matriculated. Farming was the primary means of income for most of the smallholder farmers (49.7%).

4.1.2. Land ownership, water source, irrigation method and physical irrigation assets

Most of the smallholder farmers (90.5%) owned the land they were farming on. The primary source of water for most of the smallholder farmers (45.3%) was from the river, and 36.1% obtained water from boreholes. Most of the smallholder farmers (41.9%) used drip irrigation and 27.0% relied on sprinkler irrigation. The physical irrigation assets that most smallholder farmers had were tanks (58.8%). Some smallholder farmers (16.9%) had none of the physical irrigation assets.

4.1.3. Type of farming, off-farm employment and group membership

Most of the smallholder farmers were practicing crop production (86.8%) alone. Unemployed smallholder farmers made up 61.1% of the participants. Most of the smallholder farmers (67.6%) had group memberships.

Table 2: Descriptive statistics results for continuous variables

Variables	N	Minimum	Maximum	Mean
Years of farming experience (years)	296	1	35	10.61
Household size (people)	296	1	32	8.15
Farm size (hectares)	296	0.5	13.0	4.186

In Table 2 above, descriptive statistics showing the total smallholder farmers number, minimum, maximum and mean values for continuous variables are outlined.

4.1.4. Years of farming experience, household size and farm size

Most of the smallholder farmers had an average of 10.6 years of farming experience. The mean household size was determined to be at 8 members. An average farm size of 7 hectares was reported among smallholder farmers.

4.2 The adoption of modern irrigation water management practices

Table 3: Modern irrigation water management practices

Category	Method	No	Yes
Irrigation scheduling	Crop-based	121 40.9%	175 59.1%
	Soil-based	61 20.6%	235 79.4%
	Weather-based	227 76.7%	69 23.3%
	Calendar-based	248 83.8%	48 16.2%
	Fixed rotation	260 87.8%	36 12.2%
Soil moisture monitoring	Feel method	215	81 27.4%

Category	Method	No	Yes
		72.6%	
	Moisture sensors	285 96.3%	11 3.7%
	Computer based models	295 99.7%	1 0.3%
Land levelling	Hand hoe	17 5.7%	279 94.3%
	Draft animals	286 96.6%	10 3.4%
	Tractor	68 23.0%	228 77.0%
	Laser levelling	290 98.0%	6 2.0%
Tail-water recovery	Pumping and recycling system	287 97.0%	9 3.0%
	Reservoir	291 98.3%	5 1.7%
Rainwater harvesting	Basin	228 77.0%	68 23.0%
	Drum	121 40.9%	175 59.1%
	Tank	123 41.6%	173 58.4%
	Cistern	289 97.6%	7 2.4%
	Gutter	205 69.3%	91 30.7%

The adoption of modern irrigation water management practices is outlined in Table 3, recorded based on the utilization of various methods and tools in each practice. A crop-based scheduling method was used by 59.1%, whereas, 79.4% used the soil-based irrigation scheduling method. Weather-based and calendar-based irrigation scheduling was used by 23.3% and 16.2% of the smallholder farmers. Fixed rotation irrigation scheduling method was used by only 12.2% of the smallholder farmers. The feel method was used by 27.4% of smallholder farmers while

3.7% used moisture sensors, and only 0.3% used computer-based models for soil moisture monitoring, respectively.

Most of the smallholder farmers used hand hoes (94.3%) and tractors (77.0%) for land levelling. Draft animals were only used by 3.4% of the smallholder farmers and 2.0% used laser levelling. Only 3.0% of the smallholder farmers were using the pumping and recycling system, and only 1.7% had reservoirs for tail-water recovery. Most of the smallholder farmers used drums (59.1%) and tanks (58.4%), followed by gutters (30.7%) and basins (23.0%) to collect and store rainwater, but only 2.4% had cisterns.

4.3 The socio-economic and socio-psychological drivers toward the adoption of modern irrigation water management practices

In this subsection, the results from binary logistic regression analyses on the dependent variables are interpreted. The results indicated the relationship and influence that socio-psychological and socio-economic drivers (independent variables) have on the adoption of the different modern irrigation water management practices (dependent variables). The Omnibus Tests of Model Coefficients, Model Summary, Hosmer and Lemeshow Test, Classification Table, and Variables in the Equation results are presented for crop-based irrigation scheduling only. The result tables for the other dependent variables can be found in the Appendices section.

The Omnibus Tests of Model Coefficients is the ‘goodness of fit’ test of the performance of the model. The pseudo-R square statistics (Cox & Snell and Nagelkerke R Square) indicates a variation from the dependent variables described by the model (Hasan, 2020; Pallant, 2005). The Classification Table shows how good the model accurately predicted the outcome category for the cases (yes or no responses) for the adoption of crop-based irrigation scheduling. The Variables in the Equation, the contribution of the socio-economic and socio-psychological drivers given (Pallant, 2005). The significant predictive ability of the model is determined by variables with $p < .05$ (Pallant, 2005). A detailed interpretation of the results is only given for variables that had a significant influence on the predictive ability of the model (Sig. value of $p < .05$) which are highlighted on the Variables in the Equation table.

4.3.1. Binary logistic regression results for Irrigation scheduling methods

4.3.1.1 Crop-based

Table 4: Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	58.373	19	<,.001
	Block	58.373	19	<,.001
	Model	58.373	19	<,.001

Table 5: Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	342.064 ^a	.179	.241
a. Estimation terminated at iteration number 20 because maximum iterations has been reached. Final solution cannot be found.			

Table 6: Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	13.684	8	.090

Table 7: Classification Table

Observed			Predicted		
			Crop-based		Percentage Correct
			No	Yes	
Step 1	Crop-based	No	52	69	43.0
		Yes	25	150	85.7
		Overall Percentage			
a. The cut value is ,500					

Table 8: Variables in the Equation_ Crop-based

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B)	
								Lower	Upper
Step 1 ^a	Socio-economic drivers								
	Age			3.384	4	.496			
	Age(1)	21.050	22667.640	.000	1	.999	1385787361.092	.000	.

Age(2)	21.095	22667.6 40	.000	1	.999	1450805031 .762	.000	.
Age(3)	21.018	22667.6 40	.000	1	.999	1342104189 .503	.000	.
Age(4)	20.307	22667.6 40	.000	1	.999	659729410. 841	.000	.
Gender(1)	-.030	.271	.012	1	.913	.971	.571	1.651
Education level			8.926	6	.178			
Education level(1)	-.050	.567	.008	1	.929	.951	.313	2.892
Education level(2)	.542	.597	.822	1	.365	1.719	.533	5.545
Education level(3)	.809	.587	1.900	1	.168	2.246	.711	7.094
Education level(4)	.892	.746	1.430	1	.232	2.439	.566	10.520
Education level(5)	1.848	.856	4.663	1	.031	6.349	1.186	33.985
Education level(6)	.855	1.001	.729	1	.393	2.350	.330	16.724
Household size	-.004	.030	.018	1	.892	.996	.938	1.057
Farm size	.108	.055	3.796	1	.051	1.114	.999	1.241
Off-farm employment status(1)	.368	.302	1.486	1	.223	1.444	.800	2.609
Group membership(1)	.265	.324	.673	1	.412	1.304	.691	2.459
Socio-psychological drivers								
INT	-.363	.322	1.273	1	.259	.695	.370	1.307
ATT	1.195	.416	8.256	1	.004	3.304	1.462	7.464
PEFF	-.171	.239	.515	1	.473	.843	.528	1.345
SCAPT	.110	.113	.938	1	.333	1.116	.894	1.394
Constant	-25.379	22667.6 40	.000	1	.999	.000		
a. Variable(s) entered on step 1: Age, Gender, Education level, Household size, Farm size, Off-farm employment status, Group membership, INT, ATT, PEFF, SCAPT.								

Table 4 above presents the model test results for the crop-based irrigation scheduling method. The model is highly significant, $\chi^2(19) = 58.373$ at $p < .001$. The model explained 24.1% (Nagelkerke R Square) variation in the adoption of crop-based irrigation scheduling. An overall of 68.2% cases was correctly classified by the model. The results indicate that only the education level Diploma (5) and attitude (ATT) significantly influenced the adoption of crop-based irrigation scheduling. The significance value for education level was $p = .031$ and $p = .004$ for attitude. The odds ratio for the predictor variables is given under the Exp(B) column (Pallant, 2005). Smallholder farmers with a diploma were 6.349 times more likely to adopt crop-based irrigation scheduling than those without a diploma. The odds ratio of answering yes

to using crop-based irrigation scheduling increases by 3.304 with every unit increase in attitude score.

4.3.1.2 Soil-based

The Omnibus Tests of Model Coefficients show that the model is significant, $\chi^2(19) = 50.302$, $p < .001$ (Appendix 2.1). The model explained 24.4% of the variance in the adoption of soil-based irrigation scheduling. The Classification Table correctly predicted 84.1% outcome categories. Only social capital (SCAPT) had a significant influence on the predictive ability of the model at $p = .037$. The odds ratio of answering yes to using soil-based irrigation scheduling increases by 1.321 with every unit increase in social capital, other variables kept constant.

4.3.1.3 Weather-based

The Omnibus Tests of Model Coefficients indicates a significant fit of the model, $\chi^2(19) = 88.820$, $p < .001$ (Appendix 2.2), 39.1% of the variability is explained by the model. A total of 83.8% cases were correctly predicted for the adoption of weather-based irrigation scheduling in the Classification Table. Gender (male) $p < .001$, the education level secondary (2) $p = .030$, household size $p = .004$, off-farm employment status (unemployed) $p = .024$, and social capital (SCAPT) $p = .006$ significantly influenced the adoption of weather-based irrigation scheduling. Males were .271 times less likely to report yes to using weather-based irrigation scheduling. Smallholder farmers who attended secondary school were .199 times less likely to answer yes to using weather-based irrigation scheduling. The probability of answering yes to using weather-based irrigation scheduling was 2.605 times higher for unemployed smallholder farmer than for those that are not employed. The odds of reporting yes to using the weather-based method were 0.878 times less likely with an increase in household size and 0.673 times less likely for social capital score.

4.3.1.4 Calendar-based

The Omnibus Tests of Model Coefficients show that the model is significant, $\chi^2(19) = 59.106$, $p < .001$ (Appendix 2.3). The model explained 30.8% of the variance caused by the predictor variables. The Classification Table correctly predicted 85.5% outcome categories. Under calendar-based scheduling, the education level Degree (6), off-farm employment status (unemployed), group membership (not in a group), and SCAPT (social capital) have a significantly influenced the adoption of calendar-based irrigation scheduling. The significant

value for education level was $p=.003$, off-farm employment status $p<.001$, group membership $p=.008$, and social capital $p=.005$. A smallholder farmer that has a degree was 94.323 times more likely to record yes to using calendar-based irrigation scheduling than one without a degree. The odds of reporting yes to using calendar-based irrigation scheduling was 0.168 times less likely for unemployed smallholder farmers, 0.305 times less likely for those not in a group, and 0.644 times less likely for those with a high social capital score.

4.3.1.5 Fixed Rotation

A significant fit of the model for the adoption of fixed rotation irrigation scheduling is recorded $\chi^2(19) = 62.919$, $p<.001$ (Appendix 2.4). The model explained 36.5% of the variance caused by the predictor variables. The model correctly classified 89.2% of the cases into their outcome categories. Different education levels significantly influenced the adoption of fixed rotation irrigation scheduling at $p=.011$ for primary (1), $p=.016$ secondary (2), $p=.034$ matriculated (3), $p=.008$ diploma (5), and $p<.001$ for degree (6). INT (intention) and ATT (attitude) also significantly influenced the adoption of fixed rotation irrigation scheduling, with significance values of $p=.002$ for intention and $p<.001$ for attitude. The odds of answering yes to using fixed rotation irrigation scheduling were 14.898 times more likely for smallholder farmers who obtained a primary school education, 16.680 times more for those who had a secondary school education, and 11.757 times more for those who had matriculated. Furthermore, the odds of answering yes to using fixed rotation irrigation scheduling was 28.719 times more likely for smallholder farmers in possession of a diploma, 148.031 times more for those with a degree, and 9.875 times more with an increase in intention score. Whereas the odds ratios for attitude is below 1, suggesting that the odds of using fixed irrigation scheduling decrease by a factor of .158 when attitude score increases.

4.3.2. Binary logistic regression results for Soil Moisture Monitoring methods

4.3.2.1 Feel method

The model fit was statistically significant for the feel method, $\chi^2(19) = 80.360$, $p<.001$ (Appendix 3.1). The model explained 34.4% variation in the adoption of the feel method for soil moisture monitoring and correctly classified 81.4% cases. The education levels Matriculated (3) and Diploma (5), farm size, and SCAPT (social capital) significantly influenced the adoption of the feel method for soil moisture monitoring. The significance value for Matriculated was $p=.016$, Diploma $p=.040$, farm size $p=.039$, and social capital $p=.006$.

Smallholder farmers who had matriculated were 5.529 times more likely to report yes to using the feel method for soil moisture monitoring than those who had not matriculated. Acquiring a diploma increased the odds of reporting yes to using the feel method for soil moisture monitoring by a factor of 5.905, while owning a larger farm increased the odds by 1.135. The odds of applying the feel method decrease by a factor of 0.701 with an increase in social capital score.

4.3.2.2 Moisture sensors

The model fit was statistically significant for moisture sensors, $\chi^2(19) = 37.898$, $p=.006$ (Appendix 3.2). The model explained 44.2% variation in the adoption of moisture sensors and correctly classified 96.6% cases. Only attitude (ATT) significantly influenced the adoption of moisture sensors for soil moisture monitoring with a significance value of $p=.038$, the other predictor variables had no influence on the adoption of soil moisture sensors. With every increase in attitude score, the probability of answering yes to using moisture sensors for soil moisture monitoring decreased by a factor of 0.041.

4.3.2.3 Computer-based models

The model was statistically insignificant for the adoption of computer-based models, $\chi^2(19) = 13.377$, $p=.819$ (Appendix 3.3). The model explained 100% of the variance in the adoption of computer-based models, 100% cases were correctly classified. The results indicate that all the predictor variables had an insignificant influence on the adoption of computer-based models for soil moisture monitoring. The adoption of computer-based models is not dependent on any of the variables.

4.3.3. Binary logistic regression results for Land Levelling methods

4.3.3.1 Hand hoe

The model was statistically insignificant for the adoption of the hand hoe land levelling practice, $\chi^2(19) = 21.504$, $p=.310$ (Appendix 4.1). The model explained 19.7% of the variance in the adoption of hand hoe, 93.9% cases were correctly classified. None of the predictor variables significantly influenced the adoption of hand hoe for land levelling.

4.3.3.2 Draft animals

The model was statistically insignificant for the adoption of the draft animals for land levelling practice, $\chi^2(19) = 15.956$, $p=.660$ (Appendix 4.2). The model explained 20.5% of the variance in the adoption of draft animals. In the Classification Table, 96.6% cases were correctly classified. None of the predictor variables significantly influenced the adoption of draft animals for land levelling.

4.3.3.3 Tractor

A statistically significant fit of the model is observed for the adoption of tractor for land levelling, $\chi^2(19) = 141.042$, $p<.001$ (Appendix 4.3). The model explained a 57.5% variation in the adoption of tractor and correctly classified 86.8% cases. The results indicate that farm size, intention (INT), attitude (ATT), and social capital (SCAPT) significantly influenced the adoption of tractors for land levelling. The significance value for farm size was $p<.001$, intention $p=.002$, attitude $p<.001$, and social capital $p=.009$. The likelihood of answering yes to using a tractor for land levelling is 1.512 times more with an increase in farm size, 7.150 times more with attitude, and 1.546 times more with social capital. However, an increase in the intentions score decreases the likelihood of answering yes to using a tractor for land levelling by a factor of 0.191.

4.3.3.4 Laser levelling

A statistically insignificant fit of the model is observed for the adoption of laser levelling, $\chi^2(19) = 24.727$, $p=.170$ (Appendix 4.4). The model explained 44.6% of the variance and correctly classified 98.3% cases. None of the predictor variables significantly influenced the adoption of laser levelling. The adoption of laser levelling is not dependent on any of the predictor variables.

4.3.4. Binary logistic regression results for Tail-water Recover System methods

4.3.4.1 Pumping system

The model fit was statistically significant for the adoption of a pumping system, $\chi^2(19)=38.030$, $p=.006$ (Appendix 5.1). The model explained 50.6% of the variance and correctly classified 97.6% cases. Only farm size significantly influenced the adoption of a pumping system for tail-water recovery with significance value of $p<.001$. The other predictor variables

had no influence on the adoption of both the pumping systems. A smallholder farmer with a large farm is 2.347 times more likely to answer yes to having a pumping system than one with a small farm size.

4.3.4.2 Reservoir

The model was statistically significant, $\chi^2(19) = 31.880$, $p=.032$ (Appendix 5.2). The model explained 64.8% of the variance and correctly classified 98% cases. Farm size significantly influenced the adoption of a reservoir at $p=.018$. With every increase in farm size, the probability of answering yes to using a reservoir for tail-water recovery increases by 3.464.

4.3.5. Binary logistic regression results for Rainwater Harvesting methods

4.3.5.1 Basin

The model was not statistically significant, $\chi^2(19) = 26.174$, $p=.125$ (Appendix 6.1). The model explained 12.8% of the variance and correctly classified 76.7% cases. None of the independent variables significantly influenced the adoption of basin for rainwater harvesting with significance values all greater than .50. The adoption of basin for rainwater harvesting is not dependent on any of the socio-economic or socio-psychological drivers.

4.3.5.2 Drum

A significant fit of the model was reported, $\chi^2(19) = 55.016$, $p<.001$ (Appendix 6.2). The model explained 22.9% of the variance and correctly classified 68.2% cases. Education levels of primary school education (1) and obtaining an ABET (4) certificate, and off-farm employment status (unemployed) have a significant influence on the adoption of drum for rainwater harvesting. The significance value for smallholder farmers primary education level was $p=.007$, ABET $p=.017$, and $p=.009$ for off-farm employment status. The likelihood of answering yes to using a drum is 4.627 times higher for a smallholder farmer who attended primary and 6.884 times higher for a smallholder farmer who attended ABET. The odds of reporting yes to using a drum decreased by a factor of 0.458 when the smallholder farmer records that they are unemployed.

4.3.5.3 Tank

The model was statistically significant for the adoption of tank for rainwater harvesting, $\chi^2(19) = 109.792$, $p < .001$ (Appendix 6.3). The model explained 41.7% of the variance and correctly classified 77.4% cases. The education levels: primary school (1), secondary school (2), matriculated (3), and ABET certificate significantly influenced the adoption of tank for rainwater harvesting. Those who had primary schooling had a significant value of $p = .003$, secondary schooling ($p = .002$), those who had matriculated ($p = .003$), and $p < .001$ for those with ABET. Household size, farm size and INT (intention) also have a significant influence on the adoption of tank for rainwater harvesting with significance values $p = .041$ for household size, $p < .001$ farm size, and $p = .011$ intention. The likelihood of reporting yes to using a tank for rainwater harvesting was 8.241 times more for smallholder farmers who attended primary school, 9.866 times more for those who attended secondary school, 8.424 times more for those who had matriculated, and 25.683 more for those who attended ABET. Smallholder farmers with larger household sizes were 1.075 times more likely to report yes to using a tank for rainwater harvesting, while those with larger farm sizes were 1.332 times more likely than those with smaller household sizes or farms. However, a smallholder farmer with a higher intention score is 0.388 times less likely to answer yes to using a tank for rainwater harvesting as opposed to a smallholder farmer with a lower intention score.

4.3.5.4 Cistern

The model was not a significant fit for the adoption of cistern for rainwater harvesting, $\chi^2(19) = 26.108$, $p = .127$ (Appendix 6.4). The model explained 42.1% of the variance and correctly classified 97.3% cases. Intention (INT) significantly influenced the adoption of a cistern for rainwater harvesting with a significance value of $p = .039$, the other predictor variables did not influence the adoption of cistern for rainwater harvesting. With every increase in the score of a smallholder farmer's intention, the likelihood of report the use of a cistern decreases by a factor of .089.

4.3.5.5 Gutter

The model demonstrated a statistically significant fit for the adoption of gutter for rainwater harvesting, $\chi^2(19) = 44.651$, $p < .001$ (Appendix 6.5). The model explained 19.8% of the variance and correctly classified 73.0% cases. The results indicate that gender (1), representing males, and farm size have a significant influence on the adoption of a gutter for rainwater

harvesting. The significance value for gender was $p=.031$ and $p=.001$ for farm size. The odds ratio of using a gutter for rainwater harvesting were 1.834 times higher for males than for females. While the odds of a smallholder farmer answering yes to using a gutter were 1.203 times more likely with a unit increase in farm size, other variables kept constant.

4.4 Constraints hindering the adoption of modern irrigation water management practices

The Likert scale results of smallholder farmers' responses on the constraints hindering the adoption of modern irrigation water management practices are outlined in Table 9 below. As applied by Middendorf *et al.* (2021), a sum of the percentages from 'strongly agree' and 'agree' responses were used, and the same applied for the 'strongly disagree' and 'disagree' responses. Means are on a scale ranging from 1 (Strongly disagree) to 5 (Strongly agree).

4.4.1 Inadequate extension services

Modern irrigation water management practices have not been introduced to 81.4% of smallholder farmers by extension officers, 91.5% have not received training on modern irrigation water management from extension officers, and 92.2% do not receive regular visits from extension officers.

4.4.2 Lack of information

With regards to information, 73.3% do not have access to information and 54.4% are not aware of modern irrigation water management practices, while 65.2% find it difficult to understand information on modern irrigation water management practices.

4.4.3 Financial constraints

Lack of funds to buy equipment hindered the adoption of modern irrigation water management practices by 97.6% of the smallholder farmers. All smallholder farmers (100%) reported that they did not have access to credit to invest in modern irrigation water management practices, while 97.3% agreed that they did not have the required funding to maintain modern irrigation water management practices.

Table 9: Constraints hindering the adoption of modern irrigation water management practices

Inadequate extension services		1=Strongly Disagree	2=Disagree	3=Neutral	4=Agree	5=Strongly Agree
46)	Modern irrigation water management practices have not been introduced to us by extension officers	17 5.7%	1 0.3%	37 12.5%	1 0.3%	240 81.1%
47)	I have not received training on modern irrigation water management from extension officers	11 3.7%	1 0.3%	13 4.4%	1 0.3%	270 91.2%
48)	I do not receive regular visits from extension officers	9 3.0%	3 1.0%	11 3.7%	5 1.7%	268 90.5%
Lack of information						
49)	I do not have access to information on modern irrigation water management practices	38 12.8%	4 1.4%	37 12.5%	1 0.3%	216 73.0%
50)	I am not aware of modern irrigation water management practices	76 25.7%	1 0.3%	58 19.6%	1 0.3%	160 54.1%
51)	It is difficult to understand information on modern irrigation water management practices	58 19.6%	3 1.0%	42 14.2%	1 0.3%	192 64.9%
Financial constraint						
51)	Lack of funding to purchase equipment hinders adoption of modern irrigation water management practices	4 1.4%	0%	3 1.0%	0%	289 97.6%
52)	I do not have access to credit to invest in modern irrigation water management practices	0%	0%	0%	1 0.3%	295 99.7
53)	I do not have the enough money needed to maintain modern irrigation water management practices	5 1.7%	1 0.3%	2 0.7%	1 0.3%	287 97.0%
Access to water						

54)	Lack access to sufficient water supply	222 75.0%	2 0.7%	7 2.4%	1 0.3%	64 21.6%
55)	Water is not regularly available on my farm	214 72.3%	1 0.3%	7 2.4%	3 1.0%	71 24.0%
56)	I share my water source with other farmers	151 51.0%	0%	5 1.7%	1 0.3%	139 47.0%
Farm location						
57)	My farm is located far from water source	146 49.3%	0%	9 3.0%	0%	141 47.6%
58)	My farm is located far from irrigation training programmes	27 9.1%	0%	1 0.3%	1 0.3%	267 90.2%
59)	My farm is located far from adopters of modern irrigation water management practices	43 14.5%	0%	12 4.1%	1 0.3%	240 81.1%
Lack of technical expertise						
60)	I have never used technology for irrigation before	65 22.0%	1 0.3%	59 19.9%	1 0.3%	170 57.4%
61)	Lack of technical skills hinders adoption of modern irrigation water management practices	18 6.1%	1 0.3%	16 5.4%	2 0.7%	259 87.5%
62)	Inability to use the technology in modern irrigation water management practices	61 20.6%	0%	57 19.3%	2 0.7%	176 59.5%

4.4.4 Access to water

Most of the smallholder farmers (75.7%) disagreed to not having access to adequate water supply, 72.6% disagreed to “Water is not regularly available on my farm”. While 51% disagreed that they share water with other smallholder farmers. On the statement “My farm is located far from water source” under farm location, 49.3% of the smallholder farmers disagreed.

4.4.5 Farm location

Most farmers (90.5%) indicated that their farms were located far from irrigation training programmes, and 81.4% also agreed that their farms were located far from adopters of modern irrigation water management practices.

4.4.6 Lack of technical expertise

Under lack of technical skills, 57.7% of the smallholder farmers had never used technology for irrigation before, 88.2% believe that lack of technical skills hinders adoption of modern irrigation water management practices, and 60.2% do not know how to use the technology in modern irrigation water management practices.

CHAPTER FIVE: DISCUSSION

A detailed discussion of the study results is presented in this chapter. The chapter consists of a brief discussion of the demographic variables, followed by a detailed discussion of the adoption of modern irrigation water management practices. The drivers towards the adoption of modern irrigation water management practices will also be discussed, and lastly the constraints hindering the adoption of modern irrigation water management practices. Secondary data from several research studies is included in the discussion.

5.1 Demographics

5.1.1. Age

The study results indicate that 36.8% of the participants were between the 40-49 and 50-59 years (36.1%). The results are consistent with the findings of Belachew *et al.* (2020), Mengistie and Kidane (2016) and Terano *et al.* (2015) who reported an average age of 41, 44, and 51 years, respectively among smallholder farmers. Similarly, Aliabadi *et al.* (2020) found that most of the smallholder farmers were between 40 and 50 years old, but that only 20% of the participants were over 50 years old. This suggests that older people over the age of 40 years old were more involved in agriculture than the younger people below 40 years of age. Contrary to other studies, Agholor and Nkosi (2020) found that the age group 18-35 years old made-up half (50%) of the participants, followed by 47% between 36 and 49 years old, and lastly 36% between 50 and 60 years old.

5.1.2. Gender

This study revealed that women (54.1%) were more involved in farming than men (45.6%). These findings are not consistent with previous research where male dominance among the participants was reported (Adejo & Opeyemi, 2019; Aliabadi *et al.*, 2020; Mengistie & Kidane, 2016; Middendorf *et al.*, 2021; Terano *et al.*, 2015; Wangu, 2014). This suggests that Bushbuckridge women are not dependent on men for physical farm work.

5.1.3. Education level

In this study, most of the participants had matriculated (37.8%). Other studies had demonstrated inconsistent results (Adejo & Opeyemi, 2019; Agholor & Nkosi, 2020; Aliabadi *et al.*, 2020; Belachew *et al.*, 2020; Wangu, 2014). Agholor and Nkosi (2020) and Belachew *et*

al. (2020) had contradicting results where 1.3 and 50% of the participants had secondary school education, 12.7 and 27% had primary education, whereas, 86 and 8% did not receive any formal education, respectively. Mengistie and Kidane (2016) found that 56.4% of the participants were illiterate and had no formal education, and only 24.6% were able to do basic reading and writing. Adejo and Opeyemi (2019) and Wangu (2014) reported secondary school as the highest education level attended by the participants. Conversely, Aliabadi *et al.* (2020) found that 25% of the participants had attained degrees. However, only 2.4% of the smallholder farmers had acquired degrees in this study suggesting that most people with degrees are not involved in farming in the area under study.

5.1.4. Source of income

Most participants depended on farming (49.7%) as their main source of income. Similarly, Moyo (2016) reported that 48.1% scheme irrigators and 57.1% independent irrigators were depending on farming for a source of income. Annor-Frempong (2013) and Zeweld *et al.* (2017) also reported that farming was the main source of income for 59 and 67% of the participants, respectively. The results suggests that most smallholder farmers depend on the profit they make from farming to maintain their livelihoods. However, Ragie *et al.* (2020) reported that 84.2% households depended on social grants, 82.0% on savings and loans, and 73.1% were employed elsewhere.

5.1.6. Years of farming experience

The results indicate that the average years of farming experience is 10.6 years. This is consistent with Aliabadi *et al.* (2020) who reported that 46% of the participants had 10 to 20 years of farming experience. Nejadrezaei *et al.* (2018) also reported a 5-to-40-year range of farming experience, where 18 years was the average farming experience. Li *et al.* (2019) found that 66.84% had over 20 years farming experience. Amengor *et al.* (2018) found an average farming experience of 25 years farming experience. Consequently, the smallholder farmers who participated in this study and those reported in other studies demonstrate that smallholder farmers were well experienced in crop production.

5.1.7. Household size

An average household size of 8 persons was recorded in the current study. Belachew *et al.* (2020) and Moyo (2016) recorded an average household size of 7 and 5.7 household members,

respectively. Whereas Mengistie and Kidane (2016) recorded 5-6 members from 40.2% households, 1-2 from 4.6%, and over 8 members from 2.4% households. It is, therefore, postulated that the larger the household size the more help a smallholder farmer may receive for farm labour.

5.1.8. Farm size

The average farm size was 4 hectares. The largest reported farm size among the smallholder farmers was 13 hectares and the smallest was 0.5 hectares. Moyo (2016) found that the mean farm size for smallholder farmers in irrigation schemes was 0.2 hectares, however, independent irrigators had larger farms of up to 20 hectares. The smallholder farmers in this study area own more farming land than expected based on comparisons with previous studies.

5.1.9. Water source

The primary source of water for most of the smallholder farmers (45.3) was from rivers. Ntai (2011) also found that most smallholder farmers obtained water from rivers, dams, and streams. Whereas Huang *et al.* (2017) reported that one of the most reliable water sources is groundwater, surface water is less reliable. However, the adoption of water management practices was negatively influenced by reliance on groundwater (Huang *et al.*, 2017). There are inconsistencies in the findings with other studies which suggests that water sources differ according to the smallholder farmers' farming location.

5.1.10. Type of farming

Most smallholder farmers only practiced crop production (86.8%). There were no smallholder farmers practicing livestock production alone, whereas 13.2% practiced both crop and livestock production. Similarly, Ragie *et al.* (2020) demonstrated that crop production was practiced by 96% households in Bushbuckridge. Contrary to the present study, 18.5% households were reported to be engaged in livestock farming in Bushbuckridge (Ragie *et al.*, 2020). The study results confirm that cultivation of crops is the main type of farming in the Bushbuckridge area.

5.1.11. Irrigation method

Drip irrigation was used by most of the participants (41.9), followed by sprinkler irrigation (27.0%) and furrow irrigation (18.9%). Mpanga and Idowu (2020) demonstrated that the use of drip irrigation increased by 71% between 2007 and 2017. However, Fan and McCann (2017)

found that only 12% of the participants employed drip irrigation in their farming practice, while 45% used sprinkler irrigation. Gunarathna *et al.* (2018) argued that furrow irrigation has low adoption rates because it is labour intensive and has low water utilization efficiency compared to sprinkler and drip irrigation. Previously, Yohannes *et al.* (2017), provided contrary evidence indicating that furrow irrigation was the most applied irrigation method. Such studies provide some conflicting findings on the use of drip and sprinkler irrigation as opposed to surface irrigation, but the timing of the study and many other factors should be considered to unravel the discrepancies.

5.1.11. Off-farm employment

The findings of the current research suggest that most smallholder farmers (61.1%) had no off-farm employment. Bjornlund *et al.* (2009) found that smallholder farmers depended on-farm income as they had no off-farm employment. However, Agholor and Nkosi (2020) found that 41% of the study participants had off-farm employment, 34% were self-employed, and only 24% had no employment. Annor-Frempong (2013) found no correlation of off-farm employment and the adoption of recommended practices. The findings suggest that most smallholder farmers depend on the profit they make on-farm to maintain their livelihoods.

5.2 The adoption of modern irrigation water management practices

5.2.1. Irrigation scheduling

Irrigation scheduling is applied differently among smallholder farmers, with 59.1% having adopted the crop-based scheduling method. More smallholder farmers irrigate their farms based on observation of the crop's condition. Similarly, Fernández (2017) stated that the crop-based method is applied to monitor crop water stress and schedule when to irrigate. However, Senzanje (2007) suggested that as a result of the lack of awareness of their crop's water requirements, smallholder farmers may be reluctant to adopt irrigation scheduling with assumptions that applying more water is better for their crops, or that irrigation scheduling is a complicated process. Pardossi and Incrocci (2011) stated that in greenhouse setups crop-based irrigation scheduling is more feasible due to the uniformity of crops than in open fields. The findings suggest that crop-based irrigation scheduling is applied differently depending on the method of crop production. The results indicate that 79.4% of the smallholder farmers have adopted the soil-based irrigation scheduling method. Smallholder farmers in the area check soil

conditions before irrigation. Yohannes *et al.* (2017) argued that irrigation scheduling that is not based on crop and soil water requirements is the reason behind poor irrigation scheme performance.

Weather-based irrigation scheduling has been adopted by 23.3% of the smallholder farmers. Frisvold and Deva (2012) reported a less than 2% adoption rate of irrigation scheduling techniques. This indicates that most smallholder farmers do not schedule irrigation based on weather variations. Calendar-based irrigation scheduling has been adopted by 16.2% of smallholder farmers. Although, Schaible and Aillery (2012) found that less than 10% adopted irrigation scheduling in the Western States of America, smallholder farmers still depended on traditional methods to decide when and the amount of water to irrigate. The results suggests that not many smallholder farmers schedule field irrigation based on the availability of farm workers. Only 12.2% of the smallholder farmers scheduled irrigation according to fixed rotation. Stevens (2007) reported that only 18% of irrigators adopted irrigation scheduling in South Africa between 2000 and 2004, with most irrigators using their traditional knowledge and methods to schedule irrigation. Jordán and Speelman (2020) also reported a very low adoption of irrigation scheduling, practiced only in fruit production. Contrary to other studies, Engler *et al.* (2016) suggested that the chances of adopting irrigation scheduling increase with the use of efficient irrigation systems such as drip irrigation. From the results, it is evident that fewer smallholder farmers schedule irrigation based on the availability of water in their fields.

5.2.2. Soil moisture monitoring

The feel method where the moisture in the soil is felt on the palm of the hand was adopted by 27.4% of the participants. USDA (2019) reported a higher adoption of the feel method by smallholder farmers (76%). Similarly, ICDC (2017) and Schaible and Aillery (2012) also reported that the feel method was mostly adopted as the soil moisture monitoring practice among smallholder farmers. ICDC (2017) stated that the feel method is easier and cheaper, whereas moisture sensors and computer systems are sophisticated and costly to implement. The study results confirm findings from previous research that smallholder farmers still use indigenous ways to monitor soil moisture.

Moisture sensors were only adopted by 3.7% of smallholder farmers. Schaible and Aillery (2012) found that less than 10% adopted soil or plant moisture sensing devices. Bjornlund *et al.* (2009) also found that soil moisture monitoring tools have been adopted by only a few

smallholder farmers. Gu *et al.* (2020) argued that soil moisture sensors are less practical for smallholder farmers as they require field installation and maintenance which could be costly. The findings indicate that smallholder farmers are still reluctant to adopt moisture sensors to monitor soil moisture in their field. However, these findings are not consistent with Mpanga and Idowu (2020) who found a 55% increase in the adoption of soil moisture sensors from 2007 to 2017.

Only 0.3% of the smallholder farmers adopted computer-based models. Schaible and Aillery (2012) reported that less than 2% adopted computer-based models to monitor water requirements based on a crop's growth stage and weather conditions. Panuska *et al.* (2015) reported that soil moisture monitoring tools have become more sophisticated over time. However, Stevens (2007) found that 72% of irrigating smallholder farmers adopted computer-based models with assistance from irrigation consultants and extension officers. Based on the findings, it can be argued that the adoption of computer-based models among most smallholder farmers in Bushbuckridge is still uncommon.

5.2.3. Land levelling

The use of hand hoes is commonly used by smallholder farmers in Bushbuckridge for land levelling. A staggering 94.3% of smallholder farmers still used the hand hoe for land levelling. Only 3.4% of smallholder farmers used draft animals for land levelling. Most of the smallholder farmers that took part in the study have never used or were no longer using animals for draught power. Walker (1989) reported that smallholder farmers relied on draft animals from land levelling. The majority of smallholder farmers (77%) used tractors to level their fields. Other smallholder farmers occasionally used tractors for land preparation and not for land levelling. The results concur with Weber (2005) that most smallholder farmers prefer using the simple tractors for land levelling over those with laser beams. These results indicate that most smallholder farmers have advanced into the use of tractors for land levelling.

Only 2% of smallholder farmers had adopted laser land levelling. Schaible and Aillery (2012) reported that the adoption of laser land levelling decreased from 27% to 16% between 1998 and 2008. However, Mahmood *et al.* (2015) reported that 51.5% of the smallholder farmers had adopted laser land levelling to an average extent. Gupta (2022) also reported that the adoption of laser land levelling is spreading across India. The findings suggest that while the

adoption of laser land levelling is common to some extent in some regions, it is less so among Bushbuckridge smallholder farmers.

5.2.4. Tail-water recovery system

A pumping and recycling system for tail-water recovery was only adopted by 3% of the smallholder farmers. The results indicate that most smallholder farmers have not adopted the tail-water recovery system to recycle their irrigation water. Reservoirs were adopted by only 1.7% of the smallholder farmers. Most smallholder farmers do not have reservoirs to collect and store irrigation runoff in their fields. Consistent with the present study findings, Adusumilli and Wang (2018) reported that the tail-water recovery was only adopted by 4.76% of smallholder farmers. Schaible and Aillery (2012) found that the adoption of tail-water recovery decreased from 22 to 8% between 1998 and 2008. Bouldin *et al.* (2004) pointed out, that the tail-water recovery system may not be applicable for some irrigation systems. However, NRCS (2007) revealed that the tail-water recovery system can be applicable to any land that has been well prepared, with properly installed irrigation systems, where runoff from irrigation or rainfall can be expected. The findings indicate that the tail-water recovery system is one of the least adopted modern irrigation water management practices.

5.3.5. Rainwater harvesting

To collect and store rainwater, 23.0% of the smallholder farmers used basins. This indicates that most smallholder farmers (77.0%) had never or are no longer using basins for rainwater harvesting. Most smallholder farmers used drums (59.1%) for rainwater harvesting. The use of drums for rainwater harvesting appears to be common among smallholder farmers in the study area. Most smallholder farmers also used tanks (58.4%) to harvest and store rainwater. Inconsistent with these findings, Kahinda *et al.* (2010) reported rainwater harvesting as the least used source of water in South Africa, with only tanks for storing rainwater used by less than 1% of rural households. The study finding present inconsistencies with previous literature suggesting that the use of tanks for rainwater harvesting varies across regions.

Only 2.4% of smallholder farmers had cisterns to collect and store rainwater. The use of cisterns is the least practiced method of rainwater harvest. Gutters were used by 30.7% of smallholder farmers to collect rainwater. Aliabadi *et al.* (2020) and Medina (2016) mentioned that modern ways of collecting rainwater involve the use of roof gutters and pipes that deliver the rainwater into tanks or cisterns. Rainwater harvesting was found to be adopted by only

5.22% of smallholder farmers (Mango *et al.*, 2017). Kumar *et al.* (2016) reported that some farmers perceived farm level rainwater harvesting structures as a waste of productive land space. Lamptey (2022) reported that 97% of cultivated land in sub-Saharan Africa is under rain-fed agriculture.

5.2 Socio-economic and socio-psychological drivers toward the adoption of modern irrigation water management practices

This subsection discusses the results of the study on the socio-economic and socio-psychological drivers toward the adoption of modern irrigation water management practices. Only drivers that significantly influenced the adoption of the different irrigation water management methods and tools are discussed.

5.2.1. Socio-economic drivers

Under the socio-economic drivers, gender, education level, household size, farm size, off-farm employment status, and group membership have an influence on the adoption of at least one of the irrigation water management methods and tools. The influences of the socio-economic drivers on adoption were either positive or negative.

5.2.1.1 Gender

Gender had a significantly negative influence ($p < .001$) on the adoption of the weather based irrigation scheduling method. This means that males are less likely than females to adopt weather based irrigation scheduling. The results are consistent with those of Alhassan *et al.* (2017) where gender had a negative but significant influence on the use of solid waste management services. However, for the adoption of gutter for rainwater harvesting in this study, gender had a positive significant influence ($p = .031$), males were more likely to use gutters for rainwater harvesting than females. Similarly, Agholor and Nkosi (2020) found that gender significantly influenced whether smallholder farmers adopt water conservation practices or not, more males (39%) adopted the practices than females (21%). Lavison (2013) also found that more men adopted organic fertilizer than women. Moyo (2016) found that scheme irrigators had the highest number of male (93.3%) household heads. Gender had a significant effect on the production of improved cassava in Nigeria (Obisesan, 2014). Like the results of this study, Mzoughi (2009) also reported mixed results for gender, which

significantly influenced the adoption of integrated crop protection practices but not the adoption of organic farming practices.

5.2.1.2 Education level

Mixed results were reported on the influence of the different education levels (primary, secondary, matriculated, ABET, Diploma, and Degree) on the adoption of various modern irrigation water management practices by smallholder farmers. Primary schooling positively influenced the adoption of fixed rotation ($p=.011$) for irrigation scheduling and drum ($p=.007$) and tank ($p=.003$) for rainwater harvesting. The results indicate that smallholder farmers who attended primary school were more likely to schedule irrigation based on water availability, as well as the use of drums and tanks for rainwater harvesting. Attending secondary school negatively influenced the adoption of weather based ($p=.030$) irrigation scheduling, but a positive influence on the adoption of fixed rotation ($p=.016$) irrigation scheduling and tank ($p=.002$) for rainwater harvesting. This suggests that smallholder farmers who attended secondary school are less likely to adopt weather based irrigation scheduling, but more likely to adopt fixed rotation irrigation scheduling and tank for rainwater harvesting. Mzoughi (2009) also reported that education level only significantly influenced the adoption of organic farming but had no influence on the adoption of integrated crop protection. A negative influence of formal schooling was also reported on the use of crops with genetic modifications (Uematsu & Mishra, 2010). Completing matric also significantly influenced the adoption of fixed rotation ($p=.034$) irrigation scheduling and tank use ($p=.003$) for rainwater harvesting. Smallholder farmers with matric certificates were more likely to use fixed rotation irrigation scheduling and a tank for rainwater harvesting than smallholder farmers who did not complete matric.

ABET positively influenced the adoption of drum ($p=.017$) and tank use ($p<.001$) for rainwater harvesting, suggesting that smallholder farmers who attended ABET were more likely to use drums and tanks for rainwater harvesting than those without drums or tanks. Crop based ($p=.031$) and fixed rotation ($p=.008$) irrigation scheduling and the feel method ($p=.040$) for soil moisture monitoring were positively influenced by the acquiring of a diploma, suggesting that smallholder farmers with a diploma were more likely to adopt crop based, fixed rotation, or the feel method than those who have no diplomas. Having a degree also had a positive influence on both the adoption of calendar based ($p=.003$) and fixed ($p<.001$) rotation irrigation scheduling. Smallholder farmers who completed their degrees were more likely to use either or both the calendar based and fixed rotation irrigation scheduling methods. Similarly, Agholor

and Nkosi (2020) found that education level has a significant influence on the adoption of water conservation practices, the higher the level of education a smallholder farmer has completed the more likely they are to adopt water conservation practices. Jordán and Speelman (2020) and Mignouna *et al.* (2011) suggested that this may be attributed to easy access to information that educated smallholder farmers have, enabling better utilization of irrigation technologies and internalizing the benefits that are derived from them. Ajewole (2010), Mwangi and Kariuki (2015), and Okunlola *et al.* (2011) also found that the education level of the farmer positively influenced their decision to adopt new technologies.

5.2.1.3 Household size

A negative influence ($p=.004$) of household size was reported on the adoption of weather based irrigation scheduling. These findings suggest that smallholder farmers with larger household size were less likely to adopt weather based irrigation scheduling than those with smaller household sizes. A positive influence ($p=.041$) of household size on the adoption of tank for rainwater harvesting was found in this study. For the adoption of tank for rainwater harvesting, smallholder farmers with more family members were more likely to use tanks than those with small household sizes. Similarly, Darkwah *et al.* (2019) found that household size positively influenced adoption of technology where technology was adopted more by smallholder farmers with larger household sizes. Moyo (2016) stated that the more the household member that worked full-time on the farm, the less likely farm labour would be problematic, the household would be able to adopt labour-intensive technologies. Asfaw and Neka (2017) and Mwangi and Kariuki (2015) also reported that larger households can carry out the labour and maintain soil and water conservation practices.

5.2.1.4 Farm size

A positive influence of farm size on the adoption of tractor ($p<.001$) for land levelling, a pumping system ($p<.001$) and reservoir ($p=.018$) for tail-water recovery, tank ($p<.001$) and gutter ($p=.001$) for rainwater harvesting was reported. This implies that smallholder farmers with larger farm sizes were more likely to use at least one of the methods than those with small farm sizes. These findings are supported by Uaiene *et al.* (2009) and Mignouna *et al.* (2011) who both reported a correlation between the size of farms and the adoption of improved agricultural technologies. Annor-Frempong (2013), Dinar *et al.* (2017), and Jordán and Speelman (2020) also reported a significant influence of farm size on the adoption of irrigation

technology, maize agronomic practices, and conservation practices, respectively. Mwangi and Kariuki (2015) stated that the size of farms plays a vital role on the adoption of new technologies, as some technologies are scale dependent. The likelihood of adopting new technologies was higher for smallholder farmers with larger farm sizes as their large farms enabled them to attempt at using the new practice on just a piece of their land (Antonili *et al.*, 2015; Uaiene *et al.*, 2009). However, farm size had a negative influence on the adoption of basin for rainwater harvesting, suggesting that smallholder farmers with larger farm sizes were less likely to use basins. Similarly, Asfaw and Neka (2017) reported that the larger the farm size, the lower the probability of adopting soil and water management practices. However, Huang *et al.* (2017) found that water management practices were more likely to be adopted in small farm sizes.

5.2.1.5 Off-farm employment status

Unemployment positively influenced the adoption of weather based ($p=.024$) irrigation scheduling, but negatively influenced the adoption of calendar based ($p<.001$) irrigation scheduling and drum ($p=.009$) for rainwater harvesting. The results indicate that unemployed smallholder farmers are more likely to schedule irrigating their fields based on weather conditions, but less likely to schedule irrigation based on the availability of workers or use drums to collect rainwater. Similarly, Mwangi and Kariuki (2015) found that off-farm income had a positive impact on technology adoption. Shiferaw *et al.* (2009) stated that decision-making, adopting and maintenance of improved practices could be influenced by off-farm employment. However, Annor-Frempong (2013) found no significant difference or correlation between the adoption of the recommended seed practices and off-farm income. Lima *et al.* (2018) found a negative influence of off-farm employment on the adoption of precision farming equipment attributed to limited time available to try the tools.

5.2.1.6 Group membership

A negative influence ($p=.008$) of group membership was reported on the adoption of calendar-based irrigation scheduling. Annor-Frempong (2013) found no significant influence of group membership on adoption with close friends having no influence on the adoption decision of recommended maize practices. However, Zeweld *et al.* (2018) reported that farmers in formal farmer organizations were 6% more likely to adopt two or more sustainable land management

practices. Smallholder farmers who had no group membership were less likely to use calendar-based irrigation scheduling than smallholder farmers who had group membership.

5.2.2. Socio-psychological drivers

All the socio-psychological drivers (intention, attitude, personal efficacy, and social capital) had a significant influence on at least one of the dependent variables.

5.2.2.1 Intention

The adoption of fixed rotation ($p=.002$) irrigation scheduling was positively influenced by intention, suggesting that smallholder farmers with higher intentions were more likely to schedule irrigation based on water availability. However, intention negatively influenced the adoption of tractor ($p=.002$) for land levelling, tank ($p=.011$) and cistern ($p=.039$) for rainwater harvesting. This suggest that smallholder farmers with higher intentions were less likely to uses tractors to level their field, or have tanks and cisterns to collect rain water. Several researchers reported that positive attitudes influenced the intention to adopt new practices (Aliabadi *et al.*, 2020; Pino *et al.*, 2017; Terano *et al.*, 2015; Zeweld *et al.*, 2017). Lima *et al.* (2018) found that the adoption of electronic identification technology was positively influenced by an intention to improve production. A positive influence of intention was reported on the adoption of precision agricultural technologies (Antolini *et al.*, 2015).

5.2.2.2 Attitude

High attitudes positively influenced the adoption of crop based ($p=.004$) irrigation scheduling and tractor ($p<.001$) for land levelling, but negatively influenced the adoption of fixed rotation ($p<.001$) irrigation scheduling and moisture sensors ($p=.038$) for soil moisture monitoring. The results suggest that smallholder farmers with positive attitudes are more likely to schedule irrigation based on the condition of the crop and/or use tractors to level their fields, whereas their likelihood of adopting fixed rotation and moisture sensors decreases. These findings are aligned with those of Zeweld *et al.* (2018) where attitude significantly influenced the adoption of crop rotation involving legumes and the use of compost but they were not associated with the adoption of agroforestry systems. Whereas Zeweld *et al.* (2017) reported that smallholder farmers with negative attitudes were not willing to adopt sustainable practices, and Mahmood *et al.* (2015) reported mixed attitudes on the adoption of different practices.

Attitude had a positive influence on the adoption of minimum tillage and row planting among smallholder farmers (Zeweld *et al.*, 2017). Aliabadi *et al.* (2020) also found that individuals with positive attitudes toward water management were more likely to participate in it instead of participating in general and unsustainable approaches. Similarly, Adusumilli and Wang (2018) reported that conservation practices are adopted mostly by smallholder farmers who felt that land conservation and changes to existing agricultural practices would protect water quality in streams and rivers. Waheed *et al.* (2015) found a significant influence of attitude towards eBook reader adoption.

5.2.2.3 Social capital

A positive influence of social capital toward the adoption of soil based ($p=.037$) irrigation scheduling and tractor ($p=.009$) for land levelling was found in the present study. Smallholder farmers who obtained their information on irrigation water management practices from fellow farmers, friend and family, or irrigation scheme groups were more likely to irrigate based on the condition of the soil and/or use a tractor for land levelling. Similarly, Zeweld *et al.* (2018) reported that social capital had a positive influence on the adoption of agroforestry systems, crop rotation and compost. Social capital had a significant influence on technology adoption (David & Ardiansyah, 2018). Bagheri and Teymouri (2021) reported that smallholder farmers are more influenced by people in their social circles when adopting practices and decision-making. Alhassan *et al.* (2017) also found a positive influence of social capital on willingness to pay for solid waste management practices.

Social capital had a great influence on the intention to adopt eco-friendly forest management techniques (Ofoegbu & Speranza, 2017). However, social capital negatively influenced the adoption of weather based ($p=.006$) irrigation scheduling, calendar based ($p=.005$) irrigation scheduling, and the feel method ($p=.006$) for soil moisture monitoring in this study. This means that smallholder farmers with more social capital are less likely to schedule irrigation based on weather conditions or the availability of labor. Buyinza *et al.* (2020) and Syan *et al.* (2019) found that social capital had no influence on the intention to adopt sustainable agricultural practices or intention to incorporate trees to coffee plantations, respectively.

5.3 Constraints hindering the adoption of modern irrigation water management practices

5.3.1. Inadequate extension service

5.3.1.1 New practices not introduced to smallholder farmers

A large proportion of smallholder farmers (81.4%) indicated that modern irrigation water management practices have not been introduced to them. Ntai (2011) also found that 60% of smallholder farmers had not received advice on irrigation water management from extension officers. Furthermore, Ntai (2011) reported that 69.7% of smallholder farmers were not satisfied with the irrigation water management support they received from extension officers. The results confirm that smallholder farmers have not adopted modern irrigation water management practices because they have not been introduced to them by extension officers.

5.3.1.2 Lack of training

Training on modern irrigation water management practices has not been received by 91.5% of smallholder farmers. Some smallholder farmers (36%) agreed that the training requirements for the adoption irrigation scheduling systems hindered them from adopting the practices (Berthold *et al.*, 2021). Yohannes *et al.* (2017) reported that smallholder farmers had no training on irrigation water management. Consequently, soil and crop water requirements were not met as a result of incorrect use of irrigation water in the fields (Yohannes *et al.*, 2017). The findings suggest that the lack of training from extension officers on modern irrigation water management practices constrained smallholder farmers from adopting various farming practices.

5.3.1.3 No access to extension services

Extension officers do not make regular visits to 92.2% of the smallholder farmers. In line with these findings, Ntai (2011) found that 89.7% of smallholder farmers only met once a year with extension officers. Yohannes *et al.* (2017) reported that smallholder farmers had limited to no access to extension services. Zeweld *et al.* (2019) argued that the inadequacy in extension services or the lack of access thereof is attributed to the isolated locations that smallholder farmers reside in where extension workers are unable to reach them. Access to extension services has been shown to impact on smallholder farmers' adoption of sustainable agricultural practices (Kumari, 2018; Wauters & Mathijs, 2014). This is consistent with the current findings

where the absence or sparse visits from extension officers has negatively impacted smallholder farmers' adoption of modern irrigation water management practices.

5.3.2. Lack of information

5.3.2.1 No access to information

Most smallholder farmers in this research lacked access to information (73.3%). Similarly, Huang *et al.* (2017) reported that access to irrigation information sources determined the adoption of sprinkler irrigation. Access to more sources of information could promote the adoption of irrigation innovations and improved water management practices (Huang *et al.*, 2017). Schaible and Aillery (2006) reported that the lack of information about the advantages of improved systems is a key constraint that prevents smallholder farmers from improving their systems. The lack of information among smallholder farmers attributed to lack of knowledge, education, and skills results in a lot of confusion, doubt, and uncertainty which hinders the adoption of modern irrigation water management practices (Bagheri & Teymouri, 2021; García *et al.*, 2020; Zeweld *et al.*, 2019). Mahmood *et al.* (2015) found that 3.3% of the participants thought that the lack of information hindered the adoption of water saving interventions. The findings all suggest that not having access to information on modern irrigation water management practices negatively impacts smallholder farmers' adoption of their farming practices.

5.3.2.2 Lack of awareness

Modern irrigation water management practices were not adopted because smallholder farmers (54.4%) were not aware of them. Other researchers also reported that lack of awareness of alternative management strategies leads to practices not being adopted, smallholder farmers adopted practices they were aware of or had been informed about (Bagheri & Teymouri, 2021; Mengistie & Kidane 2016; Mwangi & Kariuki, 2015; Zeweld *et al.*, 2019). Most smallholder farmers were only aware of crop based (76.8%) irrigation scheduling and the feel method (60.8%) for soil moisture monitoring (Berthold *et al.*, 2021). Annor-Frempong (2013) found that 80% of smallholder farmers who were aware of the recommended maize practices adopted them. The results confirm that most smallholder farmers have not adopted modern irrigation water management practices because they are not aware of the availability of such practices.

5.3.2.3 Do not understand the information provided

Information on modern irrigation water management practices is regarded as difficult to understand by 65.2% of smallholder farmers surveyed in this study. Similarly, Berthold *et al.* (2021) found that 29% of smallholder farmers receive information on irrigation scheduling tools that is difficult for them to understand. Danso *et al.* (2021) argued that farmers are frequently confronted with a variety of irrigation technologies and crop options, and selecting the most efficient technology to produce profitable crops is not an easy task. Most smallholder farmers are reluctant to adopt modern irrigation water management practices because they do not fully understand the information they receive regarding the practices.

5.3.3. Financial constraint

5.3.3.1 Lack of funding to purchase equipment

The lack of funding to purchase equipment was found to hinder the adoption of modern irrigation water management practices by 97.6% of smallholder farmers. Consistent with these findings, Bjornlund *et al.* (2008) found that one of the main reasons as to why smallholder farmers do not adopt improved water use efficiency practices is their financial status. Schaible and Aillery (2012) found that 28.4% of irrigators could not finance improvements, whereas 25.6% found high installation cost of improvements as a constraint toward adoption. Lima *et al.* (2018) found that only 9% of smallholder farmers stated that the cost of equipment did not hinder the adoption of electronic identification technology in sheep farming. The results confirm that not having access to funding to buy the equipment required to install or establish modern irrigation water management practices was a constraint for most smallholder farmers within the study area.

5.3.3.2 No access to credit

No access to credit to invest in modern irrigation water management practices was selected by 100% of the participants. Schaible and Aillery (2006) also reported that financial constraints and access to credit are known constraints in most farms requiring irrigation, which limit adoption. Smallholder farmers lack the financial capital needed to invest in new practices and prefer adopting practices that are affordable to them (Bagheri & Teymouri, 2021; Bjornlund *et al.*, 2008). Obisesan (2014) reported that most smallholder farmers who could access credit adopted improved technologies for production than those without access to credit. This

indicates that smallholder farmers without access to credit were constrained from investing in modern irrigation water management practices.

5.3.3.3 No money for maintenance

Most smallholder farmers (97.3%) recorded that they do not have adequate funding to maintain modern irrigation water management practices. Similarly, Morrison (2005) reported that financial capital impedes the adoption of innovations that can be implemented easily, with demonstrable benefits. Lack of access to funding also hinders intentions to adopt technology and sustainable practices (Adebayo *et al.*, 2018). Jordán and Speelman (2020) found that access to resources and financial capital encourages adoption of irrigation technologies. The results suggest that smallholder farmers perceive modern irrigation water management practices to require capital for regular maintenance.

5.3.4. Access to water

5.3.4.1 Inadequate water supply

The majority of the smallholder farmers (75.7%) disagreed to not having access to adequate water supply. In contrast to this finding, Moyo (2016) found that inadequate access to water was a major constraint for growing crops in backyard gardens. However, Mendelsohn and Dinar (2003) argued that excess amounts of surface water discourage smallholder farmers from investing in and adopting irrigation technologies or reducing water consumption. The smallholder farmers had enough water at their disposal hence they did not consider inadequate water supply as a constraint toward the adoption of modern irrigation water management practices.

5.3.4.2 Irregular water availability

The statement, “Water is not regularly available on my farm” was contradicted by 72.6% of the smallholder farmers. On the other hand, Senzanje (2007) reported that irregular water supply hindered proper irrigation scheduling. Schaible and Aillery (2012) found that 14.8% of irrigators could not adopt water conservation practices because of uncertainty about the future availability of water. Danso *et al.* (2021) reported that under no scarcity conditions, if a significant level of subsidy is provided, smallholder farmers could be motivated to convert to

a better irrigation technology. However, the results of this study suggests that water availability did not pose as a constraint to smallholder farmers in their farming practices.

5.3.4.3 Shared water source

Most smallholder farmers (51%) disagreed to sharing their water source with other smallholder farmers. Danso *et al.* (2021) reported that the probability of changing to efficient irrigation technologies is low even under full water access. This implies that smallholder farmers' decision to adopt modern irrigation water management practices was not constrained as a result of sharing a water source with other smallholder farmers.

5.3.5. Farm location

5.3.5.1 Distance from water source

Most of the smallholder farmers (49%) disagreed that their farms were located far from water sources. On the contrary, Shallo *et al.* (2020) found that distance from water source had a negative impact on the adoption of biogas technology. Asfaw and Neka (2017) and Belachew *et al.* (2020) reported that the distance from a farmer's home to the farm negatively influenced the adoption of soil and water conservation practices, the likelihood of adopting the practices decreases as the distance between the farm and the farmer's home increases. However, farm distance from water source was not a constraint on the adoption of modern irrigation water management practices for smallholder farmers in this study.

5.3.5.2 Distance from training programmes

Smallholder farmers (90.5%) agreed that they were located far from irrigation training programmes. The level of participation in government programs had an impact on the adoption of water management practices (Huang *et al.*, 2017). Isgin *et al.* (2008) stated that the farm location determines which agricultural services are easily accessible to smallholder farmers, which ultimately influences the decision-making process toward adoption. Furthermore, smallholder farmers in isolated locations are not visited by extension officers which places further constraints on them from obtaining the information they require to adopt certain methods (Zeweld *et al.*, 2019). These results suggest that not residing near irrigation training programmes results in smallholder farmers not gaining the practical knowledge required to adopt modern irrigation water management practices.

5.3.5.3 Distance from other adopters

Farms that were located far from adopters of modern irrigation water management practices were reported to hinder adoption by 81.4% of the smallholder farmers. Ghadim and Pannell (1999) reported that farm distance from an adopter of an innovation and the ability of the farmer to visit the adopter frequently influenced the adoption of agricultural innovation. Smallholder farmers that live or have their farms far from other adopters cannot easily access information on the innovation, learn valuable skills and therefore have doubts about various innovations (Ghadim & Pannell, 1999). Chirwa (2005) found also a negative correlation of farm distance and the adoption of maize technologies. The results suggest that smallholder farmers do not adopt practices that are not common in their area.

5.3.6. Lack of technical expertise

5.3.6.1 Have never used technology for irrigation

Smallholder farmers (57.7%) in this study identified having no experience using technology for irrigation as a constraint toward the adoption of modern irrigation water management practices. Ghadim and Pannell (1999) reported that smallholder farmers that have experience with practices similar to new innovative practices being introduced are more likely to adopt the new practices. Bjornlund *et al.* (2009) found that most smallholder farmers had adopted irrigation water management practices that were practical to them. This suggests that smallholder farmers prefer adopting practices they have practical experience in, rather than practices they are unfamiliar with.

5.3.6.2 Lack of technical skills

The adoption of modern irrigation water management practices was reported to be constrained by lack of technical expertise by 88.2% of the smallholder farmers. Maheswari *et al.* (2008) also found that the lack of technical skills hindered the adoption of precision technology. Yohannes *et al.* (2017) reported that the main constraints hindering proper irrigation water management by smallholder farmers are the lack of technical knowledge and inefficient irrigation equipment. Lima *et al.* (2018) found that smallholder farmers who lacked technical knowledge were less likely to adopt modern agricultural technologies. Antolini *et al.* (2015) had also reported previously that smallholder farmers who had some form of mechanization technology or had already adopted the technologies had a higher probability of adopting

precision agricultural technologies. The present study confirms that technical skills are important in the adoption of modern irrigation water management practices.

5.3.6.3 Inability to use technology

Not knowing how to use the technology in modern irrigation water management practices inhibited 60.2% smallholder farmers from adopting the practices. Some modern irrigation water management practices such as soil moisture monitoring with moisture sensor and computerized models are too sophisticated for smallholder farmers to implement (ICDC, 2017). Antolini *et al.* (2015) reported that challenges in adopting specific technologies had a negative impact on smallholder farmers' adoption of new technologies. Furthermore, smallholder farmers prefer technologies that are not sophisticated (Antolini *et al.*, 2015). The findings indicate that most smallholder farmers have not started using technology in their farms but are still using indigenous ways to irrigate.

CHAPTER SIX: CONCLUSION AND RECOMMENDATIONS

Conclusion

New and improved ways of monitoring and controlling irrigation water application and water use efficiency to adapt to low water availability owing to climate change are crucial. Previous research has showed that the adoption of improved practices such as soil and water conservation practices and agricultural technologies vary across different regions. However, studies should be conducted on the adoption of modern irrigation water management practices. Hence, the first objective of this study was to investigate the adoption of modern irrigation water management practices by smallholder farmers in Bushbuckridge Local Municipality.

The results revealed that crop-based and soil-based irrigation scheduling methods have been adopted by most smallholder farmers. The feel method has been adopted by most smallholder farmers for soil moisture monitoring, while the use of hand hoes and tractors were mostly used for land levelling. The use of drums and tanks were the most methods adopted for rainwater harvesting. The methods mentioned are the most common among smallholder farmers as these are found to be more compatible for their scale of production and the resources they have. These results suggest that there is a low adoption rate of modern irrigation water management practices among smallholder farmers; implying that the simple and indigenous practices of irrigation water management are still mostly used by smallholder farmers in the area. The second objective sought to identify the socio-economic and socio-psychological drivers toward the adoption of modern irrigation water management practices.

Socio-economic drivers, gender, education level, household size, farm size, off-farm employment status, and group membership significantly influenced the adoption of some of the modern irrigation water management practices. These results suggest that the socio-economic status of smallholder farmers determined whether they adopt modern irrigation water management practices. The socio-psychological drivers, intention, attitude, personal efficacy, and social capital had a significant influence on the adoption of the modern irrigation water management practices. The findings suggest that when smallholder farmers are intentional, have positive attitudes, believe in their potential to succeed, and have good social capital they are most likely to adopt modern irrigation water management practices.

The third and last objective of the study was to examine the constraints faced by smallholder farmers toward the adoption of modern irrigation water management practices. Most smallholder farmers reported that they are constrained by the inadequacy of extension services, lack of information on modern irrigation water management practices, lack of financial capital, farm distance from adopters and training programmes, as well as lack of technical expertise to operate the technologies involved in modern irrigation water management practices. Such studies suggest that most smallholder farmers would adopt modern irrigation water management practices if they had adequate extension services, received reliable and understandable information, and had financial capital. Furthermore, if smallholder farmers lived close to other adopters and irrigation training programmes, also having the technical skills for operating various technologies the adoption of modern irrigation water management practices would not be so low.

This research is expected to contribute to the construction of future research studies related to the adoption of modern irrigation water management practices and add to the existing knowledge gap. It will also provide policymakers, government organisations, and extension officers insight into the socio-economic and socio-psychological drivers that influence adoption, as well as the various constraints. However, the limitations of the study should be noted. The lack of prior research studies on the adoption of modern irrigation water management practices, particularly in Bushbuckridge Local Municipality and surrounding areas limited the scope of the literature review and discussion in this study.

Furthermore, due to the small sample size, the results may not be a general representation of the target population of smallholder farmers. Resource limitations such as time constraints and lack of smallholder farmers' participation resulted in a sample selection based on availability and willingness to participate. This may have resulted in sampling bias against other smallholder farmers within the target population who were not included in the study. It should also be noted that even after careful explanation of the questions and response options on the questions, some of the smallholder farmers may have provided false or incorrect answers which may have altered the study findings.

Recommendations

It is important to raise awareness about resource scarcity given the expected declines in water supply as a result of the negative effects of climate change. For regions facing water shortages,

government and non-government organizations should implement policies and programs that encourage irrigation water management and enhance smallholder farmers' awareness of modern irrigation water management practices. Awareness campaigns on modern irrigation water management practices are recommended to promote adoption and provide smallholder farmers with the appropriate information. The Department of Agriculture should fund campaigns for Agricultural Extension Officers to raise awareness on the adoption of modern irrigation water management practices to smallholder farmers. Awareness campaigns should be hosted regularly at local community halls or sports fields accessible to smallholder farmers in those rural communities.

Raising awareness to smallholder farmers on the importance and the benefits of adopting modern irrigation water management practices could change their intentions, attitudes, and personal efficacy and help them make informed decisions. Agricultural stakeholders such as researchers, financiers, and policymakers should involve smallholder farmers in the evaluation process of improved agricultural practices. This could aid in determining the compatibility of those practices to smallholder farmers' requirements and current practices.

Implementation of effective policies is also necessary to encourage smallholder farmers to adopt improved management practices. Policymakers should implement policies that allow smallholder farmers to gain access to financial capital and fund expensive practices to encourage them to adopt modern irrigation water management practices. Policies that necessitate the establishment of educational and training programmes on the implementation of modern irrigation water management practices by the Department of Agriculture should be developed. Smallholder farmers should be visited regularly by extension officers for effective dissemination and adoption of modern irrigation water management practices.

More research is required on the adoption of modern irrigation water management practices by smallholder farmers in Bushbuckridge Local Municipality. A larger sample size is recommended for more accurate results that can be generalised to the target population. Other sampling methods such as random sampling can be used to get a general representation of the population of smallholder farmers. Questionnaires can be translated to participants' native language for better understanding of survey questions. Furthermore, priority should be given to the training and motivation of extension officers to disseminate modern irrigation water management practices to smallholder farmers. It is important to obtain extension officers'

perceptions on the dissemination of improved agricultural practices and the approaches used in the dissemination process.

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APPENDICES

1. Survey Questionnaire

INFORMATION SHEET AND INFORMED CONSENT FORM

My name is Tiisetso Christain Mashego I am a Masters student at the University of Mpumalanga, I am working with the approval of the School of Agricultural Sciences and my Supervisor is Dr Jorine Ndoro, and co-supervisor Prof. Victor Mlambo. I am conducting a study on 'Adoption of modern irrigation water management practices by smallholder farmers'.

I would like to invite you to participate in this research.

If you decide to take part in this study please note the following;

Your participation is completely voluntary.

All the identifying information that you have provided will remain confidential.

You have the right to withdraw from the study at any point without any penalty.

There is no direct risk of physical and legal harm in this study.

Answering the questionnaire will take approximately 30-45 minutes. The information collected will be used to write a report, conference presentations and academic publications.

Participation agreement

I.....have read and understood the document. I have been given an opportunity to ask questions about the research and they have been answered to my satisfaction. I agree to participate.

Signature of the participant.....

Date.....

SECTION A: SURVEY QUALITY CONTROL

Questionnaire Number:	Enumerator Name:
Community Name :	Ward:

SECTION B: DEMOGRAPHICS AND HOUSEHOLD DATA

(Tick the appropriate box)

1)	Age	0=Below 20	1=20-29	2=30-39	3=40-49	4=50-59	5=60+
2)	Gender	0=Female	1=Male				
3)	Education Level	0=No school	1=Primary	2=Secondary	3=Matriculated	4=ABET	5=Diploma 6=Degree
4)	Years of farming experience						
5)	Household size						

6)	Source of income	0=Pension	1=Social grant (child/disability/ covid relief)	2=Farming	3=Remittance	4=Own Business (registered)	5=Informal Trader
7)	Land ownership	0=Yes		1=No	2=Renting	3=Permission to occupy	
8)	Water source	0=Borehole	1=River	2=Dam	3=Tap water		4=Rain
9)	Irrigation method	0=Drip irrigation	1=Sprinkler irrigation		2=Furrow irrigation		3=Other
10)	Physical irrigation assets	0= Tank	1= Water pump		2= Generator		3=None
11)	Type of farming	0=Crop	1=Livestock			2=Mixed	
12)	Farm size						
13)	Off-farm employment status	0=Employed	1=Unemployed				
14)	Group membership	0=Yes	1=No				

SECTION C: The adoption of modern irrigation water management practices by smallholder farmers
(Tick the appropriate box)

Irrigation scheduling		0= No	1= Yes
15)	Crop based		
16)	Soil based		
17)	Weather based		
18)	Calendar schedule		
19)	Fixed rotation		
Soil moisture monitoring			
20)	Feel method		
21)	Moisture sensors		
22)	Computer based models		
Land levelling			
23)	Hand hoe		
24)	Draft animals		
25)	Tractor		
26)	Laser levelling		
Tail-water recovery			
27)	Pumping system		
28)	Reservoir		
Rainwater harvesting			
29)	Basin		
30)	Drum		
31)	Tank		
32)	Cistern		
33)	Gutter		

SECTION D: Socio-psychological drivers toward adoption of modern irrigation water management practices

(Tick the appropriate box)

Adoption intention		1=Strongly Disagree	2=Disagree	3=Neutral	4=Agree	5=Strongly Agree
34)	I am willing to adopt modern irrigation water management practices					
35)	I intend to adopt modern irrigation water management practices in the near future					
36)	I want to try modern irrigation water management practices on my farm					

(Tick the appropriate box)

ATTITUDE		1=Strongly Disagree	2=Disagree	3=Neutral	4=Agree	5=Strongly Agree
37)	I feel comfortable using modern irrigation water management practices					
38)	I think modern irrigation water management practices promote water use efficiency					
39)	I feel that modern irrigation water management practices are compatible with my irrigation practices					
PERSONAL EFFICACY						
40)	I believe I can successfully implement modern irrigation water management practices on my farm					
41)	I have the skills required to adopt modern irrigation water management practices					
42)	Modern irrigation water management practices are easy to adopt					
SOCIAL CAPITAL						
43)	Other smallholder farmers provide me with information on irrigation water management					
44)	I receive information about irrigation water management through friends and family.					
45)	Being part of an irrigation scheme has improved how I manage irrigation water					

SECTION E: Constraints faced by smallholder farmers towards adoption of modern irrigation water management practices

(Tick the appropriate box)

Inadequate extension services		1=Strongly Disagree	2=Disagree	3=Neutral	4=Agree	5=Strongly Agree
46)	Modern irrigation water management practices have not been introduced to us by extension officers					
47)	I have not received training on modern irrigation water management from extension officers					
48)	I do not receive regular visits from extension officers					
Lack of information						
49)	I do not have access to information on modern irrigation water management practices					
50)	I am not aware of modern irrigation water management practices					
51)	It is difficult to understand information on modern irrigation water management practices					
Financial constraint						
51)	Lack of funding to purchase equipment hinders adoption of modern irrigation water management practices					
52)	I do not have access to credit to invest in modern irrigation water management practices					
53)	I do not have the enough money needed to maintain modern irrigation water management practices					
Access to water						
54)	I do not have access to adequate water supply					
55)	Water is not regularly available on my farm					
56)	I share my water source with other farmers					
Farm location						
57)	My farm is located far from water source					
58)	My farm is located far from irrigation training programmes					

59)	My farm is located far from adopters of modern irrigation water management practices					
Lack of technical expertise						
60)	I have never used technology for irrigation before					
61)	Lack of technical skills hinders adoption of modern irrigation water management practices					
62)	Inability to use the technology in modern irrigation water management practices					

THANK YOU!!!

2. Binary logistic regression results for Irrigation scheduling methods

2.1 Soil-based

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	50.302	19	<,001
	Block	50.302	19	<,001
	Model	50.302	19	<,001

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	250.859 ^a	.156	.245
a. Estimation terminated at iteration number 20 because maximum iterations has been reached. Final solution cannot be found.			

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	14.700	8	.065

Classification Table^a

Observed	Predicted		
	Soil-based		Percentage Correct
	No	Yes	

Step 1	Soil-based	No	20	41	32.8
		Yes	6	229	97.4
	Overall Percentage				
a. The cut value is .500					

Variables in the Equation_ Soil-based

		B	S.E.	Wald	df	Sig.	Exp(B)	95% EXP(B)	C.I. for
								Lower	Upper
Step 1 ^a	Socio-economic drivers								
	Age			.965	4	.915			
	Age(1)	19.760	10602.882	.000	1	.999	381530504.115	.000	.
	Age(2)	.032	1.364	.001	1	.981	1.033	.071	14.969
	Age(3)	.433	1.380	.098	1	.754	1.542	.103	23.077
	Age(4)	.141	1.413	.010	1	.921	1.151	.072	18.341
	Gender(1)	.213	.333	.408	1	.523	1.237	.644	2.376
	Education level			7.854	6	.249			
	Education level(1)	-.088	.581	.023	1	.880	.916	.293	2.861
	Education level(2)	1.044	.677	2.378	1	.123	2.841	.753	10.715
	Education level(3)	.990	.656	2.274	1	.132	2.691	.743	9.743
	Education level(4)	.758	.878	.745	1	.388	2.134	.382	11.925
	Education level(5)	1.680	1.172	2.052	1	.152	5.363	.539	53.377
	Education level(6)	.242	1.084	.050	1	.823	1.274	.152	10.668
	Household size	-.012	.036	.115	1	.735	.988	.920	1.060
	Farm size	.060	.067	.805	1	.370	1.062	.931	1.211
	Off-farm employment status(1)	.257	.383	.450	1	.502	1.293	.610	2.739
	Group membership(1)	.707	.396	3.182	1	.074	2.028	.933	4.409
	Socio-psychological drivers								
	INT	-.469	.349	1.803	1	.179	.626	.315	1.241
	ATT	.491	.431	1.300	1	.254	1.634	.703	3.799
	PEFF	.371	.249	2.212	1	.137	1.449	.889	2.362
	SCAPT	.278	.133	4.351	1	.037	1.321	1.017	1.715
	Constant	-3.028	1.931	2.459	1	.117	.048		
a. Variable(s) entered on step 1: Age, Gender, Education level, Household size, Farm size, Off-farm employment status, Group membership, INT, ATT, PEFF, SCAPT.									

2.2 Weather-based

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	88.820	19	<,001
	Block	88.820	19	<,001
	Model	88.820	19	<,001

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	232.638 ^a	.259	.391
a. Estimation terminated at iteration number 6 because parameter estimates changed by less than .001.			

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	5.163	8	.740

Classification Table^a

Observed			Predicted		
			Weather-based		Percentage
			No	Yes	Correct
Step 1	Weather-based	No	216	11	95.2
		Yes	37	32	46.4
	Overall Percentage				83.8
a. The cut value is .500					

Variables in the Equation_ Weather-based

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B)	
								Lower	Upper
Step 1 ^a	Socio-economic drivers								
	Age			5.461	4	.243			
	Age(1)	-.804	2.252	.128	1	.721	.447	.005	36.961

	Age(2)	-2.261	2.174	1.082	1	.298	.104	.001	7.384
	Age(3)	-2.109	2.174	.941	1	.332	.121	.002	8.604
	Age(4)	-1.677	2.196	.583	1	.445	.187	.003	13.843
	Gender(1)	-1.306	.370	12.478	1	<.001	.271	.131	.559
	Education level			5.543	6	.476			
	Education level(1)	-.726	.647	1.259	1	.262	.484	.136	1.720
	Education level(2)	-1.614	.743	4.715	1	.030	.199	.046	.855
	Education level(3)	-.710	.687	1.067	1	.302	.492	.128	1.891
	Education level(4)	-.499	.896	.311	1	.577	.607	.105	3.512
	Education level(5)	-.884	.843	1.100	1	.294	.413	.079	2.156
	Education level(6)	-1.148	1.102	1.084	1	.298	.317	.037	2.752
	Household size	-.130	.046	8.133	1	.004	.878	.802	.960
	Farm size	.065	.069	.888	1	.346	1.067	.932	1.221
	Off-farm employment status(1)	.958	.424	5.104	1	.024	2.605	1.135	5.978
	Group membership(1)	-.628	.432	2.112	1	.146	.534	.229	1.245
	Socio-psychological drivers								
	INT	.656	.391	2.814	1	.093	1.926	.895	4.145
	ATT	-.091	.440	.043	1	.836	.913	.385	2.162
	PEFF	-.369	.267	1.914	1	.166	.692	.410	1.166
	SCAPT	-.397	.143	7.682	1	.006	.673	.508	.890
	Constant	2.801	2.719	1.061	1	.303	16.458		
	a. Variable(s) entered on step 1: Age, Gender, Education level, Household size, Farm size, Off-farm employment status, Group membership, INT, ATT, PEFF, SCAPT.								

2.3 Calendar-based

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	59.106	19	<.001
	Block	59.106	19	<.001
	Model	59.106	19	<.001

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	203.290 ^a	.181	.308

a. Estimation terminated at iteration number 20 because maximum iterations has been reached. Final solution cannot be found.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	11.969	8	.153

Classification Table^a

Observed			Predicted		
			Calendar-based		Percentage
			No	Yes	Correct
Step 1	Calendar-based	No	241	7	97.2
		Yes	36	12	25.0
	Overall Percentage				85.5
a. The cut value is .500					

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B)	
								Lower	Upper
Step 1 ^a	Socio-economic drivers								
	Age			3.389	4	.495			
	Age(1)	-19.915	10555.987	.000	1	.998	.000	.000	.
	Age(2)	.060	1.464	.002	1	.967	1.062	.060	18.705
	Age(3)	-.238	1.481	.026	1	.872	.788	.043	14.375
	Age(4)	-1.434	1.594	.810	1	.368	.238	.010	5.419
	Gender(1)	.375	.378	.987	1	.320	1.456	.694	3.053
	Education level			11.828	6	.066			
	Education level(1)	1.363	1.176	1.342	1	.247	3.906	.390	39.172
	Education level(2)	1.271	1.232	1.064	1	.302	3.563	.319	39.837
	Education level(3)	1.047	1.211	.747	1	.387	2.849	.265	30.607
	Education level(4)	1.268	1.368	.858	1	.354	3.553	.243	51.931
	Education level(5)	2.124	1.329	2.554	1	.110	8.367	.618	113.231
	Education level(6)	4.547	1.519	8.961	1	.003	94.323	4.806	1851.220
	Household size	-.018	.046	.158	1	.691	.982	.896	1.075
	Farm size	.031	.078	.164	1	.686	1.032	.886	1.202

	Off-farm employment status(1)	-1.783	.437	16.662	1	<.001	.168	.071	.396
	Group membership(1)	-1.187	.450	6.956	1	.008	.305	.126	.737
Socio-psychological drivers									
	INT	-.138	.363	.144	1	.705	.871	.427	1.776
	ATT	-.285	.525	.295	1	.587	.752	.269	2.105
	PEFF	-.454	.297	2.341	1	.126	.635	.355	1.136
	SCAPT	-.440	.157	7.855	1	.005	.644	.474	.876
	Constant	4.480	2.390	3.513	1	.061	88.198		
a. Variable(s) entered on step 1: Age, Gender, Education level, Household size, Farm size, Off-farm employment status, Group membership, INT, ATT, PEFF, SCAPT.									

2.4 Fixed rotation

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	62.919	19	<.001
	Block	62.919	19	<.001
	Model	62.919	19	<.001

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	156.206 ^a	.191	.366
a. Estimation terminated at iteration number 7 because parameter estimates changed by less than .001.			

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	4.737	8	.785

Classification Table^a

Observed			Predicted		
			Fixed rotation		Percentage Correct
			No	Yes	
Step 1	Fixed rotation	No	253	7	97.3

		Yes	25	11	30.6
	Overall Percentage				89.2
a. The cut value is .500					

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B)	
								Lower	Upper
Step 1 ^a	Socio-economic drivers								
	Age			.047	4	1.000			
	Age(1)	-.271	1.776	.023	1	.879	.763	.023	24.800
	Age(2)	-.198	1.573	.016	1	.900	.820	.038	17.918
	Age(3)	-.265	1.599	.027	1	.868	.767	.033	17.612
	Age(4)	-.174	1.646	.011	1	.916	.840	.033	21.152
	Gender(1)	-.299	.458	.427	1	.513	.741	.302	1.819
	Education level			13.937	6	.030			
	Education level(1)	2.701	1.064	6.447	1	.011	14.898	1.852	119.863
	Education level(2)	2.814	1.167	5.810	1	.016	16.680	1.692	164.424
	Education level(3)	2.464	1.162	4.502	1	.034	11.757	1.207	114.543
	Education level(4)	2.012	1.544	1.697	1	.193	7.476	.362	154.273
	Education level(5)	3.358	1.269	6.996	1	.008	28.719	2.386	345.684
	Education level(6)	4.997	1.451	11.854	1	<.001	148.031	8.607	2545.902
	Household size	-.083	.058	2.082	1	.149	.920	.821	1.030
	Farm size	.104	.091	1.288	1	.256	1.109	.927	1.327
	Off-farm employment status(1)	.582	.546	1.137	1	.286	1.790	.614	5.216
	Group membership(1)	-1.004	.512	3.852	1	.050	.366	.134	.999
	Socio-psychological drivers								
	INT	2.290	.746	9.418	1	.002	9.875	2.288	42.630
	ATT	-1.844	.556	10.993	1	<.001	.158	.053	.471
	PEFF	-.607	.310	3.835	1	.050	.545	.297	1.001
	SCAPT	.017	.197	.007	1	.932	1.017	.691	1.496
	Constant	-3.929	3.630	1.171	1	.279	.020		
a. Variable(s) entered on step 1: Age, Gender, Education level, Household size, Farm size, Off-farm employment status, Group membership, INT, ATT, PEFF, SCAPT.									

3. Binary logistic regression results for Soil Moisture Monitoring methods

3.1 Feel method

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	80.360	19	<,001
	Block	80.360	19	<,001
	Model	80.360	19	<,001

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	267.058 ^a	.238	.344
a. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.			

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	4.947	8	.763

Classification Table^a

Observed			Predicted		
			Feel method		Percentage
			No	Yes	Correct
Step 1	Feel method	No	199	16	92.6
		Yes	39	42	51.9
	Overall Percentage				81.4
a. The cut value is .500					

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B)	
								Lower	Upper
Step 1 ^a	Socio-economic drivers								
	Age			24.294	4	<,001			

	Age(1)	-2.261	1.613	1.965	1	.161	.104	.004	2.459
	Age(2)	-2.292	1.425	2.585	1	.108	.101	.006	1.652
	Age(3)	-1.305	1.418	.847	1	.357	.271	.017	4.366
	Age(4)	.317	1.454	.047	1	.828	1.373	.079	23.711
	Gender(1)	.130	.320	.166	1	.684	1.139	.608	2.133
	Education level			10.334	6	.111			
	Education level(1)	1.125	.641	3.078	1	.079	3.081	.876	10.829
	Education level(2)	.452	.720	.394	1	.530	1.571	.383	6.440
	Education level(3)	1.710	.712	5.762	1	.016	5.529	1.369	22.341
	Education level(4)	.562	1.037	.293	1	.588	1.754	.230	13.394
	Education level(5)	1.776	.866	4.200	1	.040	5.905	1.081	32.266
	Education level(6)	1.671	1.111	2.263	1	.133	5.319	.603	46.929
	Household size	.001	.034	.001	1	.980	1.001	.936	1.070
	Farm size	.127	.061	4.258	1	.039	1.135	1.006	1.281
	Off-farm employment status(1)	.325	.374	.755	1	.385	1.383	.665	2.877
	Group membership(1)	-.700	.387	3.266	1	.071	.497	.233	1.061
Socio-psychological drivers									
	INT	.340	.323	1.107	1	.293	1.406	.746	2.650
	ATT	-.433	.423	1.045	1	.307	.649	.283	1.487
	PEFF	-.242	.260	.865	1	.352	.785	.471	1.308
	SCAPT	-.356	.131	7.413	1	.006	.701	.543	.905
	Constant	1.395	1.859	.563	1	.453	4.036		
a. Variable(s) entered on step 1: Age, Gender, Education level, Household size, Farm size, Off-farm employment status, Group membership, INT, ATT, PEFF, SCAPT.									

3.2 Moisture sensors

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	37.898	19	.006
	Block	37.898	19	.006
	Model	37.898	19	.006

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	56.123 ^a	.120	.442
a. Estimation terminated at iteration number 20 because maximum iterations has been reached. Final solution cannot be found.			

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	1.745	8	.988

Classification Table^a

Observed			Predicted		
			Moisture sensors		Percentage
			No	Yes	Correct
Step 1	Moisture sensors	No	284	1	99.6
		Yes	9	2	18.2
	Overall Percentage				96.6
a. The cut value is .500					

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B)	
								Lower	Upper
Step 1 ^a	Socio-economic drivers								
	Age			6.657	4	.155			
	Age(1)	20.370	19614.747	.000	1	.999	702171002.489	.000	.
	Age(2)	17.285	19614.747	.000	1	.999	32105713.514	.000	.
	Age(3)	16.247	19614.747	.000	1	.999	11371756.584	.000	.
	Age(4)	16.210	19614.747	.000	1	.999	10957538.014	.000	.
	Gender(1)	-.309	.835	.137	1	.712	.734	.143	3.771
	Education level			1.046	6	.984			

	Education level(1)	20.410	6522.186	.000	1	.998	731389750.072	.000	.
	Education level(2)	19.462	6522.186	.000	1	.998	283160277.542	.000	.
	Education level(3)	.029	7232.805	.000	1	1.000	1.030	.000	.
	Education level(4)	-.954	9565.891	.000	1	1.000	.385	.000	.
	Education level(5)	19.491	6522.186	.000	1	.998	291748265.376	.000	.
	Education level(6)	2.661	16144.991	.000	1	1.000	14.306	.000	.
	Household size	-.065	.090	.529	1	.467	.937	.785	1.117
	Farm size	.259	.150	2.996	1	.083	1.296	.966	1.738
	Off-farm employment status(1)	1.060	.984	1.161	1	.281	2.887	.420	19.862
	Group membership(1)	1.062	1.081	.965	1	.326	2.892	.347	24.079
Socio-psychological drivers									
	INT	.975	1.169	.695	1	.404	2.650	.268	26.190
	ATT	-3.196	1.537	4.324	1	.038	.041	.002	.832
	PEFF	2.251	1.223	3.387	1	.066	9.500	.864	104.458
	SCAPT	-.132	.306	.185	1	.667	.877	.481	1.598
	Constant	-41.322	20670.680	.000	1	.998	.000		
a. Variable(s) entered on step 1: Age, Gender, Education level, Household size, Farm size, Off-farm employment status, Group membership, INT, ATT, PEFF, SCAPT.									

3.3 Computer-based models

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	13.377	19	.819
	Block	13.377	19	.819
	Model	13.377	19	.819

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	.000 ^a	.044	1.000
a. Estimation terminated at iteration number 20 because maximum iterations has been reached. Final solution cannot be found.			

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	.000	8	1.000

Classification Table^a

Observed			Predicted		
			Computer-based models		Percentage
			No	Yes	Correct
Step 1	Computer-based models	No	295	0	100.0
		Yes	0	1	100.0
	Overall Percentage				100.0
a. The cut value is .500					

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1 ^a	Socio-economic drivers								
	Age			.000	4	1.000			
	Age(1)	-34.348	30059.314	.000	1	.999	.000	.000	.
	Age(2)	-29.298	21228.772	.000	1	.999	.000	.000	.
	Age(3)	-22.621	24423.564	.000	1	.999	.000	.000	.
	Age(4)	-28.102	23879.132	.000	1	.999	.000	.000	.
	Gender(1)	-4.703	4782.671	.000	1	.999	.009	.000	.
	Education level			.000	6	1.000			

	Education level(1)	8.817	9004.84 3	.000	1	.999	6750.850	.000	.
	Education level(2)	19.581	20667.8 76	.000	1	.999	319199689. 795	.000	.
	Education level(3)	27.980	13481.6 65	.000	1	.998	1417473497 092.324	.000	.
	Education level(4)	43.965	16573.9 79	.000	1	.998	1241360923 7794404000 .000	.000	.
	Education level(5)	38.799	23839.0 29	.000	1	.999	7079667136 2401984.00 0	.000	.
	Education level(6)	79.789	18798.9 55	.000	1	.997	4485249796 4986110000 0000000000 00000.000	.000	.
	Household size	1.218	898.865	.000	1	.999	3.380	.000	.
	Farm size	5.414	728.609	.000	1	.994	224.625	.000	.
	Off-farm employment status(1)	-6.701	8975.12 4	.000	1	.999	.001	.000	.
	Group membership(1)	-.345	9805.41 6	.000	1	1.000	.709	.000	.
Socio-psychological drivers									
	INT	10.969	4909.37 1	.000	1	.998	58061.310	.000	.
	ATT	-8.158	4337.45 7	.000	1	.998	.000	.000	.
	PEFF	-19.931	2242.57 3	.000	1	.993	.000	.000	.
	SCAPT	4.961	1867.45 1	.000	1	.998	142.731	.000	.
	Constant	-21.163	26301.8 89	.000	1	.999	.000		
a. Variable(s) entered on step 1: Age, Gender, Education level, Household size, Farm size, Off-farm employment status, Group membership, INT, ATT, PEFF, SCAPT.									

4. Binary logistic regression results for Land Levelling methods

4.1 Hand hoe

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	21.504	19	.310
	Block	21.504	19	.310
	Model	21.504	19	.310

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	108.644 ^a	.070	.197
a. Estimation terminated at iteration number 20 because maximum iterations has been reached. Final solution cannot be found.			

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	6.564	8	.584

Classification Table^a

Observed			Predicted		
			Hand hoe		Percentage
			No	Yes	Correct
Step 1	Hand hoe	No	0	17	.0
		Yes	1	278	99.6
	Overall Percentage				93.9
a. The cut value is .500					

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B)	
								Lower	Upper
Step 1 ^a	Socio-economic drivers								
	Age			8.328	4	.080			

	Age(1)	-20.530	21900.5 91	.000	1	.999	.000	.000	.
	Age(2)	-18.258	21900.5 91	.000	1	.999	.000	.000	.
	Age(3)	-18.349	21900.5 91	.000	1	.999	.000	.000	.
	Age(4)	-17.841	21900.5 91	.000	1	.999	.000	.000	.
	Gender(1)	.255	.582	.193	1	.661	1.291	.413	4.038
	Education level			5.023	6	.541			
	Education level(1)	.941	1.127	.697	1	.404	2.563	.281	23.354
	Education level(2)	1.868	1.474	1.606	1	.205	6.476	.360	116.46 5
	Education level(3)	.139	1.156	.014	1	.904	1.149	.119	11.086
	Education level(4)	.239	1.542	.024	1	.877	1.270	.062	26.076
	Education level(5)	-.699	1.290	.294	1	.588	.497	.040	6.228
	Education level(6)	-1.474	1.656	.793	1	.373	.229	.009	5.876
	Household size	-.102	.059	2.933	1	.087	.903	.804	1.015
	Farm size	.050	.115	.186	1	.666	1.051	.839	1.317
	Off-farm employment status(1)	-.844	.708	1.421	1	.233	.430	.107	1.722
	Group membership(1)	.051	.685	.006	1	.941	1.052	.275	4.031
Socio-psychological drivers									
	INT	.567	.512	1.229	1	.268	1.764	.647	4.808
	ATT	-.129	.731	.031	1	.860	.879	.210	3.681
	PEFF	.158	.515	.094	1	.759	1.171	.427	3.210
	SCAPT	.289	.222	1.689	1	.194	1.335	.864	2.063
	Constant	18.222	21900.5 91	.000	1	.999	81972827.7 80		
a. Variable(s) entered on step 1: Age, Gender, Education level, Household size, Farm size, Off-farm employment status, Group membership, INT, ATT, PEFF, SCAPT.									

4.2 Draft animals

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	15.956	19	.660

	Block	15.956	19	.660
	Model	15.956	19	.660

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	71.458 ^a	.052	.205
a. Estimation terminated at iteration number 20 because maximum iterations has been reached. Final solution cannot be found.			

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	3.558	8	.895

Classification Table^a

Observed			Predicted		
			Draft animals		Percentage
			No	Yes	Correct
Step 1	Draft animals	No	286	0	100.0
		Yes	10	0	.0
	Overall Percentage				96.6
a. The cut value is .500					

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for	
								EXP(B)	
								Lower	Upper
Step 1 ^a	Socio-economic drivers								
	Age			.940	4	.919			
	Age(1)	-1.624	23991.582	.000	1	1.000	.197	.000	.
	Age(2)	16.869	21603.017	.000	1	.999	21179699.710	.000	.
	Age(3)	16.467	21603.017	.000	1	.999	14181889.942	.000	.
	Age(4)	17.721	21603.017	.000	1	.999	49659457.502	.000	.

	Gender(1)	.266	.707	.141	1	.707	1.304	.326	5.215
	Education level			2.162	6	.904			
	Education level(1)	-.750	1.554	.233	1	.629	.472	.022	9.929
	Education level(2)	-17.861	5266.826	.000	1	.997	.000	.000	.
	Education level(3)	.769	1.524	.255	1	.614	2.158	.109	42.747
	Education level(4)	-17.393	8757.455	.000	1	.998	.000	.000	.
	Education level(5)	1.337	1.567	.728	1	.393	3.809	.177	82.172
	Education level(6)	-17.454	14898.687	.000	1	.999	.000	.000	.
	Household size	-.013	.093	.018	1	.892	.987	.823	1.185
	Farm size	-.041	.136	.090	1	.765	.960	.735	1.253
	Off-farm employment status(1)	-.036	.737	.002	1	.961	.965	.228	4.088
	Group membership(1)	1.900	1.167	2.650	1	.104	6.683	.679	65.819
	Socio-psychological drivers								
	INT	.103	.715	.021	1	.885	1.109	.273	4.503
	ATT	-.293	.989	.088	1	.767	.746	.107	5.182
	PEFF	.207	.758	.075	1	.785	1.230	.278	5.435
	SCAPT	.404	.321	1.584	1	.208	1.498	.798	2.811
	Constant	-23.350	21603.017	.000	1	.999	.000		
	a. Variable(s) entered on step 1: Age, Gender, Education level, Household size, Farm size, Off-farm employment status, Group membership, INT, ATT, PEFF, SCAPT.								

4.3 Tractor

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	141.042	19	<,.001
	Block	141.042	19	<,.001
	Model	141.042	19	<,.001

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
------	-------------------	----------------------	---------------------

1	178.016 ^a	.379	.575
a. Estimation terminated at iteration number 20 because maximum iterations has been reached. Final solution cannot be found.			

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	7.991	8	.434

Classification Table^a

Observed			Predicted		
			Tractor		Percentage
			No	Yes	Correct
Step 1	Tractor	No	39	29	57.4
		Yes	10	218	95.6
	Overall Percentage				86.8
a. The cut value is .500					

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B)	
								Lower	Upper
Step 1 ^a	Socio-economic drivers								
	Age			3.893	4	.421			
	Age(1)	1.641	1.965	.698	1	.403	5.163	.110	242.860
	Age(2)	.703	1.738	.164	1	.686	2.021	.067	60.993
	Age(3)	1.464	1.748	.702	1	.402	4.324	.141	132.934
	Age(4)	.580	1.789	.105	1	.746	1.786	.054	59.526
	Gender(1)	.573	.400	2.053	1	.152	1.773	.810	3.881
	Education level			2.104	6	.910			
	Education level(1)	.409	.892	.210	1	.647	1.505	.262	8.644
	Education level(2)	-.120	.922	.017	1	.897	.887	.146	5.402
	Education level(3)	-.190	.916	.043	1	.836	.827	.137	4.982
	Education level(4)	.796	1.201	.440	1	.507	2.218	.211	23.342
	Education level(5)	.383	1.127	.116	1	.734	1.467	.161	13.357

	Education level(6)	20.780	14169.14	.000	1	.999	1057911174.280	.000	.
	Household size	.075	.047	2.557	1	.110	1.078	.983	1.181
	Farm size	.414	.103	15.973	1	<.001	1.512	1.235	1.852
	Off-farm employment status(1)	-.571	.452	1.596	1	.206	.565	.233	1.370
	Group membership(1)	.693	.500	1.920	1	.166	1.999	.750	5.324
Socio-psychological drivers									
	INT	-1.657	.522	10.072	1	.002	.191	.069	.531
	ATT	1.967	.569	11.932	1	<.001	7.150	2.342	21.831
	PEFF	.525	.284	3.403	1	.065	1.690	.968	2.950
	SCAPT	.435	.167	6.777	1	.009	1.546	1.114	2.145
	Constant	-7.043	2.589	7.403	1	.007	.001		
a. Variable(s) entered on step 1: Age, Gender, Education level, Household size, Farm size, Off-farm employment status, Group membership, INT, ATT, PEFF, SCAPT.									

4.4 Laser levelling

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	24.727	19	.170
	Block	24.727	19	.170
	Model	24.727	19	.170

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	33.934 ^a	.080	.446
a. Estimation terminated at iteration number 20 because maximum iterations has been reached. Final solution cannot be found.			

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	.304	8	1.000

Classification Table^a

Observed			Predicted		
			Laser levelling		Percentage Correct
			No	Yes	
Step 1	Laser levelling	No	290	0	100.0
		Yes	5	1	16.7
	Overall Percentage				98.3
a. The cut value is .500					

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% EXP(B)	C.I.for
								Lower	Upper
Step 1 ^a	Socio-economic drivers								
	Age			.179	4	.996			
	Age(1)	.406	21529.383	.000	1	1.000	1.501	.000	.
	Age(2)	18.309	19335.593	.000	1	.999	89441972.125	.000	.
	Age(3)	18.824	19335.593	.000	1	.999	149715921.102	.000	.
	Age(4)	2.106	19574.234	.000	1	1.000	8.212	.000	.
	Gender(1)	-1.740	1.207	2.079	1	.149	.176	.016	1.869
	Education level			3.891	6	.691			
	Education level(1)	-19.062	3723.104	.000	1	.996	.000	.000	.
	Education level(2)	-19.622	4454.254	.000	1	.996	.000	.000	.
	Education level(3)	-3.021	1.687	3.208	1	.073	.049	.002	1.330
	Education level(4)	-1.070	1.611	.441	1	.506	.343	.015	8.065
	Education level(5)	-1.502	1.898	.626	1	.429	.223	.005	9.190
	Education level(6)	-5.542	14085.490	.000	1	1.000	.004	.000	.
	Household size	-.291	.172	2.872	1	.090	.748	.534	1.047
	Farm size	-.015	.231	.004	1	.947	.985	.626	1.549
	Off-farm employment status(1)	.267	1.162	.053	1	.818	1.306	.134	12.743

	Group membership(1)	-.951	1.293	.541	1	.462	.386	.031	4.867
	Socio-psychological drivers								
	INT	8.070	2611.187	.000	1	.998	3197.688	.000	.
	ATT	-1.473	3.191	.213	1	.644	.229	.000	119.251
	PEFF	22.890	2572.192	.000	1	.993	8729462355.809	.000	.
	SCAPT	-.705	.445	2.507	1	.113	.494	.206	1.183
	Constant	-161.117	26640.713	.000	1	.995	.000		
a. Variable(s) entered on step 1: Age, Gender, Education level, Household size, Farm size, Off-farm employment status, Group membership, INT, ATT, PEFF, SCAPT.									

5. Binary logistic regression results for Tail-water Recover System methods

5.1 Pumping system

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	38.030	19	.006
	Block	38.030	19	.006
	Model	38.030	19	.006

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	42.570 ^a	.121	.506
a. Estimation terminated at iteration number 20 because maximum iterations has been reached. Final solution cannot be found.			

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	22.999	8	.003

Classification Table^a

Observed			Predicted		
			Pumping system and recycling system		Percentage Correct
Step 1	Pumping system and recycling system	No	286	1	99.7
		Yes	6	3	33.3
	Overall Percentage				97.6

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1 ^a	Socio-economic drivers								
	Age			3.512	4	.476			
	Age(1)	-1.395	23530.638	.000	1	1.000	.248	.000	.
	Age(2)	12.061	21803.115	.000	1	1.000	173008.334	.000	.
	Age(3)	14.395	21803.115	.000	1	.999	1784285.730	.000	.
	Age(4)	12.612	21803.115	.000	1	1.000	300284.406	.000	.
	Gender(1)	-1.083	1.162	.868	1	.351	.339	.035	3.304
	Education level			3.493	6	.745			
	Education level(1)	-1.411	1.990	.503	1	.478	.244	.005	12.052
	Education level(2)	1.230	1.980	.386	1	.535	3.421	.071	165.853
	Education level(3)	-.566	2.025	.078	1	.780	.568	.011	30.075
	Education level(4)	-16.823	7137.547	.000	1	.998	.000	.000	.
	Education level(5)	-18.061	7185.586	.000	1	.998	.000	.000	.
	Education level(6)	-14.042	14173.491	.000	1	.999	.000	.000	.
	Household size	.059	.082	.513	1	.474	1.061	.903	1.246
	Farm size	.853	.228	14.035	1	<.001	2.347	1.502	3.667
	Off-farm employment status(1)	-.413	1.162	.127	1	.722	.661	.068	6.455
	Group membership(1)	.797	1.172	.463	1	.496	2.220	.223	22.074
	Socio-psychological drivers								
	INT	12.537	3440.698	.000	1	.997	278369.760	.000	.
	ATT	.408	2.537	.026	1	.872	1.503	.010	217.235
	PEFF	-.926	.858	1.165	1	.280	.396	.074	2.128
	SCAPT	-.055	.402	.019	1	.891	.947	.431	2.080
	Constant	-82.642	27772.882	.000	1	.998	.000		

a. Variable(s) entered on step 1: Age, Gender, Education level, Household size, Farm size, Off-farm employment status, Group membership, INT, ATT, PEFF, SCAPT.

5.2 Reservoir

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	31.880	19	.032
	Block	31.880	19	.032
	Model	31.880	19	.032

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	18.844 ^a	.102	.648
a. Estimation terminated at iteration number 20 because maximum iterations has been reached. Final solution cannot be found.			

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	.080	8	1.000

Classification Table^a

Observed			Predicted		
			Reservoir		Percentage
			No	Yes	Correct
Step 1	Reservoir	No	289	2	99.3
		Yes	4	1	20.0
	Overall Percentage				98.0
a. The cut value is .500					

Variables in the Equation

	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B)	
							Lower	Upper
	Socio-economic drivers							

Step 1 ^a	Age			3.962	4	.411			
	Age(1)	15.222	17132.9 92	.000	1	.999	4081672.01 3	.000	.
	Age(2)	-9.374	17356.5 77	.000	1	1.000	.000	.000	.
	Age(3)	6.477	17132.9 91	.000	1	1.000	650.242	.000	.
	Age(4)	7.266	17132.9 91	.000	1	1.000	1431.141	.000	.
	Gender(1)	.374	2.036	.034	1	.854	1.453	.027	78.604
	Education level			2.614	6	.855			
	Education level(1)	11.476	4964.44 4	.000	1	.998	96353.100	.000	.
	Education level(2)	15.644	4964.44 3	.000	1	.997	6222520.78 0	.000	.
	Education level(3)	13.990	4964.44 3	.000	1	.998	1190472.64 2	.000	.
	Education level(4)	2.325	6345.38 9	.000	1	1.000	10.225	.000	.
	Education level(5)	- 11.600	7598.36 2	.000	1	.999	.000	.000	.
	Education level(6)	-.615	13620.0 82	.000	1	1.000	.540	.000	.
	Household size	.056	.126	.201	1	.654	1.058	.827	1.353
	Farm size	1.243	.527	5.563	1	.018	3.464	1.234	9.729
	Off-farm employment status(1)	.888	2.706	.108	1	.743	2.430	.012	488.88 8
	Group membership(1)	-1.347	1.725	.609	1	.435	.260	.009	7.646
	Socio-psychological drivers								
	INT	9.105	1877.39 6	.000	1	.996	9001.959	.000	.
	ATT	13.240	2635.01 7	.000	1	.996	562207.964	.000	.
	PEFF	22.352	2077.52 8	.000	1	.991	509720543 3.153	.000	.
	SCAPT	-.676	.728	.861	1	.353	.509	.122	2.120

	Constant	-254.919	25780.655	.000	1	.992	.000		
a. Variable(s) entered on step 1: Age, Gender, Education level, Household size, Farm size, Off-farm employment status, Group membership, INT, ATT, PEFF, SCAPT.									

6. Binary logistic regression results for Rainwater Harvesting methods

6.1 Basin

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	26.174	19	.125
	Block	26.174	19	.125
	Model	26.174	19	.125

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	292.884 ^a	.085	.128
a. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.			

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	8.752	8	.364

Classification Table^a

Observed			Predicted		
			Basin		Percentage
			No	Yes	Correct
Step 1	Basin	No	222	6	97.4
		Yes	63	5	7.4
	Overall Percentage				76.7
a. The cut value is .500					

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% EXP(B)	C.I. for
								Lower	Upper
Step 1 ^a	Socio-economic drivers								
	Age			4.377	4	.357			
	Age(1)	-.831	1.499	.307	1	.580	.436	.023	8.229
	Age(2)	-.044	1.299	.001	1	.973	.957	.075	12.197
	Age(3)	-.396	1.311	.091	1	.763	.673	.052	8.782
	Age(4)	-1.132	1.363	.690	1	.406	.322	.022	4.658
	Gender(1)	-.465	.302	2.376	1	.123	.628	.347	1.135
	Education level			5.578	6	.472			
	Education level(1)	-.036	.619	.003	1	.954	.965	.287	3.243
	Education level(2)	.059	.648	.008	1	.928	1.061	.298	3.776
	Education level(3)	-.632	.648	.951	1	.330	.531	.149	1.894
	Education level(4)	.097	.794	.015	1	.903	1.101	.232	5.225
	Education level(5)	-1.265	.957	1.747	1	.186	.282	.043	1.841
	Education level(6)	-.369	1.297	.081	1	.776	.692	.054	8.796
	Household size	-.040	.036	1.249	1	.264	.961	.896	1.031
	Farm size	-.127	.065	3.780	1	.052	.881	.775	1.001
	Off-farm employment status(1)	.312	.333	.879	1	.348	1.367	.711	2.626
	Group membership(1)	.485	.365	1.759	1	.185	1.624	.793	3.323
	Socio-psychological drivers								
	INT	-.354	.309	1.318	1	.251	.702	.383	1.285
	ATT	-.190	.408	.216	1	.642	.827	.372	1.841
	PEFF	-.073	.249	.086	1	.769	.929	.570	1.515
	SCAPT	.128	.125	1.035	1	.309	1.136	.889	1.452
	Constant	2.425	1.809	1.798	1	.180	11.304		
a. Variable(s) entered on step 1: Age, Gender, Education level, Household size, Farm size, Off-farm employment status, Group membership, INT, ATT, PEFF, SCAPT.									

6.2 Drum

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	55.016	19	<,001
	Block	55.016	19	<,001
	Model	55.016	19	<,001

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	345.420 ^a	.170	.229
a. Estimation terminated at iteration number 4 because parameter estimates changed by less than .001.			

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	4.622	8	.797

Classification Table^a

Observed			Predicted		
			Drum		Percentage Correct
			No	Yes	
Step 1	Drum	No	55	66	45.5
		Yes	28	147	84.0
	Overall Percentage				68.2
a. The cut value is .500					

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B)	
								Lower	Upper
Step 1 ^a	Socio-economic drivers								
	Age			6.114	4	.191			
	Age(1)	.394	1.532	.066	1	.797	1.483	.074	29.862
	Age(2)	1.116	1.415	.622	1	.430	3.054	.191	48.910

	Age(3)	1.367	1.424	.922	1	.337	3.924	.241	63.894
	Age(4)	.532	1.448	.135	1	.713	1.703	.100	29.100
	Gender(1)	.170	.269	.401	1	.527	1.186	.700	2.009
	Education level			13.640	6	.034			
	Education level(1)	1.574	.580	7.369	1	.007	4.827	1.549	15.040
	Education level(2)	1.045	.604	2.995	1	.084	2.844	.871	9.292
	Education level(3)	.953	.589	2.621	1	.105	2.594	.818	8.223
	Education level(4)	1.929	.806	5.726	1	.017	6.884	1.418	33.424
	Education level(5)	.228	.727	.098	1	.754	1.256	.302	5.224
	Education level(6)	-.160	1.275	.016	1	.900	.852	.070	10.362
	Household size	.030	.030	.952	1	.329	1.030	.971	1.093
	Farm size	.022	.055	.170	1	.680	1.023	.919	1.138
	Off-farm employment status(1)	-.780	.300	6.742	1	.009	.458	.254	.826
	Group membership(1)	.276	.324	.728	1	.394	1.318	.699	2.488
	Socio-psychological drivers								
	INT	-.557	.335	2.769	1	.096	.573	.297	1.104
	ATT	-.174	.399	.190	1	.663	.840	.384	1.837
	PEFF	.303	.242	1.571	1	.210	1.354	.843	2.174
	SCAPT	.034	.114	.089	1	.765	1.035	.827	1.295
	Constant	.262	1.938	.018	1	.892	1.300		
a. Variable(s) entered on step 1: Age, Gender, Education level, Household size, Farm size, Off-farm employment status, Group membership, INT, ATT, PEFF, SCAPT.									

6.3 Tank

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	109.792	19	<.001
	Block	109.792	19	<.001
	Model	109.792	19	<.001

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	292.065 ^a	.310	.417

a. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	15.474	8	.051

Classification Table^a

Observed			Predicted		
			Tank		Percentage Correct
			No	Yes	
Step 1	Tank	No	80	43	65.0
		Yes	24	149	86.1
	Overall Percentage				77.4
a. The cut value is .500					

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B)	
								Lower	Upper
Step 1 ^a	Socio-economic drivers								
	Age			7.147	4	.128			
	Age(1)	-.285	1.647	.030	1	.862	.752	.030	18.950
	Age(2)	.194	1.524	.016	1	.899	1.214	.061	24.083
	Age(3)	.871	1.531	.324	1	.569	2.389	.119	48.011
	Age(4)	-.112	1.566	.005	1	.943	.894	.042	19.265
	Gender(1)	.524	.297	3.111	1	.078	1.688	.943	3.022
	Education level			16.205	6	.013			
	Education level(1)	2.109	.703	8.991	1	.003	8.241	2.076	32.715
	Education level(2)	2.289	.724	9.992	1	.002	9.866	2.386	40.790
	Education level(3)	2.131	.706	9.103	1	.003	8.424	2.110	33.632
	Education level(4)	3.246	.901	12.981	1	≤.001	25.683	4.393	150.143
	Education level(5)	1.567	.845	3.440	1	.064	4.792	.915	25.096
	Education level(6)	.710	1.374	.267	1	.606	2.033	.138	30.050
	Household size	.073	.036	4.183	1	.041	1.075	1.003	1.153

	Farm size	.287	.067	18.106	1	<.001	1.332	1.167	1.520
	Off-farm employment status(1)	.204	.325	.394	1	.530	1.226	.649	2.318
	Group membership(1)	.627	.363	2.983	1	.084	1.872	.919	3.813
	Socio-psychological drivers								
	INT	-.947	.373	6.451	1	.011	.388	.187	.806
	ATT	.434	.479	.820	1	.365	1.543	.603	3.947
	PEFF	.467	.279	2.800	1	.094	1.595	.923	2.755
	SCAPT	.209	.130	2.605	1	.107	1.233	.956	1.589
	Constant	-4.865	2.084	5.447	1	.020	.008		
a. Variable(s) entered on step 1: Age, Gender, Education level, Household size, Farm size, Off-farm employment status, Group membership, INT, ATT, PEFF, SCAPT.									

6.4 Cistern

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	26.108	19	.127
	Block	26.108	19	.127
	Model	26.108	19	.127

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	40.147 ^a	.084	.421
a. Estimation terminated at iteration number 20 because maximum iterations has been reached. Final solution cannot be found.			

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	.797	8	.999

Classification Table^a

Observed	Predicted	
	Cistern	

			No	Yes	Percentage Correct
Step 1	Cistern	No	288	1	99.7
		Yes	7	0	.0
	Overall Percentage				97.3
a. The cut value is .500					

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B)	
								Lower	Upper
Step 1 ^a	Socio-economic drivers								
	Age			3.457	4	.484			
	Age(1)	16.143	22010.428	.000	1	.999	10250676.766	.000	.
	Age(2)	14.159	22010.428	.000	1	.999	1410229.311	.000	.
	Age(3)	12.086	22010.428	.000	1	1.000	177403.695	.000	.
	Age(4)	-4.521	22358.081	.000	1	1.000	.011	.000	.
	Gender(1)	.901	1.034	.761	1	.383	2.463	.325	18.677
	Education level			.995	6	.986			
	Education level(1)	-3.027	7450.378	.000	1	1.000	.048	.000	.
	Education level(2)	14.627	6375.887	.000	1	.998	2252053.374	.000	.
	Education level(3)	13.781	6375.887	.000	1	.998	966100.282	.000	.
	Education level(4)	-1.732	10703.365	.000	1	1.000	.177	.000	.
	Education level(5)	15.073	6375.887	.000	1	.998	3516435.596	.000	.
	Education level(6)	34.366	7488.443	.000	1	.996	841117673701947.600	.000	.
	Household size	.211	.126	2.787	1	.095	1.234	.964	1.580
	Farm size	-.151	.209	.519	1	.471	.860	.571	1.296
	Off-farm employment status(1)	3.673	1.975	3.460	1	.063	39.375	.821	1888.067

	Group membership(1)	.159	1.406	.013	1	.910	1.173	.075	18.433
	Socio-psychological drivers								
	INT	-2.418	1.171	4.263	1	.039	.089	.009	.885
	ATT	5.807	3.517	2.726	1	.099	332.571	.337	327877.240
	PEFF	-1.615	.967	2.789	1	.095	.199	.030	1.324
	SCAPT	-.543	.422	1.658	1	.198	.581	.254	1.328
	Constant	-43.242	22915.298	.000	1	.998	.000		
a. Variable(s) entered on step 1: Age, Gender, Education level, Household size, Farm size, Off-farm employment status, Group membership, INT, ATT, PEFF, SCAPT.									

6.5 Gutter

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	44.651	19	<,001
	Block	44.651	19	<,001
	Model	44.651	19	<,001

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	320.631 ^a	.140	.198
a. Estimation terminated at iteration number 20 because maximum iterations has been reached. Final solution cannot be found.			

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	4.384	8	.821

Classification Table^a

Observed			Predicted		
			Gutter		Percentage
			No	Yes	Correct
Step 1	Gutter	No	191	14	93.2

	Yes	66	25	27.5
	Overall Percentage			73.0
a. The cut value is .500				

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B)	
								Lower	Upper
Step 1 ^a	Socio-economic drivers								
	Age			3.616	4	.460			
	Age(1)	19.377	22413.678	.000	1	.999	260094315.456	.000	.
	Age(2)	20.447	22413.678	.000	1	.999	758830472.659	.000	.
	Age(3)	20.185	22413.678	.000	1	.999	583627458.997	.000	.
	Age(4)	19.655	22413.678	.000	1	.999	343634059.468	.000	.
	Gender(1)	.606	.281	4.668	1	.031	1.834	1.058	3.179
	Education level			3.397	6	.758			
	Education level(1)	.734	.741	.982	1	.322	2.083	.488	8.892
	Education level(2)	.895	.778	1.324	1	.250	2.448	.533	11.254
	Education level(3)	1.214	.756	2.580	1	.108	3.367	.765	14.807
	Education level(4)	1.222	.902	1.835	1	.176	3.393	.579	19.876
	Education level(5)	1.240	.877	2.000	1	.157	3.455	.620	19.264
	Education level(6)	.941	1.382	.464	1	.496	2.562	.171	38.446
	Household size	.017	.031	.301	1	.583	1.017	.957	1.082
	Farm size	.185	.056	10.798	1	.001	1.203	1.077	1.343
	Off-farm employment status(1)	-.328	.302	1.182	1	.277	.720	.399	1.301
	Group membership(1)	-.064	.339	.036	1	.849	.938	.483	1.822
	Socio-psychological drivers								
	INT	-.653	.357	3.351	1	.067	.520	.258	1.047
	ATT	.563	.506	1.235	1	.267	1.755	.651	4.736
	PEFF	-.033	.277	.014	1	.906	.968	.563	1.665
	SCAPT	-.188	.119	2.481	1	.115	.829	.656	1.047

	Constant	- 21.620	22413.6 78	.000	1	.999	.000		
a. Variable(s) entered on step 1: Age, Gender, Education level, Household size, Farm size, Off-farm employment status, Group membership, INT, ATT, PEFF, SCAPT.									