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Adoption of Bundled Drought-Tolerant Maize Varieties and Index Insurance in Mozambique: A Case Study of Smallholder Farmers in Manica Province.

By

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Declaration

I, Asiimwe Mary Gorrette, hereby declare that this dissertation titled “Adoption of Bundled Drought-Tolerant Maize Varieties and Index Insurance in Mozambique: A Case Study of Smallholder Farmers in Manica Province” is my own work and has never been previously submitted for the purpose of obtaining any degree in this or any other higher education institution for the honor of any academic qualification. All sources referred to in the preparation of this work have been duly acknowledged using citations and references. This dissertation is presented in partial fulfillment of the requirements for obtaining the degree of Master of Science in Agricultural Economics from Eduardo Mondlane University.

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ABSTRACT

Drought remains a severe threat to global maize production, especially in Sub-Saharan Africa, where production is mainly rain-fed. In Mozambique, where over 90% of rural households cultivate maize under rain-fed systems, repeated drought is a threat to production. In response, bundled drought-tolerant maize (DTM) varieties and index insurance have been promoted to reduce vulnerability and encourage sustainable production. However, adoption rates remain low. This study analysed the determinants of uptake and the yield impacts of bundled DTM and index insurance in Manica Province. The study used a Randomized Control Trial, where a set of farmers in the treatment group received subsidies to encourage adoption of the bundled technologies, whereas those in the control group did not. The analysis employed descriptive statistics, a binary logistic regression, and Propensity Score Matching (PSM). The results showed that 25.7% of the respondents adopted bundled DTM and index insurance, and factors like the number of drought years experienced, awareness of DTM, fertilizer use, having savings, and voucher-based subsidy, either alone or when combined with education sessions, positively influenced adoption. Furthermore, PSM results indicate that adopters of the bundled technology had 2.43 kg/ha higher maize yields compared to non-adopters, although this effect was insignificant. These findings suggest that access to financial resources and information is crucial for enhancing adoption. Therefore, to increase adoption, policymakers should focus on strengthening farmer awareness campaigns, particularly those emphasizing the attributes of combining DTM with index insurance, supporting savings and credit structures, and expanding institutional support through targeted subsidy schemes.

Keywords: Bundled drought-tolerant maize; Index insurance; Adoption; Yield impact; Mozambique.

List of acronyms

AGG - Accelerating Genetic Gains in Maize and Wheat

AIC - Akaike Information Criterion

ATT - Average Treatment effect on the Treated

BIC - Bayesian Information Criterion

CEPPAG- Research Center for Agricultural Policies and Programs

CIMMYT- International Maize and Wheat Improvement Centre

DTM - Drought Tolerant Maize

DTMA - Drought Tolerant Maize for Africa

EUT - Expected Utility Theory

FAO - United Nations Food and Agriculture Organization

GDP – Gross Domestic Product

Ha - Hectare

IITA - International Institute of Tropical Agriculture

ITT - Intent-To-Treat

IV - Instrumental Variable

Kg – Kilogram

MAE - Ministerio de Administracao Estatal

MRR - Market, Risk and Resilience

NARS - National Agricultural Research Systems

NCBA CLUSA - National Cooperative Business Association CLUSA International

NGO - Non-Governmental Organization

NN - Nearest Neighbor

PSM - Propensity Score Matching

RCT - Randomized Controlled Trial

SDG - United Nations Sustainable Development Goal

SSA - Sub-Saharan Africa

STMA - Stress Tolerant Maize for Africa

UNFPA- United Nations Population Fund

WFP- World Food Programme

CHAPTER 1: INTRODUCTION

1.1 Background

Over the past two decades, climate change, in particular drought stress, has been cited as a serious threat to global maize production and food security (Manuel et al., 2020; Mavume et al., 2021; Nguyen et al., 2023; Makuya et al., 2024). Drought, which manifests as a period of prolonged water stress, is sometimes associated with total crop failure, which compromises the food security and livelihoods of many families worldwide, especially in Sub-Saharan Africa (SSA) countries, where production is predominantly rain-fed (Nhantumbo et al., 2021).

Available data in line with the negative effects of drought on maize production show that every year, maize yield reduce by about 15% globally and between 10-25% in SSA (Fisher et al., 2015; Ayedun, 2018). However, in SSA countries that experience repeated droughts, such as Mozambique, where droughts happen every 3-4 years, the yield losses can be more than the reported averages (World Bank, 2019; World Bank, 2020). An example was in 2023/2024, where provinces such as Manica, Sofala, and Gaza experienced maize yield losses of about 36%, 34%, and 25%, respectively, as a result of the El Niño-induced drought (FAO, 2024; Toreti et al., 2025). Even worse, projections indicate that by 2065, these yield losses could increase to about 45% in Mozambique's drought-prone areas (World Bank, 2020; Chisanga et al., 2022). Such projections are worrying and signal considerable challenges for the country's food sector, drawing the attention of government and development partners to promote the uptake of climate-resilient practices as a way of enhancing smallholder farmers' resilience and safeguarding food security.

Over time, the government and development partners have invested in building the adaptive capacity of smallholder farmers to reduce vulnerability to drought. As such, several climate adaptation strategies have been introduced, notable ones being drought-tolerant maize (DTM) varieties and index insurance (Fisher et al., 2015; CIMMYT, 2022). DTM varieties were introduced to the country by the Drought Tolerant Maize for Africa (DTMA) project in 2007 to ensure yield stability during droughts (da luz Quinhentos et al., 2014). As Simtowe et al. (2019) noted, DTM varieties can maintain up to 30% of their yield potential when faced with moderate mid-season droughts. While this is appealing, the protection offered by DTM varieties is only available during moderate droughts, and in case of early-season or severe droughts, the yield benefits are eroded, and farmers remain exposed to losses (Awondo et al., 2020; Boucher et al., 2024).

In contrast, index insurance that was introduced in 2012 is able to protect farmer livelihoods during droughts by providing financial compensation against losses from all forms of drought. Nonetheless, the associated high premiums make it unaffordable for smallholder farmers, discouraging widespread adoption (World Bank, 2011; Carter et al., 2014; Tadesse et al., 2015; Awondo et al., 2020). Drawing on these stand-alone limitations, a combination of these two technologies, referred to as bundled in this study, has been widely promoted to address the limitations and offer a relatively affordable approach for managing the drought risk (Feed the Future, 2021; Boucher et al., 2024).

Bundled DTM and index insurance offers a complementary benefit where DTM provides biological protection during mild and moderate droughts, and index insurance offers financial protection in the form of seed replacements when the droughts become severe (Lybbert & Carter, 2015; Awondo et al., 2020; Boucher et al., 2024). Because index insurance covers losses under extreme droughts, the risk associated with planting DTM varieties under rain-fed systems is reduced, and in turn, the biological protection offered by DTM allows insurers to offer lower premiums due to reduced payout risk, which encourages investment (Feed the Future, 2021; Boucher et al., 2024).

Boucher et al. (2024) provide evidence of the bundle's ability to encourage investment and enhance farmer resilience. The authors report that adopters of bundled DTM and index insurance in Mozambique and Tanzania who experienced drought shocks subsequently increased their agricultural investment at both the extensive and intensive margins, unlike the non-adopters. Similarly, Bulte et al. (2020) note that bundling certified seeds and index insurance motivated farmers to increase their total investments and cultivated land. Furthermore, Lybbert & Carter (2015) also claim that bundling DTM with index insurance results in stable gross farmer income levels under severe drought conditions. The authors note that when using bundled DTM and index insurance, the certainty equivalent is 7.2% higher than that of the traditional technology. As noted above, bundled DTM and index insurance has the capacity to create an economic buffer by lowering the risk averseness of adopters and encouraging investment.

1.2 Problem statement and justification

In Mozambique, maize is one of the key food security crops and is cultivated by about 80% of rural households (Zant, 2024), yet it suffers severe production losses due to recurrent droughts. In many cases, these droughts lead to complete crop failure, which leaves farmers without seed for replanting, thus jeopardizing household food security and incomes. To reduce farmers' vulnerability to drought shocks, climate adaptation practices such as bundled DTM and index insurance have been consistently promoted to safeguard farmers' livelihoods during both moderate and extreme droughts.

Bundled DTM and index insurance provides protection and an observable benefit in severe drought years, even when DTM varieties fail, enabling farmers not only to recover but also to exceed their pre-shock production levels. Studies by Feed the Future in 2021 indicate that Mozambican farmers were receptive to the bundle and over 50 metric tons of insured seeds were sold (Feed the Future, 2021). However, because the benefits of this innovation are not apparent every year, farmers, especially those who are unfamiliar with insurance, may underestimate its value and choose not to adopt or may dis-adopt if they do not experience an immediate return on their investment. This inconsistency in the bundle’s outcomes complicates efforts to promote its sustained use among the vulnerable households. As such, promoting widespread uptake requires an understanding of the drivers of smallholder farmers' decisions to adopt this bundled innovation.

Whereas previous studies, including Hill et al. (2013), Fisher et al. (2015), Tadesse et al. (2015), Simtowe et al. (2019), Machangu-Motcho (2023), and Jiba et al. (2024) have explored farmer adoption decisions with respect to DTM and index insurance, most have tended to focus on these technologies when used individually. As a result, there is scanty literature about the determinants of adoption of the bundled innovation. This overlooks the unique attributes associated with the bundle, which can hinder efforts to promote its adoption in vulnerable communities. Furthermore, Lybbert & Carter (2015) and Awondo et al. (2020) who emphasize the uncertain nature of benefits and the high cost of insured DTM seeds compared to conventional seeds, as some of the barriers to adoption are based on the innovation's design. To this end, the socioeconomic, behavioural, and institutional factors that shape technology adoption in developing countries remain largely underexplored. Moreover, previous studies such as Lybbert & Carter (2015), Awondo et al. (2020), and Boucher et al. (2024) mainly emphasize the bundle’s potential to safeguard food security, reduce vulnerability to droughts, and enhance smallholder farmers' resilience, but the extent to which it impacts point-in-time yields is not well-documented. Thus, based on this background, this study sought to examine the determinants of adoption of bundled DTM and index insurance in Manica Province, a key maize-growing region frequently affected by drought. The study further investigates the potential of this bundled technology in enhancing yields for smallholder farmers.

Understanding the determinants of adoption of bundled DTM and index insurance and its impact on maize yields is relevant in the following ways: First, it provides valuable insights needed by both the public and private sectors to develop policies for investing in and scaling up resilience-enhancing agricultural technologies among vulnerable communities in Mozambique. Second, this study adds valuable insights to the ongoing global discussions on the adoption of agricultural strategies that reduce farmers' vulnerability to the adverse effects of drought. Finally, the findings from this study are crucial for reducing farmers' vulnerability to droughts and supporting the safety of food security and household incomes, thereby helping to meet the Sustainable Development Goals (SDGs) 1(No Poverty), 2(Zero Hunger), and 13 (Climate Action) by 2030.

1.3 Objectives

1.3.1 General Objective

To evaluate the determinants and impact of adoption of bundled Drought-Tolerant Maize Varieties and Index Insurance among smallholder farmers in Manica Province.

1.3.2 Specific Objectives

1. To characterize the adopters and non-adopters of bundled Drought-Tolerant Maize varieties and Index insurance.
2. To identify the factors influencing the decision of smallholder farmers to adopt bundled Drought-Tolerant Maize and Index insurance.
3. To estimate the impact of adopting bundled Drought-Tolerant Maize and Index insurance on maize yields among smallholder farmers.

CHAPTER 2: LITERATURE REVIEW

This chapter encompasses an analysis of existing studies related to this study. It includes a review of climate risks in Mozambique and the impact of drought on maize. It also provides an understanding of the important concepts such as drought-tolerant maize, index insurance, and bundled DTM and index insurance. Furthermore, the chapter presents an overview of the determinants of adoption of climate-resilient agricultural technologies and ends with a review of the impacts of adopting bundled agricultural innovations on crop productivity.

2.1 Climate risks in Mozambique

Mozambique is highly susceptible to climate change and climate variability and is prone to several severe weather events like droughts, floods, and cyclones (World Bank, 2019; Manuel et al., 2020; Hove et al., 2025). According to Brida et al. (2013) and Hove et al. (2025), the country experiences one climate disaster every year and ranks among the 10 most vulnerable countries to climate change. This susceptibility to climate disasters is partly because of its extensive coastline and location at the downstream end of 9 major rivers (Manuel et al., 2020; World Bank, 2023). Moreover, factors such as the high poverty rate, heavy reliance on rain-dependent agriculture, and weak socio-economic infrastructure further aggravate the country's vulnerability (Hove et al., 2025). As a result, climate adaptation measures are crucial to safeguard the livelihoods of vulnerable households.

The rising temperatures, declining precipitation rates, and rising sea levels also add to the vulnerability of the country to climate disasters like droughts and floods. On average, there has been an increase in temperatures by 0.6ºC and a reduction in mean annual rainfall by about 2.5mm every decade since 1960 (Michelle et al., 2018; Clim-HEALTH Africa, 2020). Similarly, based on World Bank estimates, temperatures in Mozambique are likely to continue increasing by 0.31ºC per decade (World Bank, 2025). Furthermore, World Bank also notes expected extreme precipitation of about 1.77 times more frequently between 2035 and 2064. With over 70% of Mozambicans dependent on rain-fed agriculture, these statistics suggest potential damaging effects (Detelinova et al., 2023). The reduction in precipitation rates and rising temperatures will likely result in droughts whereas the extreme precipitation will cause floods resulting into destructions of agricultural and residential land (Hove et al., 2025).

Additionally, Mozambique has a history of exposure to extreme climate disasters. For instance, in the last 35 years, the country has encountered about 75 climatic disasters, consisting 13 droughts, 25 floods, 14 cyclones, and 23 epidemics (USAID, 2023; Graham, 2023). Among these, floods, droughts, and cyclones are listed as the most frequent disasters, and on average, Mozambique faces a tropical cyclone or a flood every 2 years and a drought every 3-4 years (Detelinova et al., 2023). Such events hamper the country's economic growth and are partly responsible for the persistent poverty levels (World Bank, 2023). For example, in 2023/2024, an El Niño-induced drought led to crop production losses corresponding to about 7% of the agriculture sector's GDP and left over 2.8 million people on the verge of food insecurity (FAO, 2024). Prior to this, in 2019, the country had been hit by two strong tropical cyclones, that is Idai and Kenneth (Nhundu et al., 2021). Cyclone Idai displaced over 3 million people, destroyed over 800,000 hectares of crops, and caused economic damages valued at about USD 3 billion. An evaluation made by the World Bank indicated that the damages caused by Cyclone Idai were about USD 800 million, out of which 260 million were incurred by the agriculture sector (World Bank, 2019). On the other hand, Cyclone Kenneth caused disruptions worth USD 100 million. Because these disasters destroy the sources of livelihood for many households, a large percentage of Mozambicans remain trapped in cycles of poverty and food insecurity in the aftermath of such events (World Bank, 2019; World Bank, 2023). As more frequent droughts and floods are anticipated to occur, Mozambique's GDP is expected to reduce by 1.1% annually and between 4 and 14% by 2050 (Arndt & Thurlow, 2015; Irish Aid, 2017). Therefore, measures that enhance the resilience of households are crucial to sustain livelihoods and encourage economic growth.

2.2 Effects of drought on maize

Drought is one of the most pressing challenges to maize production as it compromises growth and yield gains. According to Nandgude et al. (2023), drought refers to an extended period of below-normal rainfall, which causes serious water shortages. When such periods occur, they alter the biochemical and physiological processes of a maize plant, leading to a decrease in photosynthesis, water, and nutrient uptake (Sah et al., 2020; Makuya et al., 2024). A decrease in such processes means slower plant growth and reduced kernel development, which eventually causes a reduction in yields (Kim et al., 2019). Such impacts are more pronounced if droughts occur at the vegetative, flowering, and kernel development stages. For instance, Sah et al. (2020) in their analysis of the effects of drought on maize found that water stress during the vegetative, flowering, and kernel development stages results in production losses of about 25, 50, and 21%, respectively. Similarly, Menkir et al. (2024) posit that drought during the flowering and kernel development stages reduces maize yields by 21-90%. As noted above, it is evident that maize is very vulnerable to drought, which means that without the adoption of resilient practices, droughts are likely to cause significant yield losses.

The vulnerability of maize production to drought is mainly because of its growth requirements and the fact that it is largely grown under rainfed conditions (Simtowe et al., 2019; Lunduka et al., 2019). Statistics indicate that globally, over 80% of maize production is rainfed (Aakash et al., 2022) and in SSA countries such as Mozambique, more than 90% of maize production is dependent on rainfall (Nhantumbo et al., 2021). Furthermore, Amaral et al. (2020) expresses that maize requires about 500-800 mm of rainfall and between 18-27°C throughout the day and 14-15°C in the night all through its cropping season. In Manica Province, where this study was conducted, the average rainfall is around 600mm, and daytime and nighttime temperatures are about 27°C and 17°C respectively, which is within the range of the growth requirements of maize (World Bank, 2021). However, the anticipated rise in temperatures and reduction in annual rainfall of about 0.6°C and 2.5mm, respectively, point to possible challenges for maize production since these changes are likely to push the environmental conditions beyond the ideal thresholds for maize (Clim-HEALTH Africa, 2020; World Bank, 2025).

Several studies have demonstrated the impact of drought on maize yields. For example, Ayedun (2018) and Deribe (2025) argue that globally, 15% of maize yields are lost annually due to droughts. Kim et al. (2019) also argue that for over 27 years, droughts have on average reduced maize yields by about 7%. In SSA, these yield impacts are higher than the global averages, and they range between 10-25% (Fisher et al., 2015). However, countries with recurrent severe droughts often experience even higher losses. For example, in Mozambique, the El Niño-induced drought in 2023/2024 caused yield losses of approximately 36%, 34%, and 25% in Manica, Sofala, and Gaza provinces, respectively (FAO, 2024; Toreti et al., 2025). The just mentioned figures clearly indicate the extent to which water stress undermines maize production, yet it is a key food security crop for millions across the globe. As such, measures intended to reduce farmer vulnerability to the adverse effects of droughts are of the utmost importance.

2.3 Drought-tolerant maize (DTM) as an Adaptation Strategy

Drought-tolerant maize (DTM) refers to a type of maize bred using conventional breeding methods to maintain yields under water-stress conditions (Kostandini et al., 2013; Lybbert & Carter, 2015). However, Simtowe et al. (2019) and Lunduka et al. (2019) offer a more specific definition. They define DTM as maize capable of producing up to 30% of its yield capacity even when exposed to 6 weeks of water stress during its critical stages of flowering and grain-filling. Breeding of DTM varieties began way back in 1997 under the African Maize Stress (AMS) project led by the International Maize and Wheat Improvement Center (CIMMYT) and the International Institute of Tropical Agriculture (IITA) (Menkir et al., 2024). During the 5 years of AMS's implementation, several drought-tolerant varieties were released. However, because the focus was on drought resilience, additional research was needed to breed varieties that could not only withstand water stress but could also adapt to the different agricultural regions and meet the preferences of smallholder farmers. Accordingly, over time, CIMMYT and IITA have implemented several projects, such as the DTMA, Stress Tolerant Maize for Africa (STMA), and Accelerating Genetic Gains in Maize and Wheat (AGG) across SSA to promote the development and diffusion of drought-resilient maize cultivars (Menkir et al., 2024). Through these projects, over 160 DTM varieties were developed and promoted across 13 SSA countries (da Luz Quinhentos et al., 2014; Fisher et al., 2015), and currently, 16 varieties have been introduced to Mozambique (Ospina et al., 2025).

In most SSA countries, DTM varieties were introduced in 2007 under the DTMA project (CIMMYT, 2022) to reduce farmer vulnerability to droughts. Evidence from several on-farm trials indicated these varieties could outperform the conventional varieties. For example, Fisher et al. (2015) claimed that under controlled and random droughts, DTM varieties outperformed commercial varieties by 83-137% and 26-47%, respectively. Likewise, CIMMYT (2013), stated that DTM varieties could yield about 20-30% higher yields compared to commercial seeds when faced with moderate droughts. However, Paul (2021) challenged these findings, arguing that much of this evidence was based on controlled trials and the exact performance of DTM varieties when exposed to field conditions was still underexplored. Therefore, in an on-farm yield trial, he found that DTM varieties could yield up to 7% higher than commercial varieties in normal years and up to 15% higher when exposed to moderate drought. However, he cautions that the adoption of DTM is more beneficial for high-performing farms, and vulnerable farmers may yield little or no benefit from uptake. Nonetheless, his findings imply that even if the controlled trials overestimate DTM's yield benefit, it still has the potential of maintaining yields, especially during moderate droughts, as compared to conventional varieties. Furthermore, beyond drought resilience, the DTM varieties also have other desirable attributes, such as disease resistance and efficient use of nitrogen (Fisher et al., 2015), which makes them particularly attractive not only because of their ability to mitigate against droughts but also their potential to increase farmers' yields.

Several scholars have documented DTM's ability to improve yields, decrease poverty incidence, and reduce farmer vulnerability to drought-related failures (Fisher et al., 2015; Oyetunde-Usman & Shee, 2023). Awotide et al. (2016) show that adoption of DTM varieties reduced food insecurity and increased maize yields and welfare by -7.0%, 602 kg/ha, and N3764.27, respectively. Consistent with this finding, Lunduka et al. (2019) in their study in Zimbabwe claim that adopters of DTM varieties attained higher yields of about 617kg/ha, an extra income of US$240/ha, and greater food security of about 9 months compared to non-adopters. However, it is worth emphasizing that these DTM benefits are realized particularly during mild to moderate droughts. As expressed by Awondo et al. (2020), Paul (2021), and Boucher et al. (2024), the protection offered by DTM varieties is more pronounced during the pollination stages, and the occurrence of early-season or severe droughts reduces their benefits and leaves farmers exposed to losses.

The dependence of DTM's benefits on the stage of droughts creates concern about its potential to protect farmers against droughts, especially at a time when frequent droughts are anticipated. Consistent with this notion, Lybbert & Carter (2015) in their study about the performance of DTM in Ecuador claim that its yield advantage decreases with an increase in drought severity, and under extreme droughts, its benefits are indifferent from those of traditional varieties. Similarly, Boucher et al. (2024) in their study carried out in Mozambique and Tanzania state that planting of DTM seeds did not protect farmers from extreme drought. This could imply that DTM varieties alone are not enough to guarantee farmer resilience to droughts, so complementing them with innovations such as insurance schemes could enhance their effectiveness.

2.4 Index Insurance as a Risk Management Tool

Index insurance is an innovative risk management tool that has been increasingly advocated for to protect farmers against production risks. Hill et al. (2013) and Zhu et al. (2025), define index insurance as an innovative approach to insurance provision that makes payments based on a predefined index. As stated by World Bank (2011) and Tadesse et al. (2015), this insurance is divided into area-yield and weather-based index insurance. Under the area-yield index insurance, payment is made if the realized yield for the area, for example, a district or county, falls below a predetermined insured yield (World Bank, 2011), where the insured yield is the predefined index calculated based on the historical area yield data. In contrast, weather-based index insurance, which is the focus of this review, provides payouts based on the manifestation of a certain weather parameter calculated over a prespecified time period at a particular meteorological station (World Bank, 2011; Muleke et al., 2025). Here, the insurance is structured to safeguard against either very high or very low weather parameters that can result in crop failures. For instance, the insurance can be designed to shield against extreme drought events, and in this way, farmers receive compensation if they experience too little rainfall that falls below the predefined index (World Bank, 2011; Haruna et al., 2017). Given that farmers are paid based on deviation from the set standard, index insurance removes the need for on-farm loss assessments, hence lowering administrative costs (Sibiko & Qaim, 2020). Furthermore, index insurance helps to overcome the challenges of traditional indemnity-based insurance, including moral hazard and adverse selection, which makes it especially attractive in developing countries where the institutional capacity for loss verification is expensive and underdeveloped (World Bank, 2011; Awondo et al., 2020).

A considerable amount of literature has been published on the attractive benefits of index insurance, especially its ability to boost farmer confidence to invest in productivity-enhancing agricultural inputs. For example, Muleke et al. (2025) found that users of weather-based insurance in Kenya reduced their use of traditional inputs and increased their use of chemical fertilizers and drought-tolerant seeds by 28.7 kg/acre and 2.6 kg/acre, respectively. Similar findings were reported by Castaing & Gazeaud (2025) who claim that farmers who received index-insurance cultivated 8% more land, used 9% more pesticides, 9% more fertilizers, and 16% more seeds. Likewise, Kramer et al. (2024) note that assignment to a weather index-based insurance treatment increased fertilizer demand in Kenya. Moreover, Haruna et al. (2017), using an endogenous treatment regression model, also found that adoption of weather-index insurance intensified fertilizer use in Northern Ghana. These findings reveal that the financial security provided by index insurance alters the risk-return trade-off, thus encouraging investment in agricultural technologies, which in turn results in higher productivity (Haruna et al., 2017; Machangu-Motcho, 2023). This implies that if index insurance is well-designed, it can be a pathway for improving farmer resilience to the adverse effects of extreme weather events as well as an incentive to intensify the use of high-quality inputs for enhanced productivity.

However, even with the attractive benefits of index insurance, most developing countries still struggle with low uptake rates. An example is in Mozambique, where, since 2012, only about 5% of smallholder farmers have adopted the index insurance (Tafese, 2016; Munyeche, 2024). These low adoption rates have been attributed to various factors, and the main challenge widely cited is the basis risk (World Bank, 2011; Tadesse et al., 2015; Sibiko & Qaim, 2020). Basis risk refers to the gap between the index trigger and the actual loss experienced by the farmer. This occurs when the index fails to match a farmer's actual losses. This way, it creates skepticism among farmers about the reliability of the technology in acting as a safety net during hazards such as droughts. Another major concern is the determination of the index. As the index is determined based on weather time series data, many developing countries face difficulties calculating the index, particularly due to missing historical data and the low density of weather stations. For example, Mozambique has only about 113 stations in 69 districts, implying that 73 districts lack weather stations (Tafese, 2016). This impedes the calculation of the index, thus hindering the implementation of index insurance.

Nonetheless, index insurance remains one of the technologies widely promoted that offers promise for climate risk mitigation. However, even with this affirmation, the true potential of index insurance is more pronounced when bundled with other agricultural inputs (Muleke et al., 2025). Therefore, integration of this innovation with complementary inputs like seeds, credit, and fertilizers is important to ensure its sustained adoption.

2.5 Bundled DTM and Index Insurance innovation

Bundled DTM and index insurance can be defined as a complementary innovation that combines the biological protection, a characteristic of DTM seeds, with the financial risk management offered by index insurance (Lybbert & Carter, 2015; Awondo et al., 2020). This bundle has been widely recognized as a solution to the individual limitations of DTM and index insurance. When bundled, DTM protects yields during moderate mid-season droughts, whereas index insurance expands the protection offered by the seed during early season and extreme droughts (Lybbert & Carter, 2015; Awondo et al., 2020; Boucher et al., 2024). In such a case, DTM stabilizes yields during moderate mid-season droughts, whereas index insurance offers payouts in the form of seed replacements only during extreme events that surpass the protection provided by DTM. The fact that the payout risk is reduced to only extreme events enables insurance suppliers to offer products at lower premiums, hence reducing the overall cost of index insurance (Lybbert & Carter, 2015; Awondo et al., 2020). This means that when used together, the result is a relatively affordable risk management solution.

Bundling DTM and index insurance has raised the expectations of many public and private sectors aiming to promote resilience-enhancing technologies. Scholars, such as Lybbert & Carter (2015), Bulte et al. (2020) and Boucher et al. (2024) document the potential of the bundle in boosting resilience and productivity among smallholder farmers when faced with drought. Boucher et al. (2024) argue that adopters of bundled DTM and index insurance in Mozambique and Tanzania who experienced drought shocks subsequently increased their agricultural investment at both the extensive and intensive margins. Additionally, the authors report that bundling index insurance with DTM varieties increased yields by 60% in the year after a severe drought shock, more than enough to compensate for the yield losses experienced during the drought. They claim that during the drought shock year, bundled DTM and index insurance had no significant effect on maize yields, however, after the shock, the lagged yield benefit was significant. This reveals that the benefits of bundled DTM and index insurance on maize yields may not be evident during severe drought shocks but manifest after the shock when farmers recover from their losses and return to production in subsequent seasons.

Bulte et al. (2020) also note that bundling certified seeds and index insurance motivated farmers to increase their total investments and cultivated land. Furthermore, Lybbert & Carter (2015) also claim that bundling DTM with index insurance results in stable gross farmer income levels under severe drought conditions. The authors note that when using bundled DTM and index insurance, the certainty equivalent is 7.2% higher than that of the traditional technology. This suggests that the bundle not only offers risk mitigation benefits but also has a crowding-in effect on investment. Drawing on the above-mentioned benefits, it is crucial to understand that this bundled product works in a way that DTM varieties protect yield losses during moderate mid-season droughts, thus mitigating the decline in long-term farm productivity (Boucher et al., 2024). On the other hand, index insurance compensates farmers' inputs, helping them recover from losses, which stabilizes productivity in the long run. It is also worth noting that these advantages are tied to the severity of droughts, underscoring the context-specific nature of the bundle (Awondo et al., 2020).

Experience from the promotion of the bundle across various SSA countries shows that farmers are responding positively to its uptake (Lybbert & Carter, 2015; Bulte et al., 2020; Boucher et al., 2024). For example, a report by Feed the Future (2021) indicated that smallholder farmers in Mozambique were receptive to the bundle, and in 2021, about 50 metric tons of insured seeds were sold across the country. This farmer receptiveness, together with the associated benefits of bundled DTM and index insurance, suggests that if properly implemented, bundled DTM and index insurance can be a pathway for ensuring long term sustainable production and enhancing the resilience of small-scale producers in vulnerable communities.

2.6 Determinants of Adoption of Climate-Resilient Agricultural Technologies.

Lindner (1987) defines the adoption of a technology as the process by which a producer chooses to take up a new production approach. Similarly, Souleymane et al. (2017) state that adoption relates to the decision of a producer to use a new technology, considering its characteristics and the expected benefits. Drawing on these definitions, this study defines adoption as the process through which a farmer chooses to plant insured DTM varieties. For a farmer to reach a decision to adopt a new technology, many factors play a role. Across the literature, several factors are identified as determinants of the decision of farmers to adopt climate-resilient agricultural practices. These have been broadly categorized into socio-economic, institutional and policy, risk and uncertainty, and technical and environmental factors.

Socio-economic factors widely cited by different authors include education, age, income, gender, and household size. However, across the different studies, there is contradictory evidence presented by different authors about the effect of these factors on adoption. For example, Chisadza et al. (2025) found that age was negatively associated with the adoption of drought-resistant varieties in Zimbabwe. They pointed out that aged farmers are unwilling to take risks, and as they advance in years, their interest in making long-term investments decreases. Similarly, Aheeyar et al. (2023) and Jiba et al. (2024) also found that age significantly affected index insurance adoption. However, Udimal et al. (2017) show a positive association between age and adoption of improved rice varieties. They argue that old age is associated with greater experience and capital which increases the propensity to adopt new technologies. Thus, the effect of age on adoption differs depending on the technologies in question. Education has also been highlighted as a significant motivator for adoption, and various authors (Machangu-Motcho, 2023; Jiba et al., 2024) agree that educated farmers are better placed to process information about new agricultural technologies, which increases their chances of adoption. Moreover, Uaiene (2011), believes that educated farmers are in a better position to search, perceive, and interpret information regarding new agricultural technologies. Gender also influences adoption, and most studies analysing this variable in developing countries have shown that men dominate the adoption of climate-resilient technologies. Actually, Jenrola & Gaspart (2021) and Manuel et al. (2022) indicate that female farmers in Mozambique are 40% unlikely to use resilient practices compared to men. This gender gap is believed to stem from the social and cultural norms that restrict women from accessing resources such as land, information, and credit.

Institutional and policy factors thought to significantly predict technology adoption include credit access, input subsidies, seed accessibility, and access to agricultural extension and information services. Manuel et al. (2022) in their study about factors influencing the uptake of improved maize varieties in Mozambique discovered that farmers with access to agricultural extension and information services were 51% and 62% more likely to adopt. Similarly, Tafese (2016), Ayedun (2018), and Dadzie (2023) point out that obtaining information through extension services and other channels of communication stimulates the adoption of drought-resilient varieties and insurance schemes. Moreover, Udimal et al. (2017) emphasize that smallholder farmers have a tendency to only adopt technologies they are aware of or have previously heard about. An evidence of how a lack of exposure to information constrains adoption was documented by Simtowe et al. (2019) who state that in 2015, only about 14% of the smallholder farmers in Uganda adopted DTM varieties, compared to the expected 22%, had the varieties been exposed to the entire target population. However, for relatively new technologies, obtaining information and accessing extension services alone is not enough, the technology should also be readily available and accessible for farmers (Fisher et al., 2015; Simtowe et al., 2019). Therefore, as much as efforts to disseminate information are important, making the technology accessible to the users is equally relevant to ensure faster diffusion. Consistent with this, Awotide et al. (2016) point out that a combination of seed access and awareness increased adoption of DTM varieties by 90% in Nigeria. However, as expressed by Udimal et al. (2017), the disseminated information should be accurate and credible to avoid misconceptions, which could result in disadoption.

Credit access has also been noted to positively influence adoption. Udimal et al. (2017) and Amarnath et al. (2023), believe that credit helps to address liquidity constraints, providing farmers with the necessary finances to invest in climate-smart technologies. This belief is also supported by Ayedun (2018) and Manuel et al. (2022), who note that credit access increased the likelihood of adopting DTM and improved maize varieties, respectively. However, it is worth noting that access to credit is still a major challenge in many developing countries because of issues like a lack of collateral and high interest rates charged by lending institutions (Awotide et al., 2016; Khan et al., 2024).

Another factor that influences farmer decisions relates to the cost of the climate-resilient technology. For instance, Fisher et al. (2015) in their study about the determinants of adoption of DTM in Southern and Eastern Africa, noted that the high price of the seeds was one of the barriers to adoption. Similarly, Mitra et al. (2022) and Amarnath et al. (2023) state that the high cost of inputs constrains the adoption of bundled climate-smart solutions. Awondo et al. (2020) also claim that the high premiums associated with insurance products make them unaffordable by smallholder farmers, which in turn discourages adoption. In many SSA countries, governments have tried to relax the challenges related to the cost of the technology by offering subsidy programs in the form of vouchers to enhance diffusion. Carter et al. (2013) and Katengeza et al. (2019) agree that subsidy strategies are an incentive for agricultural technology adoption. Specifically, Carter et al. (2013) report that vouchers increased the uptake of fertilizers and improved seeds in rural Mozambique. Similarly, Katengeza et al. (2019) found that participation in input subsidy programmes increased the likelihood of adopting DTM varieties in Malawi. However, Shukla et al. (2022) in a two stage randomized trial conducted in India found that farmers who received seed subsidies were 20-30% unwilling to purchase seed in the long run. Likewise, Xu et al. (2009), note that fertilizer subsidies offered in Zambia led to crowding out of the private sector and a decline in fertilizer use in the long run. This reveals that the impact of subsidy programs is not universal.

In relation to the risk and uncertainty, Katengeza et al. (2019) and Chisadza et al. (2025) agree that previous drought experience increases the chances of adopting drought-tolerant varieties. Similarly, Tadesse et al. (2015), Sibiko & Qaim (2020), and Kramer et al. (2024) posit that farmers with a history of exposure to uncertainties express greater willingness to adopt risk management strategies like index insurance. Nonetheless, Dadzie (2023) reports that risk-averse farmers are more unlikely to use technologies that offer stochastic benefits unless subsidized or insured. Additionally, technical and environmental factors, for example, severe weather events including droughts and floods and technology adoption have been investigated. Fisher et al. (2015) in their analysis of the determinants of DTM adoption in Southern and Eastern Africa emphasized that the increasing climate variability in the nature of repeated droughts makes climate-resilient technologies like DTM relevant. In the same manner, Tafese (2016) reported that the occurrence of floods increased the willingness of Mozambican farmers to adopt weather-based index insurance. Likewise, Hou et al. (2023) point out that farmers' perception of drought severity increased their probability of adopting DTM by 8.1%.

The above reviewed studies indicate that the factors shaping the decisions of farmers to adopt climate-resilient agricultural practices differ depending on the type of technology and the geographical location. Also, in the review, no study specifically focused on the adoption of bundled DTM and index insurance.

2.7 Impact of adoption of bundled agricultural innovations on crop productivity

The literature on the effects of combining agricultural technologies on productivity presents a complex and multifaceted picture. However, most of the studies point to positive impacts. For example, Asante et al. (2024) discovered that the uptake of multiple climate-smart farming practices in Ghana significantly increased maize yields by 548 kg/acre. Likewise Dejene et al. (2025) state that adopters of bundled climate-smart solutions in Ethiopia had 45.10% higher maize yields as compared to non-adopters. In addition, Belissa & Marr (2018) note that combining index-based insurance with credit and inputs increased land productivity in Ethiopia. In Tanzania, Mugula et al. (2023) argue that bundling sustainable agricultural practices increased crop yields by about 28%. The authors further note that these gains could reach 45% in water stress regions. Also, Mitra et al. (2022) and Abetu et al. (2024) agree that combining inputs and services reduces variations in productivity and can increase agricultural yields by approximately 32%. In

Mozambique, Boucher et al. (2024) report that bundling DTM and index insurance increased yields of adopters by 60% in the year after a severe drought shock. Specifically, they state that adopters harvested 335 kg/ha more maize yields compared to non-adopters. Further, Thierfelder et al. (2016) argue that bundling DTM varieties with conservation agriculture practices led to about 89% increase in maize yields in the long run. Altogether, these reports reveal that using a combination of technologies can yield more returns in comparison to individual methods.

In contrast, scholars such as Michler et al. (2019), Boucher et al. (2024), Samoy-Pascual et al. (2025) agree that the positive impacts of combining agricultural technologies are not universal. Boucher et al. (2024) state that bundling DTM and index insurance had a negative but statistically insignificant effect on maize yields in the season of a drought shock in Tanzania and Mozambique. Samoy-Pascual et al. (2025) also found that adoption of bundled technologies had insignificant yield benefits among rice farmers in Philippines. Similarly, Michler et al. (2019) argue that adoption of climate-smart agricultural technologies in Zimbabwe showed no yield gains. This review draws attention to the fact that the benefits of combining agricultural technologies may differ considerably depending on the agricultural systems, type of technologies combined, and the management practices. This implies that the findings may depend on a specific context and should not be generalized.

From the above-mentioned review, it is worth noting that there has been relatively little evidence related to the impact of bundling DTM and index insurance on maize yields. Among the reviewed studies, only Boucher et al. (2024) focused on the impact of bundled DTM and index insurance, however the observed impact was reported considering how the bundle performed during subsequent seasons after a drought. Nonetheless, the growing interest and potential of bundling DTM varieties and index insurance underscores the need for further analysis of its impacts on maize yields.

CHAPTER 3: METHODOLOGY

3.1 Theoretical Framework

Smallholder farmers in Manica Province practice rain-fed maize production, which continually exposes them to the detrimental impacts of climate-related risks such as droughts. Because farmers are uncertain when the droughts will occur, adoption of bundled DTM and Index Insurance provides an option for mitigating against both production and financial losses. However, as Hiebert (1974) and Dercon & Christiaensen (2011) note, risk-averse farmers are hesitant to adopt a new technology when imperfect information and uncertainty exist. Therefore, risk-averse farmers in this study may delay adoption because of doubts about the payout mechanism of index insurance and the bundle's benefits, which are dependent on the occurrence and the severity of drought (Paul, 2018). Hence, to understand how smallholder farmers make adoption decisions when faced with risk and uncertainty, this study used the Expected Utility Theory (EUT).

EUT was initially suggested by Daniel Bernoulli in 1738 and then developed by John von Neumann and Oskar Morgenstern in 1947 (Starmer, 2000; Tinh et al*.,* 2021). According to Kushawaha & Sharma (2023) and Sepulveda et al. (2024), EUT assumes that individuals are rational when making decisions and choose options that maximize their expected utility, especially when faced with uncertainty. For this study, a farmer will decide to adopt bundled DTM and index insurance based on whether the expected benefits from adoption in case drought occurs outweigh those of non-adoption.

Let us assume U_{i1} and U_{i0} represent the net benefit U_i derived by household i from adopting bundled DTM and index insurance, and from non-adoption, respectively. A household is likely to adopt bundled DTM and index insurance if the net gain of uptake is greater than that of no uptake.

$$U_i = U_{i1} - U_{i0} > 0 \qquad 1$$

But U_i is a latent variable, and only the binary choice taking the value of 1 for the adoption of bundled DTM and index insurance, or 0 otherwise, is observed. This binary choice to adopt bundled DTM and index insurance can be expressed as:

$U_i = X\beta_{i1} + \varepsilon_{i1}$ (in case of adoption) and $U_i = X\beta_{i0} + \varepsilon_{i0}$ (in case of no adoption) where X = observable vector of characteristics of the household; β_i = vector of coefficients, and ε_{i1} and ε_{i0} are random error terms representing the unobservable elements that are specific to a household.

Adoption occurs if $U_{i1} > U_{i0}$. However, this choice depends on random elements of the utility function. Therefore, for the household $i,$ the likelihood of adoption can be presented as;

$$P_1 = P(U_{i1} > U_{i0}) \qquad 2$$

$$P_1 = P(U_{i1} = X\beta_{i1} + \varepsilon_{i1} > U_{i0} = X\beta_{i0} + \varepsilon_{i0}) \qquad 3$$

$$P_1 = P(\varepsilon_{i0} - \varepsilon_{i1} < X\beta_{i1} - X\beta_{i0}) \qquad 4$$

$$P_1 = P(\varepsilon_{i0} < X\beta) \qquad 5$$

$$P_1 = \phi(X\beta) \qquad 6$$

where ϕ= cumulative distribution function, β= model parameters to be computed, and X= set of covariates explaining the adoption of bundled DTM and index insurance.

In equation 6, this study assumes that ϕ follows a logistic cumulative distribution function, and in such a scenario, the chance of adoption can be predicted using the logit model. Based on this theoretical framework, this study assumes that the probability of adopting bundled DTM and index insurance is a function of socioeconomic, institutional, policy, and environmental factors. Consequently, the logit model provides an empirical means to estimate how each factor influences the likelihood of adoption by examining the marginal effects on the log-odds of adoption.

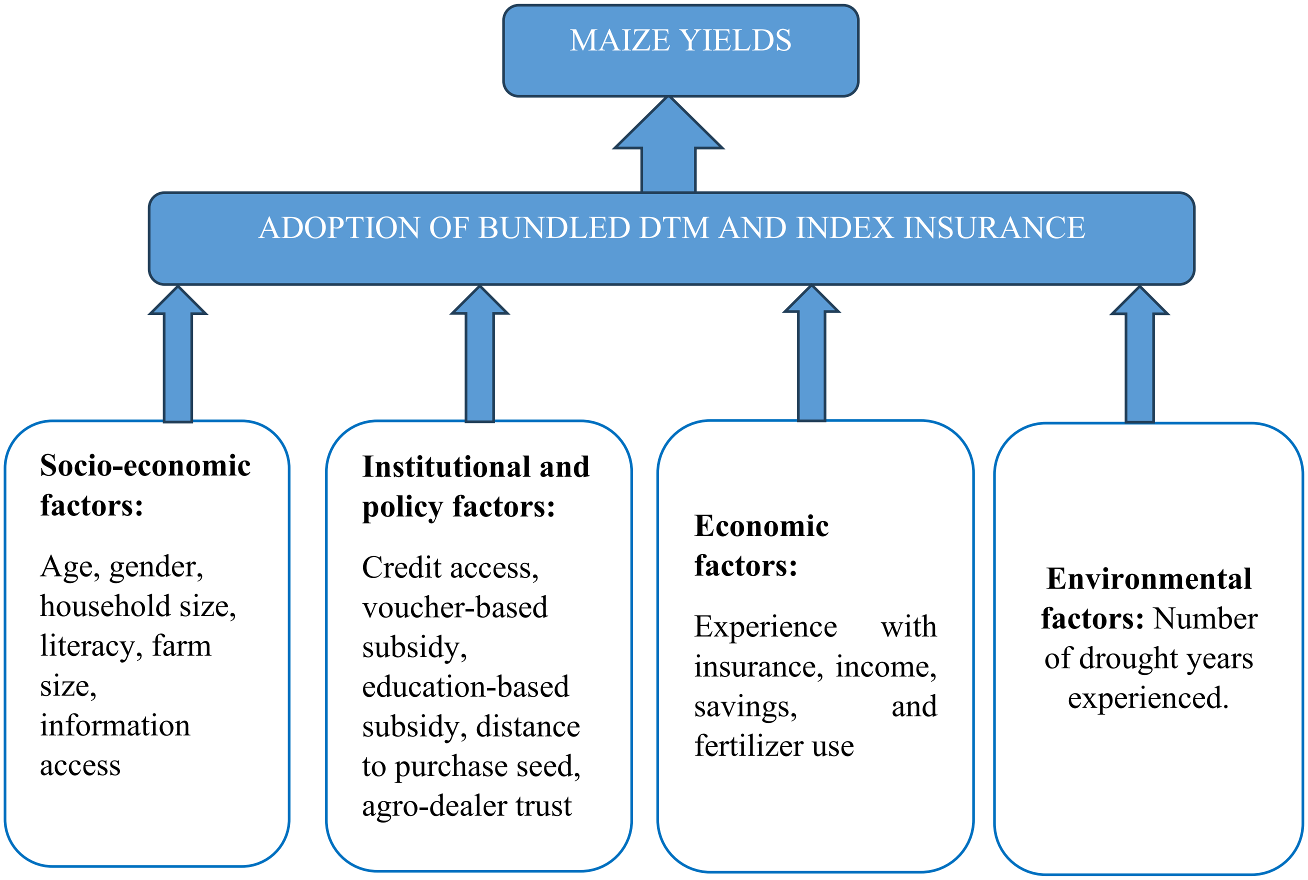
The logit model is represented in Equation 7;

$$\rho(Y_i = 1|X_i) = \frac{e^{\beta_0+\beta_1X_1+\beta_2X_2+\beta_3X_3+\cdots\beta_nX_n}}{1+e^{\beta_0+\beta_1X_1+\beta_2X_2+\beta_3X_3+\cdots\beta_nX_n}} \qquad 7$$

Where $\beta_0, \beta_1 \ldots\ldots \beta_n$ represents the set of parameters to be computed, and $X_1 \ldots\ldots X_n$ represents the set of covariates (socioeconomic, institutional, policy, and environmental factors) influencing the adoption of bundled DTM and index insurance.

3.2 Conceptual Framework

The conceptual framework illustrated in Figure 1 assumes that the dependent variable (adoption of bundled DTM and index insurance) is a function of several independent variables grouped as socio-economic, institutional and policy, economic, and environmental factors. Additionally, as mentioned in earlier studies by Lybbert & Carter (2015) and Boucher et al. (2024), when adopters of bundled DTM and index insurance experience its benefits, they increase their investments in maize production, which ultimately leads to increased maize yields, the outcome variable for this study. These interdependencies between the outcome variable (maize yields), the dependent variable, and the explanatory variables are visually presented in Figure 1 below.



Source: Author's conceptualization.

Figure 1: Conceptual framework

3.3 Characterization of the adopters and non-adopters of bundled DTM and Index Insurance

To characterize users and non-users of bundled DTM and index insurance, frequency analysis, including frequency distributions, graphs, percentages, and tables, were used. The variables were divided into two groups, namely, the dummy or categorical and the continuous variables. Characteristics based on the dummy or categorical variables were described using the cross-tabulation analysis using two-way frequency tables and column percentages, whereas the continuous variables were examined using the independent-samples t-test. This approach made it possible to compare the users and non-users basing on their: (i) sociodemographic attributes; (ii) policy and institutional characteristics; (iii) economic; and (iv) environmental characteristics. Comparing the two groups provided insights into the differences in farmer characteristics that can support or impede the uptake of bundled DTM and index insurance.

3.4 Factors influencing smallholder farmers' decision to adopt bundled DTM and Index Insurance

To identify the factors impelling the decision of smallholder farmers to adopt bundled DTM and index insurance, this study used regression analysis following a binary logistic regression model. This model was chosen because the response variable (adoption of bundled DTM and index insurance), was dichotomous, denoted by 1 for adopters and 0 otherwise. In situations when the dependent variable is binary, models such as the Linear Probability Model (LPM), probit, and logit are commonly used (Wooldridge, 2002). According to Wooldridge (2002) and Vasisht (2007), LPM is rarely used in empirical studies for binary outcomes because it assumes that the probability of success and the covariates are linearly related, leading to predictions that are not constrained to 0 and 1. Furthermore, the authors also argue that it works under the assumption that the probability changes by a fixed amount, which is very unlikely.

Thus, nonlinear transformations that keep the estimated probabilities within the limit of 0 and 1, such as the probit and logit models, are considered more suitable for the binary responses. As Allison (1999) and Hosmer Jr et al. (2013) note, these two models produce almost similar predictions, although the logit model is considered more robust as it assigns higher probabilities to extreme events because of the slightly flatter tails in the logistic distribution compared to the standard normal distribution in probit (Allison, 1999; Hosmer Jr et al., 2013). Additionally, the logit model allows for the calculation of odds ratios, which make it easier to interpret the association between the covariates and the probability of the response variable (in this case, the adoption of bundled DTM and index insurance). For this reason, this study used the binary logistic regression model because of its great flexibility and simplicity in interpreting binary variables (Muhongayire, 2012; Dhraief et al., 2019). Furthermore, binary logistic regression is well established in the literature for modelling binary dependent variables in agricultural technology adoption, as demonstrated by Horowitz & Savin (2001), Bonabana-Wabbi (2002), Dhraief et al. (2019), Muluneh et al. (2022), and Akinwale et al. (2024).

Thus, using the logistic distribution, the probability of adoption (ρ) can be presented as in Equation 8. Let us assume Y_i is the dependent variable, with $Y = 1$ representing adoption of bundled DTM and index insurance and $Y = 0$ representing non-adoption.

$$\rho(Y_i = 1|X_i) = \frac{e^{\beta_0 + \beta_i X_i}}{1+e^{\beta_0 + \beta_i X_i}} \qquad 8$$

Where;

$p(Yi = 1)$ = Probability that farmer i adopts bundled DTM and index insurance

X_i = Set of explanatory variables (socioeconomic, economic, institutional, policy, and environmental)

β_i = Set of parameters quantifying the effect of each predictor on the likelihood of uptake of bundled DTM and index insurance.

To facilitate interpretation, Equation 8 can be linearized through the logit transformation as shown in Equation 9

$$\ln\left(\frac{\rho(Y=1|X)}{1-\rho(Y=1|X)}\right) = \beta_0 + \beta_i X_i \qquad 9$$

In Equation 9, the parameters indicate the change in the logarithm of the odds ratio (log-odds) resulting from a unit change in the predictor variable. Nevertheless, it is crucial to note that the coefficients do not reflect changes in the absolute probability but rather in its logarithm (Horowitz & Savin, 2001). For this study, odds ratios and p-values were reported to determine which factors are more or less likely to influence the adoption of bundled DTM and index insurance, with significance levels set at 10%, 5%, and 1%.

To capture the key significant factors affecting the uptake of bundled DTM and index insurance, two approaches were adopted. First, a full-model approach that included all covariates was executed and then followed by a stepwise logistic regression to identify and retain the key variables with a significant effect on adoption. The stepwise logistic model was applied following the decision rules used by Lima et al. (2018) and Peshin et al. (2018), with inclusion and exclusion levels set at 0.05 and 0.10, respectively, to select the relevant variables. These two approaches were later compared using suggestions by Hosmer Jr et al. (2013) and Samsuri & Suprihatin (2021) to determine the best-fit approach. The approach that exhibited greater efficiency was chosen as the best-fit model, and its results were reported as the determinants of the adoption of bundled DTM and index insurance.

3.4.1 Goodness of fit diagnosis

After fitting both the binary logistic regression model (full-model approach) and the stepwise logistic regression model to the sample dataset, the study evaluated model adequacy to determine how well the two approaches fit and which one best described the observed data. Following the goodness-of-fit tests described in Wooldridge (2002), Hosmer Jr et al. (2013) and Ailobhio & Ikughur (2024), this study used the Likelihood Ratio test and the Hosmer-Lemeshow test to check for the joint significance of the coefficients and the overall model fit.

The Likelihood ratio (LR) test was performed to compare the constrained (null) and unconstrained (full) models to assess the joint significance of the estimated coefficients. The most suitable model was selected based on the smallest likelihood ratio (Ailobhio & Ikughur, 2024). This likelihood ratio test is expressed as;

$$LR = -2[In(L_{restricted}) \ - In(L_{unrestricted})] \tag{10}$$

Alternatively, the Hosmer-Lemeshow (HL) test made it possible to assess the overall quality of the model fit. Specifically, it evaluated how the observed outcomes matched the expected outcomes. Using the HL test, the study tested the null hypothesis that the model fits the data against the alternative hypothesis that the model does not fit the data. A chi-square statistic with a p-value greater than 0.05 would suggest that we fail to reject the null hypothesis, implying that the model fits the data well (Hosmer Jr et al., 2013; Ailobhio & Ikughur, 2024). The Hosmer-Lemeshow statistic is mathematically calculated using the expression;

$$\mathrm{HL} = \sum_{g=1}^{G} \frac{\sum(\mathrm{y_i} - ŋ_i)^2}{\mathrm{n_g} ŋ_g (1 - ŋ_g)} \tag{11}$$

Where $ŋ_g$ represents the number of observations in the g^{th} group.

Furthermore, the choice between the two approaches was made by evaluating the binary logistic regression model and the stepwise logistic regression using the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) to select the approach that fits the data well without being too complicated (Jones, 2011; Ailobhio & Ikughur, 2024). According to Ailobhio & Ikughur (2024) AIC penalizes model complexity and helps to prevent model overfitting. In contrast, BIC balances the goodness-of-fit with model complexity (Jones, 2011). While comparing, the model with the lower AIC and BIC values is generally preferred (Jones, 2011; Ailobhio & Ikughur, 2024). As such, the two approaches were compared, and the one with the lower AIC and BIC values was chosen as the ideal model for identifying the factors influencing the adoption of bundled DTM and index insurance.

3.4.2 Model diagnostics

When performing a binary logistic regression, several assumptions must be met. One such assumption is that there should be no multicollinearity among the explanatory variables. Multicollinearity occurs when there is a linear relationship among the predictors in a multiple regression (Senaviratna & Cooray, 2019). When this occurs, it makes it hard to isolate the impact of each predictor on the response variable, resulting in misleading conclusions. Additionally, multicollinearity inflates standard errors, which causes unreliable parameter estimates that affect confidence intervals and hypothesis tests (Midi et al., 2010; Senaviratna & Cooray, 2019). As such, it is important to check for multicollinearity among the explanatory variables.

Different authors used different methods for detecting multicollinearity. For example Dube (2016) used the Variance Inflation Factor (VIF) and contingency coefficient. Nalunkuuma (2013) and Wanjira (2021) used the VIF and the Pearson correlation coefficient. In this study, we refer to the studies by Nalunkuuma (2013) and Wanjira (2021) and use the VIF method and Pearson correlation coefficient to check for multicollinearity.

The Pearson correlation coefficient method measures the strength of relationship among pairs of predictors (Wanjira, 2021). As a rule of thumb, a correlation coefficient above 0.8 between two variables suggests multicollinearity (Senaviratna & Cooray, 2019). Pearson correlation coefficient can be computed using the equation;

$$r = \frac{\sum x_i y_i - \overline{nxy}}{\sqrt{(\sum x_i^2 - nx^{-2}) - \sqrt{(\sum y_i^2 - ny^{-2})}}} \qquad 12$$

Where r is the sample correlation coefficient, n is the sample size, x_i, y_i are sample points indexed with i and $\overline{x}$ is the mean of the x variable and y is the mean of the y variable.

One major limitation of the Pearson correlation coefficient method is that it only accounts for the association between two variables and fails to indicate whether there is a linear dependence among three or more predictors. Accordingly, the VIF method was used to detect whether two or more independent variables were highly correlated. VIF showed how much of the variance was inflated by multicollinearity. A VIF value above 10 shows the presence of multicollinearity, however Senaviratna & Cooray (2019) claim that for weaker models, such as logistic regression, a value above 2.5 can indicate a problem. VIF can be mathematically computed using the equation;

$$\text{VIF} = \frac{1}{1-R^2} \qquad 13$$

Where R^2 is the coefficient of determination among the predictor variables.

3.4.3 Variables used in the model

The variables used for the analysis were selected using the purposeful selection method. As expressed by Hosmer Jr et al. (2013), purposeful selection involves choosing variables with reference to theory and previous studies. Therefore, the variables presented in Table 1 were chosen in accordance with a theoretical and empirical review of research on adoption of climate-resilient agricultural technologies, with particular attention to factors determining the adoption of bundled DTM and index insurance in Manica Province. The response variable was the adoption of bundled DTM and index insurance, coded as 1 if the farmer planted insured DTM seeds and 0 otherwise. All explanatory variables, their operationalizations, and expected signs are outlined in Table 1.

Table 1: Description of covariates and their expected signs

Variable name	Type	Description	Expected Sign
Subsidy strategies	Categorical	1=Voucher; 2=Education; 3=Voucher +Education	+
Age	Continuous	Age of the farmer in years	-
Literacy	Dummy	1 if the farmer can read/write; 0 otherwise	+
Gender	Dummy	1 if male; 0 if female	+
Household size	Continuous	Number of household members	+
Farm size	Continuous	Primary area (ha) owned by the household	+
Hired labour	Dummy	1 if household hired labour; 0 otherwise	+
Information access	Dummy	1 if there is a TV set at home; 0 otherwise	+
Experience with insurance	Dummy	1 if ever purchased any form of insurance; 0 otherwise	+
Credit	Dummy	1 if the farmer had credit access; 0 otherwise	+
Distance to purchase seed	Continuous	Distance (km) to purchase seed	-
Drought years	Continuous	Number of drought years experienced by the household	+
Savings	Dummy	1 if farmer saves; 0 otherwise	+
Fertilizer use	Dummy	1 if the farmer uses fertilizers; 0 otherwise	+
DTM awareness	Dummy	1 if the farmer is aware of DTM; 0 otherwise	+
Income	Continuous	Amount of income received from maize sales	+
Agro-dealer trust	Dummy	1 if high trust; 0 if low trust	+

Source: Adapted by the Author

According to Table 1, subsidy strategies divided into education-based and voucher-based are expected to positively influence adoption by reducing the financial burden and improving a farmer's understanding of the benefits of combining DTM and index insurance. This positive influence of subsidies on adoption has also been established by other studies, such as Carter et al. (2013), Omotilewa et al. (2019), and Suprehatin (2021). Age is hypothesized to negatively influence adoption because older farmers tend to be more conservative and reluctant to take on new technologies compared to younger farmers (Aheeyar et al., 2023). Furthermore, because the benefits of this bundle are more evident when severe droughts occur, older farmers may lose interest in adopting a technology that depends on the uncertain droughts in fear that they might not live long enough to enjoy the benefits. Literacy, particularly a farmer's ability to read and write, is expected to be positively associated with adoption. This is because farmers who can read and write are expected to easily understand the information about the agronomic requirements and benefits of combining DTM and index insurance (Chichongue et al., 2019; Wanjira, 2021; Jiba et al., 2024). More still, being a female is expected to decrease the likelihood of adoption, mainly because female farmers are constrained by social and cultural dynamics that limit their control over resources like land, credit, and information (Jenrola & Gaspart, 2021).

Households with larger families are expected to be positively associated with adoption of bundled DTM and index insurance because of greater labour availability (Manuel et al., 2022; Asante et al., 2024). Similarly, it is assumed that households with larger farm sizes incur greater loss when droughts happen, so they are expected to adopt bundled DTM and index insurance to protect their farms against the drought risk. This expectation is based on reports by previous studies, such as Asante et al. (2024), who report that an increase in the size of the farm by one acre increases the chances of adopting climate-smart technologies by 47%. Furthermore, past use of any form of insurance and awareness of DTM is expected to positively influence adoption, as previous exposure to such technologies is expected to influence how farmers perceive and interpret the information related to the bundled package (Tafese, 2016; Kolapo et al., 2023). Owning a TV, which is used as a proxy for information access, is thought to positively impact the uptake of bundled DTM and index insurance because farmers are expected to learn about the benefits of the bundled package through the awareness campaigns presented on national televisions (Mwangi & Kariuki, 2015; Chichongue et al., 2019). Farmers' access to financial resources, such as sales from crops used as a proxy for income, credit access, and owning savings, is assumed to have a positive influence on adoption because it enables households to access the necessary funds for purchasing the bundled package (Tambo & Abdoulaye, 2012).

Experiencing more years of drought is expected to positively influence adoption as farmers continuously exposed to droughts will take up measures such as bundled DTM and index insurance to safeguard their livelihoods (Asante et al., 2024). Moreover, as this bundled package is currently promoted by agrodealers, the variable agrodealer trust is hypothesized to positively affect adoption. This is because a high trust in the kind of inputs sold by the local agrodealer will likely increase the willingness to purchase and test other related inputs. In contrast, travelling an additional km to purchase seed is expected to negatively affect the adoption of the bundled technology as longer distances could mean higher transaction costs (Awotide et al., 2016; Wanjira, 2021).

3.5 Impact of adopting bundled DTM and Index Insurance on maize yields among smallholder farmers

To estimate the impact of adopting bundled DTM and index insurance on maize yields, the Propensity Score Matching (PSM) method was used. The dataset for this study originates from a RCT designed to examine the effect of two subsidy programs on the uptake of bundled DTM and index insurance. As such, methods like Intent-to-treat (ITT) and Instrumental Variable (IV), traditionally used under RCTs, would be considered more appropriate. However, as Duflo et al. (2007), argue, the ITT estimator is relevant when assessing the causal effect of being assigned to a treatment (in this case, the subsidy program) but fails to estimate the impact of being assigned to a treatment on the outcome (maize yields). Therefore, ITT was considered unsuitable for this study. On the other hand, the IV method was also considered unsuitable because the insured seeds were available to all farmers during the study period, irrespective of the treatment. Additionally, there was potential non-compliance since not all farmers who received the vouchers redeemed them.

Given the abovementioned limitations, this study used the PSM method proposed in 1983 by Rosenbaum and Rubin. Although farmers were randomized to treatment groups (subsidy programs), we assume that actual adoption of bundled DTM and index insurance was endogenous and subject to selection bias as farmers chose to either adopt or not to. This implies that farmers adopting bundled DTM and index insurance and those not adopting are likely to be different, not just because of adoption but also due to attributes that influence participation and maize yields. In situations such as these, comparing the two groups would create bias (Dube, 2016). Therefore, PSM provides an alternative for controlling the observable selection bias arising from farmers' self-selection into adoption, leading to a more reliable estimate of the impact of use on maize yields. PSM does this by matching a treated unit with a similar nontreated unit, and an average of the difference between these two units across all the participants is termed the average impact of adoption for the adopters (Bryson et al., 2002). The choice of PSM was motivated by studies such as Sinyolo (2020), Wordofa et al. (2021), and Ngango & Seungjee (2021), which reveal that PSM reduces observable selection bias when assignment to the treatment is not random by comparing groups with similar observable characteristics. To conduct PSM, the study followed the below mentioned steps;

1. Estimation of the Propensity Scores.

The propensity score, which represents the estimated probability that a farmer adopts bundled DTM and index insurance given his or her observable characteristics, was estimated using a logit model, as shown in Section 3.3.2. Based on the arguments by Augurzky & Schmidt (2001) and Bryson et al. (2002) who recommend that matching using only the significant covariates produces better ATT estimation results, only the explanatory variables that significantly affected adoption were considered in the propensity score calculation. The equation for the logit model is shown in equation 13:

$$p(X_i) = P(T_i = 1|X_i) = \frac{e^{\beta_0+\beta_i X_i}}{1+e^{\beta_0+ \beta_i X_i}} \qquad 14$$

Where; $p(X_i)$ is the propensity score; $P(T_i = 1|X_i)$ indicates adoption (1) or non-adoption (0) and X_i is the vector of covariates.

2. Pairing Adopters and Non-Adopters

To establish a valid counterfactual, adopters were matched with non-adopters using comparable propensity scores. According to Becker & Ichino (2002), there are three common matching estimators, that is Nearest Neighbor (NN) matching, Radius Matching, and Kernel Matching. NN Matching is where each user is matched to the nearest non-user(s) based on propensity score. However, sometimes the NN matches may be poor, especially if the nearest control unit has a completely different propensity score, resulting in a biased estimation of the treatment effect. To address the issue of poor matches associated with NN, radius matching and kernel matching can be used. Radius matching ensures that every treated unit is matched with only the control units whose propensity scores lie within predetermined neighbourhoods, thereby eliminating bias in estimating the treatment effect. In contrast, Kernel matching involves matching all treated units to control units using weighted averages, where the weights are inversely correlated to the distance in between their propensity scores (Sizemore & Alkurdi, 2019; Habineza et al., 2020; Wordofa et al., 2021). The choice of the matching algorithm used for this study was based on the approach employed by Dube (2016) and Yitbarek (2017), and the suggestions by Caliendo & Kopeinig (2008). The data was tested with all the matching algorithms, and the one that had the lowest pseudo-R^2, balanced all covariates while maintaining the largest matched sample size, was chosen as the ideal matching estimator and used to estimate the ATT.

3. Estimation of Average Treatment Effect on the Treated.

Upon successful matching, the Average Treatment Effect on the Treated (ATT) was estimated. ATT indicates the average impact of adopting bundled DTM and index insurance on adopters' yields. It is defined as;

$$ATT = E[Y_1 \mid T_i = 1] - E[Y_0|T_i = 1] \qquad 15$$

where:

Y_1 and Y_0 = are the potential yields with and without adoption, respectively

$E[Y_0|T_i = 1]$ =is the counterfactual (yield that treated farmers would have had if they had not adopted), predicted from matched non-users.

T_i = is the treatment status of i^{th} farmer and takes two values: $T_i = 1$ if the farmer used insured seeds, and $T_i = 0$ = if the farmer is a non-user.

However, since the counterfactual is unobservable, an alternative component is necessary to estimate ATT. A component like $E[Y_0|T_i = 0]$, which represents the mean outcome for untreated individuals, is not recommended for use in calculating ATT because it is assumed that the determinants of adopting bundled DTM and index insurance are similar to those determining total maize yields (Caliendo & Kopeinig, 2008). Therefore, ATT can also be written as:

$$E[\,Y_1 \mid T = 1\,] - E[Y_0|T = 0] = ATT + \; E[Y_0|T = 1] - E[Y_0|T = 0] \qquad 16$$

where the right-hand side of equation 16 is the selection bias. So, ATT is only realized if;

$$E[Y_0|T = 1] - E[Y_0|T = 0] = 0 \qquad 17$$

To provide an unbiased causal estimate when using the PSM method, the assumptions of conditional independence and common support must be met (Sizemore & Alkurdi, 2019; Habineza et al., 2020). Conditional independence (CIA), also called unconfoundedness, assumes that selection into a treatment group strictly depends on the observable characteristics (Caliendo & Kopeinig, 2008). This assumption suggests that the outcome variable and the treatment are independent (Dube, 2016). For this study, this means that conditional on the observable characteristics, the outcome of the users and non-users of bundled DTM and index insurance need to be independent of adoption. CIA is important as it ensures that the observable differences between treated and untreated units are considered, hence controlling for selection bias (Caliendo & Kopeinig, 2008). This assumption can be expressed using the mathematical notation in equation 18.

$$(Y_1, Y_0) \perp T/X \qquad 18$$

Another assumption is the common support, also known as the overlap condition. This assumes that given similar characteristics (X), there is a positive probability of adoption and non-adoption (Caliendo & Kopeinig, 2008; Sizemore & Alkurdi, 2019). This means that the probability of treated and untreated units must range between 0 and 1 for all values of X. This assumption also sets out that the characteristics of the treated and untreated groups are comparable. The condition is expressed as shown in equation 19.

$$0 < P(T = 1 \mid X) < 1 \qquad 19$$

When these are observed, a positive, statistically significant ATT indicates that the adoption of bundled DTM and index insurance increases maize yields among treated farmers, after controlling for observable differences.

3.5.1 Validation and Robustness of the Results

When employing the PSM method, it is important to check for the reliability of the estimates. To this end, this study used several validation methods as suggested by Becker & Ichino (2002), Becker & Caliendo (2007), Nannicini (2007), and Caliendo & Kopeinig (2008) to test for the validity and reliability of the PSM estimates. First, the common support region was validated by plotting the propensity scores for the treatment and control groups in a box plot. This graphic analysis facilitated the comparison of areas of overlap between the groups, and any observations located in regions outside the common support were removed from the final analysis.

Second, a covariate balance check was conducted to assess the matching quality using T-tests and standardized differences for both adopters and non-adopters before and after matching. The relevance of conducting these two tests was to verify that the observed differences among the groups were due to the treatment effect other than to covariates. Accordingly, T-tests with p-values greater than 0.05 and standardized differences below 10% after matching suggested a good balance.

Furthermore, because the PSM method does not account for unobservable selection bias, a sensitivity analysis test was conducted to determine whether the PSM results were robust to potential unobserved confounders (Becker & Caliendo, 2007). To carry out this analysis, the study used the sensatt command and the propensity matching estimator commands as suggested by Nannicini (2007) and Becker & Ichino (2002), respectively. The sensatt command results were used to compare the ATT estimates before and after matching on the simulated confounder to assess how sensitive the baseline ATT results were to violations of the conditional independence assumption of PSM.

3.6 Study area

The study was carried out in Manica Province, found in the central part of Mozambique. Manica province has a total land area of about 61,661km^2 and is bordered on the North by Tete, on the South by Gaza, on the west by Zimbabwe, on the Southeast by Inhambane, and on the East by Sofala (Ministerio de Administracao Estatal, MAE, 2005). The province's strategic location in the Eastern Highlands allows it to experience a subtropical highland climate composed of hot summers and relatively cold winters. On average, the province receives about 600mm of rainfall, with November up to March as the wettest months, whereas the months between April and October are characterised by hot conditions (MAE, 2005; World Bank, 2021). The province is a key maize-growing region in Mozambique, and every year, it produces about 148,000 tonnes of maize, which is around 15-16% of Mozambique's total maize output (Amaral et al., 2020). However, droughts are a significant challenge to maize production in the province (World Bank, 2021; FAO, 2024; Toreti et al., 2025), and for the longest time, the province has been an area of focus for climate adaptation interventions such as bundled DTM and index insurance. Currently, Manica Province is the primary zone of commercialization for this bundled package, making it a suitable study site (Fang & Richards, 2018; Malacarne, 2019; Boucher et al., 2024).

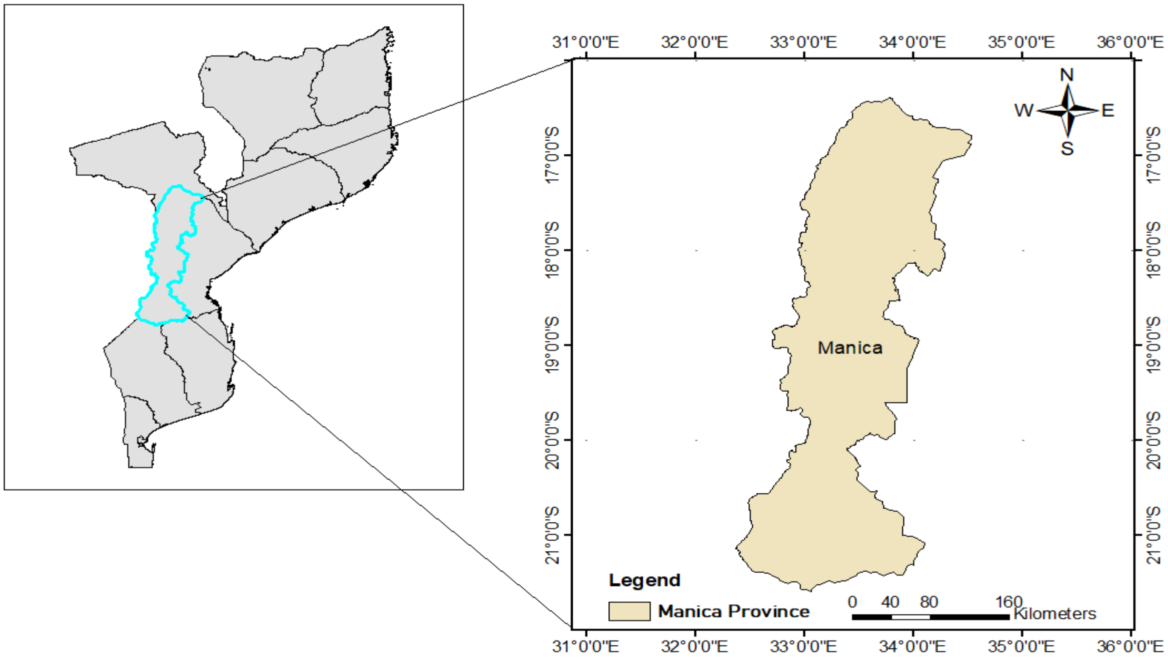


Figure 2: Map of Mozambique highlighting Manica Province

3.7 Data collection method

The data used for this study is from a Randomized Control Trial (RCT) experiment used to assess how two subsidy strategies, voucher-based and education subsidy programs, influence the adoption of bundled DTM and index insurance. To select participants, 5 districts, namely Barue, Gondola, Guro, Sussundenga, and Vanduzi, were considered. These districts were chosen because they account for about 80% of the total maize produced in the province (Mabilana et al., 2012; Amaral et al., 2020), and comprised of active agrodealer networks that promoted bundled DTM and index insurance. Taking into consideration the distribution of the agrodealer networks across the 5 districts, a total of 80 communities (20 from each of Barue, Guro, and Sussundenga; 12 from Vanduzi; and 8 from Gondola) were grouped with at least 4 communities being served by each agrodealer. These communities were then randomly assigned to 4 treatment groups (0=Control, T1=Voucher-only, T2=Education-only, T3=Voucher + Education) to ensure that each group had 20 communities. Randomization according to communities served by an agrodealer helped to ensure balance on agroecological conditions, market access, growing conditions, and learning opportunities across treatments. Within each community, 14 maize-growing households were then randomly selected from a list of registered maize farmers, leading to a total sample size of 1,120 farming households from 80 villages in Manica province. Subsidy programs were then distributed according to the treatments, but the product remained available to all farmers in the study. After the season, the data were then collected using questionnaires to capture aspects such as farmer characteristics, as well as institutional, policy, and environmental factors relevant for understanding how smallholder farmers make adoption decisions. The current study employed post-project data, excluding 66 farmers because of missing data, and considered the subsidy programs as one of the explanatory variables.

CHAPTER 4: RESULTS AND DISCUSSION

This chapter presents the analysis and discussion of results based on the 3 objectives of the study. These were: to characterize the adopters and non-adopters of bundled Drought-Tolerant Maize varieties and Index insurance; to identify the factors influencing smallholder farmers' decision to adopt bundled Drought-Tolerant Maize and Index insurance; and to estimate the impact of adopting bundled Drought-Tolerant Maize and Index insurance on maize yields among smallholder farmers.

4.1 Description of the data

A descriptive summary of the variables included in this study is presented in Table 2. According to the table, only about 25.7% of the respondents adopted bundled DTM and index insurance. Participation in none or any of the subsidy programs was evenly distributed across the sample, with roughly 25% in each group. The average household size was approximately 8 people, which is slightly above the 5.8 and 7.4 persons per household reported for Manica Province by the Alliance for a Green Revolution in Africa (AGRA) (2017) and Findeis et al. (2019), respectively. The mean age of the respondents was 45 years, suggesting limited youth participation, as most participants were outside the 15-35 age range defined as youth in Mozambique (UNFPA, 2023). This finding aligns with previous studies by Mpinda et al. (2025) and Katya Kule et al. (2025) who report that the adoption of climate-resilient farming practices is dominated by productive middle-aged farmers between 40 and 48 years.

Literacy levels were modest, with only about 42% of respondents able to read and write. Households experienced drought for an average of 3.7 years, travelled about 9 kilometres to purchase seed, and owned an average farm size of 3.1 hectares. With respect to gender, 67% of the respondents were men, signifying that adoption of bundled DTM and index insurance is likely gender biased, favouring males as compared to their female counterparts. This finding can be linked to the financial burden associated with purchasing the relatively costly insured seeds, as well as the social and cultural dynamics in Africa, which favour men when it comes to accessing resources such as information, credit, and land. This is consistent with the studies conducted by Fisher & Carr (2015) and Mérida Lindgren (2021), who claim that men often dominate the adoption of risk-mitigating technologies.

Additionally, among the respondents, 20.9% had access to credit, and 34% possessed savings. Experience with insurance and fertilizer use was limited, at about 7.4% and 3.5%, respectively. Access to information and awareness of DTM were 27% and 28%, respectively, suggesting a possible knowledge gap. Furthermore, 61% of the respondents reported trust in agrodealers, indicating that agrodealers could be a credible channel for disseminating information about the bundled product. Also, only 7% of the respondents reported using hired labour, which suggests that most farmers rely on family labour.

Table 2: Descriptive Statistics

Variable	Mean	Std. dev.	Min	Max
Adoption DTM and Index Insurance	0.2565	0.4369	0	1
Subsidy strategies				
No subsidy	0.2514	0.4340	0	1
Voucher only	0.2550	0.4361	0	1
Education only	0.2386	0.4264	0	1
Voucher and Education	0.2550	0.4361	0	1
Household size	7.8684	4.3976	1	46
Age	45.2247	14.6763	17	94
Literacy	0.4201	0.4938	0	1
Income	18.6992	25.8231	0	100
Drought years	3.7436	2.0182	0	10
Distance to purchase seed	9.0045	28.2893	0	800
Farm size	3.1041	3.5309	0	40
Credit	0.2088	0.4065	0	1
Experience with Insurance	0.0741	0.2620	0	1
Gender	0.6685	0.4710	0	1
Information access	0.2647	0.4414	0	1
DTM awareness	0.2764	0.4474	0	1
Fertilizer use	0.0345	0.1826	0	1
Saving	0.3404	0.4741	0	1
Agro dealer trust	0.6107	0.4878	0	1
Hired labour	0.0687	0.2530	0	1

4.2 Characterization of adopters and non-adopters of bundled DTM and Index Insurance

This section details the output of the attributes of users and non-users of bundled DTM and index insurance. It starts with a description of how adopters and non-adopters were distributed across the districts included in the study. This is followed by the characteristics of the two groups based on dummy and categorical variables. Finally, the section ends with characteristics based on the continuous variables.

Distribution of adopters and non-adopters by district

Figure 3 indicates variations in adoption of bundled DTM and index insurance across the 5 districts. Most of the adopters lived in Guro, followed by Barue, Sussundenga, and Vanduzi, with Gondola having the smallest number. This result is likely due to two situations. On one hand, it may indicate spatial similarity in the uptake of agricultural practices, where farmers in neighbouring districts like Guro and Barue showed higher adoption rates compared to those in somewhat distant districts like Gondola. On the other hand, these differences could be because of the sampling procedure, where fewer communities were chosen from Vanduzi and Gondola compared to the other districts. Generally, it is essential to note that the uptake rates of bundled DTM and index insurance were low across all the districts and throughout, non-adopters were more than adopters.

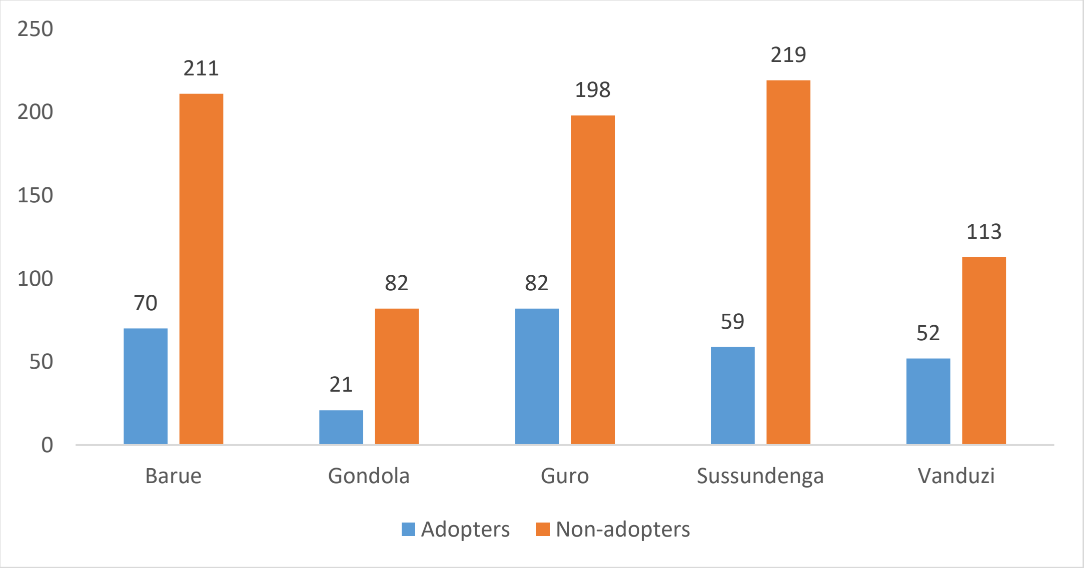


Figure 3: Distribution of adopters and non-adopters by district

Characteristics according to dummy and categorical variables

Table 3 shows a summary of the characteristics of farmers who adopted bundled DTM and index insurance and those who did not, based on the selected dummy and categorical variables. Out of the 1107 farmers considered for this study, 284 were adopters of bundled DTM and index insurance, and 823 were non-adopters. From Table 3, significant disparities in the means between adopters and non-adopters were observed for DTM awareness, fertilizer use, and possession of savings. This implies that, on average, adopters reported greater awareness of DTM, higher fertilizer use, and more possession of savings compared to the non-adopters. Conversely, variables such as gender, literacy levels, experience with insurance, use of hired labour, trust in agro-dealers, credit, and information access showed no significant mean differences between adopters and non-adopters.

According to Table 3, the proportion of farmers aware of DTM was higher among adopters (35.92%) compared to non-adopters (24.79%). A plausible explanation for this finding is that knowledge of the performance and benefits of DTM, especially under drought conditions, reduces the uncertainty associated with the bundled product, hence making farmers more receptive to its adoption. Furthermore, the use of fertilizers was higher among adopters (6.34%) compared to non-adopters (2.45%). This finding could point to two possible explanations. First, it could imply that farmers with experience of using improved agricultural inputs are more inclined to use complementary inputs such as bundled DTM and index insurance. Also, it could be because the adoption of insured seeds encouraged investment in high-quality inputs like fertilizers to maximize productivity. This result concurs with Kramer et al. (2024) who found that the adoption of index-based insurance increased fertilizer demand in Kenya. More still, adopters possessed more savings than non-adopters. This could be because having savings provides farmers with the necessary finances to invest in purchasing the bundled product. This difference corresponds with the findings of Gikonyo et al. (2022) who reported that households with savings were more likely to adopt climate-smart agriculture technologies.

Table 3: Comparison of adopters and non-adopters based on dummy variables

Variable	Description	Adopters (%)	Non-adopters (%)	z-statistic
Gender	Male	67.25	66.71	-0.17
Literacy	Can read and write	43.31	41.56	-0.52
Experience with insurance	Yes	7.75	7.29	-0.25
DTM awareness	Yes	35.92	24.79	-3.62***
Hired labour	Yes	7.39	6.68	-0.41
Agro dealer trust	High trust	57.39	62.33	1.47
Fertilizer use	Yes	6.34	2.45	-3.09***
Savings	Yes	45.36	30.1	-4.64***
Credit	Yes	23.59	19.93	-1.31

Information access	Yes	26.41	26.49	0.03

Note: *** denotes statistical significance at 1% level.

Comparison of adopters and non-adopters based on subsidy treatments

Figure 4 indicates the distribution of farmers who adopted bundled DTM and index insurance and those who did not across the different subsidy treatments. It reveals that a larger percentage of adopters were under the voucher-based (44.33%) and voucher + education (43.26%) subsidy treatments, whereas non-adopters dominated the no subsidy (7.09%) and the education-only (5.32%) subsidy treatments. This implies that financial incentives, such as vouchers that lower the cost of investing in the bundle, are more effective at promoting adoption than training sessions alone.

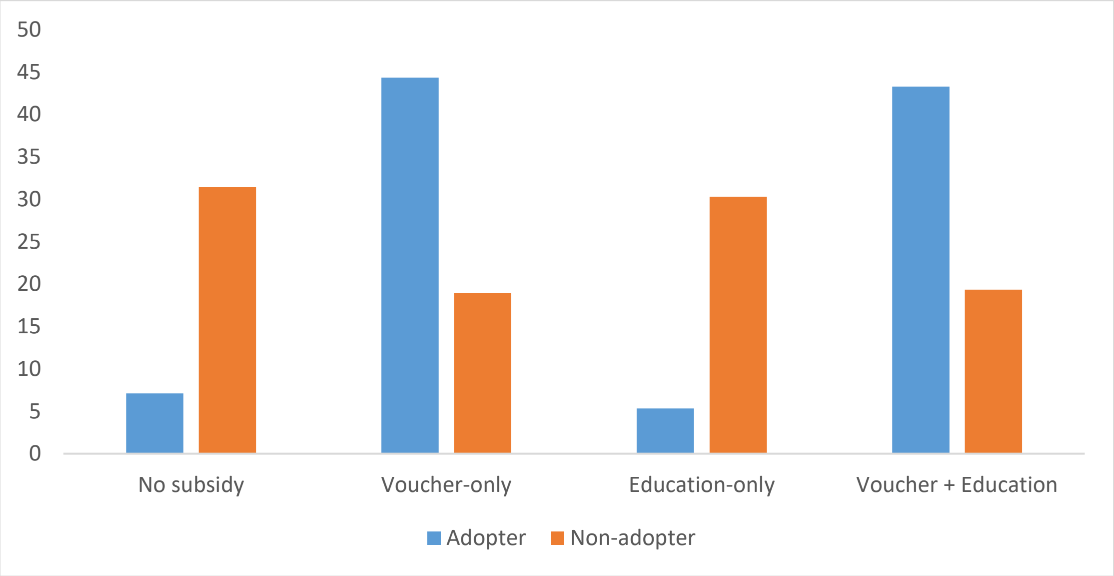


Figure 4: Distribution of adopters and non-adopters according to subsidy treatments.

Characteristics based on continuous variables

Table 4 shows significant mean differences between users and non-users of bundled DTM and index insurance for farm size. On the other hand, there was no significant mean difference in the age, household size, number of drought years experienced, income and the distance travelled to purchase seed for both users and non-users of bundled DTM and index insurance.

According to Table 4, adopters had, on average, 0.66 ha larger farm sizes than non-adopters. This is possibly because households with larger farms incur greater losses when droughts happen, so planting insured DTM varieties is a means of safeguarding against both production and financial losses. Similarly, in developing countries, owning larger farms is often linked to greater wealth, suggesting that farmers who own bigger farms are better equipped with the needed funds for covering the required upfront costs of the bundled product. This finding conforms with that of Makate et al. (2019) who state that household wealth associated with ownership of larger farm sizes significantly influenced the adoption of drought-tolerant maize and conservation agriculture in Zimbabwe. The authors claim that wealthier households owned larger farms and were better able to purchase agricultural inputs such as drought-tolerant seeds.

Table 4: Comparison of adopters and non-adopters based on continuous variables

Variable	Adopters (n=284)		Non-adopters (n=823)		t-test
	Mean	Std.dev	Mean	Std.dev	
Age	45.49	14.63	45.13	14.70	-0.35
Household size	7.74	4.21	7.91	4.46	0.56
Farm size	3.59	4.35	2.93	3.18	-2.72***
Drought years	3.82	2.14	3.72	1.96	-0.76
Income	17.35	23.02	19.17	26.72	1.02
Distance to purchase seed	7.15	13.52	9.64	31.82	1.28

Note: *** denotes statistical significance at 1% level.

4.3. Factors influencing smallholder farmers' decision to adopt bundled Drought-Tolerant Maize and Index Insurance.

The binary logistic regression model was used to identify the factors influencing the uptake of bundled DTM and index insurance in Manica Province. Before running the regression, the covariates were tested for multicollinearity. The VIF results shown in Appendix 1 indicated no multicollinearity, as all VIF values were below 5. Similarly, the Pearson Correlation Coefficient results in Appendix 2 were all below 0.8, suggesting absence of correlation amongst the explanatory variables, signalling that multicollinearity was not a problem.

To identify the factors with a significant effect on adoption of bundled DTM and index insurance, two approaches were employed: a full model approach (Table 6) that included all independent variables and a stepwise logistic model (Table 7) that retained only the variables that significantly affected adoption. These two models were compared as shown in Table 5 to select the best model. According to Table 5, a comparison of the full model and the stepwise logistic regression shows that the log-likelihood of the full model was relatively higher than that of the stepwise regression model. However, the stepwise model yielded lower AIC and BIC values, indicating better efficiency. Additionally, the Hosmer-Lemeshow test statistic indicated good fit for both models, but the stepwise model showed better calibration, as evidenced by a smaller difference (6.06) between observed and expected values and a larger p-value (0.6405). Therefore, this study considered the stepwise logistic model as the ideal model because of its simplicity and better fitness for the data. Thus, the factors reported to influence adoption of bundled DTM and index insurance are based on the results from the stepwise logistic regression model.

Table 5: Model comparison

Model	N	ll(null)	ll(model)	AIC	BIC	Hosmer-Lemeshow χ^2
Full	1,054	-601.858	-467.54	975.09	1074.30	12.89 (p-value = 0.1157)
Stepwise	1,054	-601.858	-473.75	963.50	1003.18	6.06 (p-value = 0.6405)

Table 7 shows that factors such as savings, DTM awareness, number of drought years experienced, fertilizer use, and voucher-based subsidy, whether used alone or in combination with education, had a positive effect on the adoption of bundled DTM and index insurance. In contrast, owning a TV used as a proxy for information access was negatively associated with adoption.

Voucher-based subsidy, either alone or in combination with education, strongly influenced adoption of bundled DTM and index insurance. Farmers who received only a voucher-based subsidy were 12.23 times more likely to adopt as opposed to those who received no subsidy. Likewise, farmers who received both a voucher and education subsidy were 11.91 times more likely to adopt. This finding reveals that voucher-based subsidy, regardless of whether used alone or in combination with education acts as an incentive for adoption of the bundled technology. This is likely because vouchers reduced the cost of purchasing the insured seeds, giving farmers an opportunity to learn about and become familiar with the benefits of the bundle. Eventually, this builds farmers' confidence in the bundle's benefits, especially in its ability to safeguard their livelihoods during extreme droughts, which enhances uptake. Similar findings are noted by Carter et al. (2013), regarding the impact of vouchers on the uptake of improved seeds and fertilizers in Mozambique. The authors state that receiving voucher coupons increased the use of fertilizers and improved seeds among the recipients.

Additionally, since the voucher plus education subsidy involved farmer training on the benefits and importance of combining DTM and index insurance, it addressed both the knowledge and liquidity challenges that could hinder adoption. With the education subsidy, farmers learnt how the bundle works, and through the voucher subsidy, the upfront costs for buying the seed were lowered. Together, this could have motivated farmers to adopt bundled DTM and index insurance. These findings are in agreement with the main hypothesis of the MRR Innovation Lab project, which assumes that learning through experimentation and education encourages the adoption of resilience-enhancing technologies (Feed the Future, 2024). These findings also align with those of Holden & Fisher (2015), Omotilewa et al. (2019), Suprehatin (2021), and Jena et al. (2023), who found that receiving subsidies addresses liquidity constraints and encourages hands-on learning, thereby providing valuable information about the technology, which accelerates adoption and diffusion.

Having savings was found to positively influence the adoption of bundled DTM and index insurance. Specifically, farmers with savings were 2.09 times more likely to adopt bundled DTM and index insurance compared to those without savings. This is possibly because owning savings enabled farmers to access the necessary financial resources to purchase the relatively costly insured seeds. Additionally, because vouchers could only cover part of the cost of the insured seeds, savings likely increased the ability of farmers to redeem the vouchers, thus increasing the chances of adoption. Another possible explanation for this finding is that having savings increases a farmer's possibility of accessing credit, especially in informal settings like from Village Savings and Loans Associations (VSLAs), which provide them with the required financial resources for buying the bundled product. This finding conforms with those of Simtowe et al. (2019), Gikonyo et al. (2022), and Jena et al. (2023), whose results indicated a positive association between savings and the use of climate adaptation techniques. These authors claim that savings are a form of collateral that can be used to access loans for financing the adoption of the technologies. Furthermore, Uaiene (2011) also emphasizes that savings enable smallholder farmers to access the capital needed to invest in new technologies.

Contrary to expectations, access to information about bundled DTM and index insurance decreases the likelihood of adoption by 29.66%. This inverse relationship can be explained in two ways. First, it might be because of inaccurate information, especially about the nature of benefits associated with combining DTM and index insurance. Because combining the two technologies is something that is still being promoted in the Province (Ospina et al., 2025), access to information about the bundle's performance likely created negative perceptions among smallholder farmers regarding its adoption (Kinyangi, 2014). Second, the descriptive statistics results in section 4.1 indicated that merely around 26.5% of the respondents owned TVs. This shows a limited coverage, which could imply that information broadcast using this medium may not adequately reach smallholder farmers in rural areas, leaving the knowledge gap unsolved. These findings are contrary to those of Chichongue et al. (2019) and Yusuf (2020), who showed that farmer ownership of communication media, such as radio, television, and mobile phones, increased the chances of adopting climate-adaptation practices in Mozambique.

Another factor that positively influences adoption is awareness of DTM. The results show that awareness of DTM increases the likelihood of adoption of bundled DTM and index insurance by 68.46%. This is possibly because understanding the benefits and performance of DTM likely reduces the uncertainty associated with the adoption of the bundle. As expressed by Udimal et al. (2017), smallholder farmers prefer adopting technologies they are familiar with. Thus, awareness of DTM could have indirectly increased the chances of adopting the bundled package. These results align with the arguments by Ayedun (2018), Lunduka et al. (2019), and Kolapo et al. (2023). The authors note that familiarity with a technology fosters trust, which enables farmers to assess the technology objectively rather than subjectively, thereby increasing the probability of uptake. Mitra et al. (2022) in their study about the adoption of bundled insurance in India, also concur with this finding as they state that previous experience with similar technologies increased the demand for the bundle.

Experiencing one additional year of drought increases the likelihood of adopting bundled DTM and index insurance by 7.26%. This finding is consistent with the expected sign, and farmers continually exposed to the repeated adverse effects of droughts may be more likely to adopt bundled DTM and index insurance to safeguard their livelihoods. Lunduka et al. (2019) also agree with these results. In their analysis, they found that experiencing droughts in the last 5 years increased the willingness to adopt DTM varieties. Also, the findings from this study align with those of Katengeza et al. (2019), Asante et al. (2024), and Ospina et al. (2025), who state that experience with drought increases the propensity to adopt risk mitigation practices.

Consistent with our expectation, fertilizer use was positively associated with the adoption of bundled DTM and index insurance. Precisely, farmers who used fertilizers were 2.58 times more likely to adopt bundled DTM and index insurance in comparison to those who did not. This can possibly be attributed to two reasons. First, farmers who have experience with using productivity-enhancing technologies like fertilizers express greater willingness to take up complementary methods that offer promise for increased productivity. Second, because the insurance component of the bundled product offers promise for replacing inputs (seeds) in case of harvest failure, farmers likely felt more confident to invest in other agricultural technologies like fertilizers to maximize yields. Similar findings are documented by Bulte et al. (2020), who note that bundling of seeds with insurance was positively associated with the adoption of complementary inputs like fertilizers. Furthermore, scholars such as Ogada et al. (2014), Tesfay (2020), Oyetunde-Usman & Shee (2023), and Muleke et al. (2025) also found a positive link between fertilizer use and investment in complementary inputs like insurance and drought-tolerant seeds.

Table 6: Results of the binary logistic regression model

Variable	Coefficient	Std. err.	Odds ratio	P>z
Subsidy strategies				
Voucher Only	2.4805	3.2848	11.9471	0.000***
Education Only	-0.1173	0.3269	0.8893	0.747
Voucher and Education	2.4623	3.2109	11.7318	0.000***
Household size	-0.0205	0.0200	0.9797	0.329
Age	-0.0061	0.0057	0.9939	0.291
Literacy	0.0321	0.1778	1.0326	0.858
Income	-0.0022	0.0034	0.9978	0.512
Drought years	0.0678	0.0448	1.0702	0.114
Distance to purchase seed	-0.0071	0.0053	0.9929	0.176
Farm size	0.0500	0.0247	1.0513	0.055*
Credit	0.1320	0.2257	1.1411	0.497
Experience with insurance	-0.1957	0.2573	0.8223	0.526
Gender	-0.1342	0.1601	0.8744	0.470
Information access	-0.3644	0.1400	0.6946	0.080*
DTM awareness	0.5462	0.3185	1.7266	0.004***
Fertilizer use	0.8381	0.9437	2.3120	0.043**
Saving	0.7086	0.3581	2.0312	0.000***
Agro-dealer trust	-0.2319	0.1329	0.7930	0.171
Hired labour	-0.0646	0.3207	0.9375	0.853
_cons	-2.6987	0.0301	0.0673	0.000***

Note: *, **, and *** denote statistically significant at 10%, 5% and 1% level, respectively.

Table 7: Stepwise logistic regression results

Variables	Coefficient	Std. Err.	Odds ratio	P>z
Subsidy strategies				
Voucher Only	2.5039	2.7031	12.2304	0.000***
Voucher and Education	2.4773	2.6247	11.9095	0.000***
Saving	0.7384	0.3599	2.0926	0.000***
Information access	-0.3518	0.1365	0.7033	0.070*
DTM awareness	0.5215	0.3033	1.6846	0.004***
Drought years	0.0701	0.0432	1.0726	0.082*
Fertilizer use	0.9475	1.0451	2.5792	0.019**
_cons	-3.3263	0.0097	0.0359	0.000***
Wald chi2	256.22			
Log likelihood	-473.7489			
Pseudo R2	0.2129			
Number of observations	1,054			

Note: *, **, and *** denote statistically significant at 10%, 5% and 1% level, respectively.

4.4 Effect of adoption of Bundled Drought-Tolerant Maize and Index Insurance on maize yields

Propensity score matching (PSM) was employed to estimate the impact of adopting bundled DTM and index insurance on maize yields. In the analysis, total maize yield per hectare for each household during the 2021/2022 agricultural season served as the outcome variable, whereas the adoption of bundled DTM and index insurance (1 = adopted, 0 = otherwise) was the treatment variable. Propensity scores were predicted with the aid of a logit model. Drawing reference from Caliendo & Kopeinig (2008) who argue that factors that influence the treatment decision are most likely to influence the outcome of interest, only the explanatory variables that had a significant effect on adoption (Section 4.3, Table 7) were included in the propensity score calculation. The variables considered include subsidy strategies (voucher-only, voucher+ education-based), number of drought years experienced, DTM awareness, savings, and fertilizer use. The education-only subsidy, which had an insignificant effect on the uptake of bundled DTM and index insurance, was removed from the subsidy strategy category, reducing the sample size to

807. This sample was considered adequate for determining the impact of bundled DTM and index insurance on maize yields. However, since the effect of these variables on the uptake of bundled DTM and index insurance have been presented in section 4.3, this section concentrates on assessing the impact of uptake on total maize yield per hectare using estimated propensity scores.

Table 8 shows that the calculated propensity scores are between 0.25 and 0.818. Adopters of bundled DTM and index insurance have propensity scores between 0.038 and 0.818, whereas non-adopters have scores from 0.025 to 0.791. This suggests that the overlap region ranges from 0.038 to 0.791, excluding propensity scores below 0.038 and above 0.791. Additionally, Table 8 indicates that the mean propensity score across all sampled households is approximately 0.320, meaning the average likelihood that participants would adopt bundled DTM and index insurance was approximately 32%. These findings and the corresponding distribution are further illustrated in Table 8 and Figure 5.

Table 8: Descriptive summary of predicted propensity scores

Categories	Obs	Min	Mean	Max	SD
Non-adopters	549	0.025	0.260	0.791	0.194
Adopters	258	0.038	0.447	0.818	0.159
Total	807	0.025	0.320	0.818	0.203

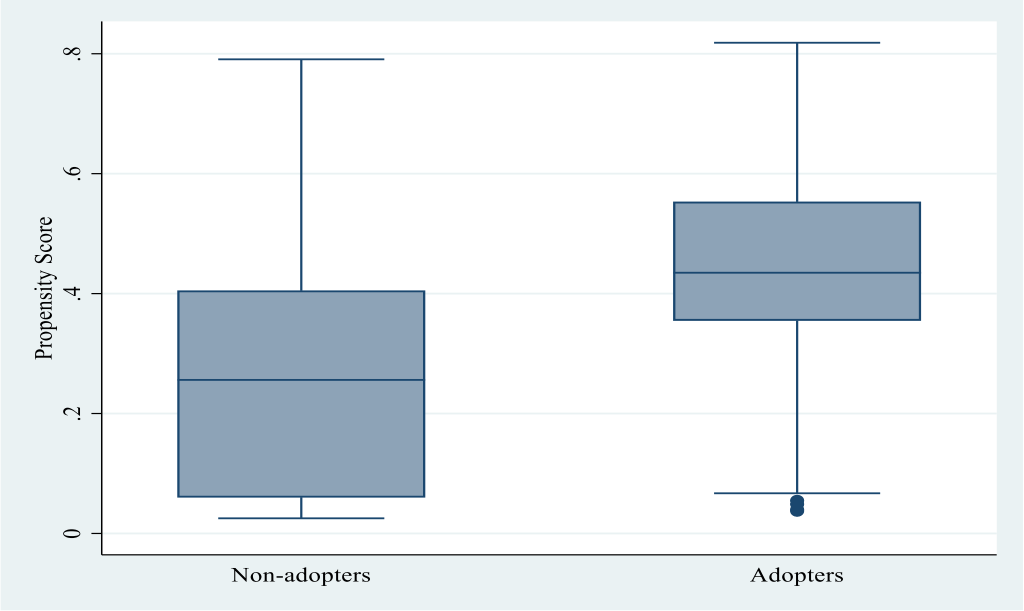


Figure 5: Matching distribution

4.4.1 Selection of matching algorithm

The decision regarding the matching algorithm to use for this study was guided by previous empirical studies, such as those of Dube (2016) and Yitbarek (2017), who selected matching algorithms based on the pseudo-R^2, the number of matched observations, and the total covariates with insignificant mean difference after matching. Furthermore, as expressed by Caliendo & Kopeinig (2008), the ideal estimator is one that yields a lower pseudo-R^2 and balances all covariates using a larger matched sample size. The results shown in Table 9 reveal that Kernel Matching with a bandwidth of 0.06 yielded the smallest pseudo R^2, with a larger matched sample size, making it the most suitable estimator for the study. Therefore, this study used the Kernel Matching estimator with a bandwidth of 0.06 to examine the impact of adopting bundled DTM and index insurance on maize yields.

Table 9: Matching algorithm results

Algorithm	Balancing test	Pseudo-R^2	Matched Sample size
Nearest Neighbor			
1	7	0.002	800
2	7	0.002	800
3	7	0.002	800
Radius Matching			
Caliper (0.01)	7	0.004	796
Caliper (0.05)	7	0.002	800
Caliper (0.1)	7	0.004	800
Kernel Matching			
Bandwidth (0.01)	7	0.001	796
Bandwidth (0.06)	**7**	**0.001**	**800**
Bandwidth (0.1)	7	0.003	800

Note: The balancing test indicates the number of covariates that have no significant effect after matching.

4.4.2 Covariate balance results

Before estimating the impact of adopting bundled DTM and index insurance, a covariate balance check should be performed to ensure that the differences amongst users and non-users are statistically insignificant. This is crucial because it confirms that the noted differences in ATT are exclusively due to the treatment effect (adoption of bundled DTM and index insurance) and not influenced by other observable factors. From Table 10, 5 of 7 variables showed significant mean differences before matching; however, after matching, all variables had statistically insignificant mean differences. This indicates that covariate balance was successfully achieved.

Table 10:Covariate balance results determined using the Kernel Matching algorithm

	Before Matching				After matching NN (0.05)			
Variable	Treated	Control	% bias	t-test	Treated	Control	% bias	t-test
Subsidy strategies								
Voucher only	0.463	0.272	40.5	5.46***	0.463	0.470	-1.6	-0.17
Voucher + Education	0.459	0.272	39.7	5.35***	0.459	0.456	0.7	0.07
Information access	0.253	0.268	-3.8	-0.45	0.251	0.248	0.8	0.09
Drought years	3.868	3.699	8.1	1.09	3.851	3.842	0.4	0.05
DTM awareness	0.319	0.257	13.7	1.84*	0.318	0.333	-3.5	-0.38
Fertilizer use	0.070	0.029	18.8	2.68***	0.063	0.054	4.1	0.42
Saving	0.459	0.306	31.8	4.26***	0.455	0.422	6.9	0.76

Note: *, and *** indicate 10% and 1% significance level, respectively.

Additionally, Table 11 presents the general test statistics for the balancing property, indicating that before matching, some level of imbalance existed amongst the treatment and control groups, as indicated by the Pseudo-R^2 (0.169), a significant likelihood ratio test, and large mean bias and median bias beyond the recommended threshold (20%). Rubin's B above 25 further confirms this imbalance. However, after matching, balance was achieved, as shown by the reduced Pseudo-R^2 (0.001) and a non-significant likelihood-ratio test (p-value of 0.994), suggesting good balance. Furthermore, the mean and median biases, as well as Rubin's B, were within the recommended ranges by (Rubin, 2001), confirming good covariate balance across groups. These results imply that the employed model is reliable, as it effectively eliminated observable distinctions between the treatment and control groups. This means that our results are reliable, and any observed distinctions are because of the treatment effect rather than to observable factors.

Table 11: Chi-square test for the joint significance of variables

Sample	Ps R2	LR chi2	p>chi2	Mean Bias	Med Bias	B	R
Unmatched	0.169	170.2	0.000	22.3	18.8	107.9*	0.40*
Matched	0.001	1.03	0.994	2.6	1.6	9	0.87

4.4.3 Impact of the adoption of bundled DTM and Index Insurance on maize yields

The results on the impact of adopting bundled DTM and index insurance showed that, after adjusting for selection bias, adopters had an average maize yield of 2.43 kg/ha higher compared to non-adopters. However, this yield benefit was insignificant. This finding can be linked to the early season and severe droughts that occurred in Manica Province during the 2021/2022 agricultural season (WFP, 2022). These droughts likely reduced the biological benefit provided by DTM, resulting in outcomes that were almost similar between adopters and non-adopters. This finding aligns with the theory related to the performance of the bundle under severe drought conditions. According to the theory, the bundle works in such a way that the protection provided by DTM varieties is more pronounced during moderate mid-season droughts, but as droughts become severe, the benefits diminish and may not differ from those of non-adopters (Lybbert & Carter, 2015). On the other hand, index insurance has no direct effects on yields but offers financial compensation in case of losses due to the extreme droughts when DTM varieties fail. This suggests that the benefits of the bundle may not be immediate short-term effects on maize yields but rather long-term gains through more stable productivity. This is because the assurance of seed replacement after a drought shock stabilizes yields in the long run and boosts farmer confidence to invest in other improved inputs like fertilizers and insured seeds. As such, the yield benefits of bundled DTM and index insurance are likely to become evident, particularly after a severe drought shock, when adopters recover from their losses with the support of the financial protection offered by index insurance and increase their investments to even higher levels than before the shock. The findings are similar to those reported by Boucher et al. (2024) who argued that bundling drought-tolerant maize with index insurance had no statistically significant effect on yields within the season when the drought shock happened. However, they note that after the drought shock, adopters had a significant maize yield difference of about 335 kg/ha higher than that of non-adopters. Nonetheless, this study concludes that the positive impact of adoption on maize yields could suggest a potential yield benefit obtained from using the bundle.

Table 12: Impact of adopting bundled DTM and Index Insurance on maize yields

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Total Maize Yield (kg per ha)	Unmatched	585.23	599.58	-14.35	37.95	-0.38
	ATT	582.76	580.33	2.43	43.74	0.06

4.4.4 Sensitivity Analysis Results

The results for the simulation-based sensitivity analysis obtained using the sensatt command are presented in this section. These results were important for evaluating the robustness of the estimated ATT results against unobservable confounding factors. The findings in Table 13 showed that baseline ATT was only slightly sensitive to the unobserved confounder, as indicated by the minimal variation in the ATT estimates. In addition, the baseline ATT estimates remained free of unobserved confounders by 91.8%. Furthermore, the selection effect is 0.970, and the outcome effect is 2.447. This implies that, for the estimated impact of adopting bundled DTM and index insurance to be invalid, there must be an unmeasured confounder that can increase the chances of uptake of the bundle by a factor of 0.970 and increase the maize yields by a factor of 2.4, which may not be practical. Overall, these results show that the unobserved confounder has an almost negligible effect because even in its presence, there is only a minimal change in the ATT estimates. This implies that our PSM results about the impact of adopting bundled DTM and index insurance on maize yields were reliable.

Table 13: Simulation-based sensitivity analysis results

Matching algorithm	Baseline ATT	Simulated ATT	Outcome effects	Selection effects
Kernel Matching	10.816	11.781	2.447	0.97

CHAPTER 5: CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

The projections of more frequent and severe droughts leave smallholder farmers with no option but to adopt climate adaptation strategies and boost their resilience. As such, climate adaptation strategies that strengthen smallholder farmers' resilience against drought impacts in vulnerable communities have been advocated. One such strategy is bundled DTM and index insurance, an agricultural innovation that enhances farmer resilience against all forms of drought. However, adoption rates for this innovation remain alarmingly low. Therefore, this study analysed the adoption of bundled DTM and index insurance in Manica Province. Specifically, the study aimed to achieve three objectives: to characterize adopters and non-adopters of bundled DTM and index insurance, to identify factors shaping the decision of smallholder farmers to adopt the bundle, and to establish the impact of uptake on maize yields.

The study used post-project data from a Randomized Control Trial implemented in Manica Province to examine how subsidy strategies influence adoption of bundled DTM and index insurance. Data was analysed using descriptive statistics to characterize adopters and non-adopters, a binary logistic regression model and a stepwise logistic approach to identify factors influencing adoption, and propensity score matching to estimate how adoption influences maize yields.

The results from descriptive statistics showed that only about 25.7% of farmers had adopted bundled DTM and index insurance. A comparison between farmers who adopted and those who did not revealed significant disparities in the means between adopters and non-adopters for DTM awareness, fertilizer use, possession of savings, and farm size. Additionally, adoption was highest among respondents who had received voucher-only and voucher + education subsidy programs, whereas most of the non-adopters did not receive any subsidy or received only the education subsidy program. In relation to the binary logistic regression, the results indicated that factors such as receiving a voucher-based subsidy (alone or combined with education), having savings, awareness of DTM, prior drought experience, and fertilizer use significantly increased the likelihood of adoption. In contrast, ownership of a TV, which was used as a proxy for information access, negatively influenced adoption. PSM results indicated that adopters of bundled DTM and index insurance had 2.43 kg/ha of maize higher than non-adopters, but the yield gain was statistically insignificant.

Generally, these results show that there are socioeconomic differences in the adoption of bundled DTM and index insurance, with women farmers, who contribute much of the needed labour for maize production, more represented among the less-privileged non-adopters. These findings also reveal that access to reliable information plays an essential role in the uptake of agricultural practices. However, it is important to note that poorly communicated information that does not sufficiently elucidate the benefits and performance of the bundled technology may discourage adoption. Furthermore, the results indicate that receiving only an education-based subsidy program had insignificant effects on the adoption of bundled DTM and index insurance. This means that access to information is not enough by itself, but rather access to financial resources through measures like savings, credit, and vouchers, which lower the financial burden associated with purchasing the insured seeds, may be more effective at encouraging adoption.

Further, the PSM results indicated a small but insignificant positive yield gain among adopters. This finding confirms the theory about the nature of performance of bundled DTM and index insurance, especially when faced with severe drought conditions. As such, the benefits of the bundle are more pronounced after a drought shock when farmers increase their investment after receiving the financial compensation. This study concludes that the modest yield gains achieved by the adopters may suggest that the role of the bundled technology may be more about improving resilience and reducing farmer vulnerability to droughts, rather than direct impacts on point-in-time maize yields. Nevertheless, the increasing frequency of droughts makes this bundled technology very relevant, so measures that scale up its adoption among farmers are paramount.

5.2 Recommendations

As noted above, scaling up the adoption of bundled DTM and index insurance will partly require improving information access and relaxing the liquidity constraints to enable farmers access information about the bundle as well as have the financial resources for purchasing the insured seed. As such, policymakers should.

Prioritize farmer awareness campaigns. Although farmer awareness campaigns through different platforms are already in place, they should be redesigned to clearly explain how and when the bundled technology confers its benefits. This will help to clear the uncertainty regarding the performance of the bundled technology, thereby enhancing uptake. However, because most farmers reside in rural areas, the campaigns should be conducted using methods that are easily accessible to the rural households. An example of platforms through which such campaigns can be conducted is the mass media channels like phones (using the Short Message Service (SMS)) and radios, along with training through the local agrodealers and extension personnel.

Access to financial resources plays a crucial role in the adoption of bundled DTM and index insurance. Financial resources can be obtained through savings and credit. Based on the results from this study, having savings and credit access increased the chances of adoption. Therefore, policymakers should focus on strengthening financial structures like Village Savings and Loans Associations (VSLAs), Savings and Credit Cooperative Organizations (SACCOs), women's groups, cooperatives, and commercial banks to improve access to financial resources for investing in the bundled technology.

Respondents who received voucher-based subsidies exhibited higher chances of adopting the bundled technology. Therefore, measures that aim at expanding institutional support to smallholder farmers should be prioritized. This can be done through targeted subsidy schemes, involving seed and input vouchers, price support programs, and insurance premium subsidies. To ensure inclusivity, this support should be directed towards the underrepresented groups, for example the youth and women, who often face liquidity challenges. In this case, farmers will have the opportunity to appreciate the benefits of the bundled technology by experimenting its use at relatively low upfront costs, which can enhance adoption in the long term. Even so, owing to the stochastic nature of benefits offered by this bundled technology, the extended support should be provided over multiple seasons to allow farmers to appreciate its benefits.

However, because the adoption of bundled DTM and index insurance showed no significant differences in maize yields between the adopters and non-adopters, this suggests that there were no measurable productivity benefits observed during the study period. Therefore, the findings from this study do not provide a strong basis for recommending the uptake of this bundled technology as a means of increasing yield outcomes for farmers. Thus, we recommend that future studies should focus on a detailed analysis of the impacts of the adoption of this bundled product to understand its overall effectiveness.

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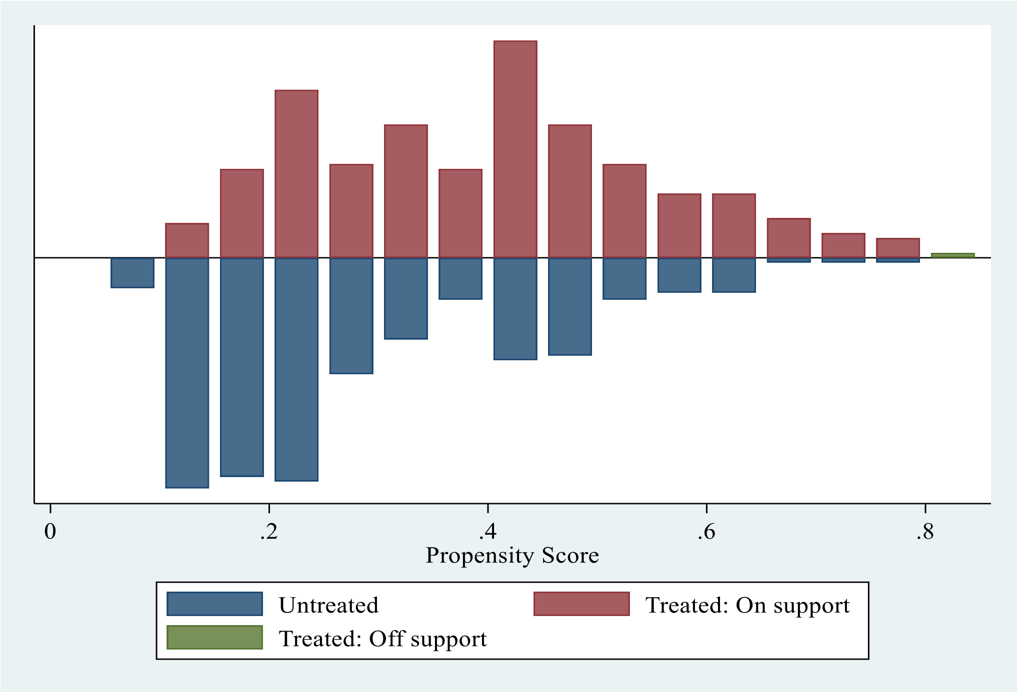
APPENDICES

Appendix 1: VIF Results

```
    Variable |       VIF       1/VIF  
-------------+----------------------
treatment_~s |
          1  |      1.52    0.656701
          2  |      1.50    0.667418
          3  |      1.51    0.663034
  hh_members |      1.11    0.900235
responden~ge |      1.05    0.952686
   education |      1.07    0.932520
income_sha~2 |      1.09    0.915762
drought_ye~s |      1.14    0.873376
improved_~ce |      1.05    0.953148
primary_area |      1.23    0.810743
      credit |      1.06    0.946527
    exp_insu |      1.09    0.920186
      gender |      1.10    0.905857
        info |      1.18    0.846802
DTM_awaren~s |      1.07    0.932602
fertilizer~e |      1.05    0.952887
      saving |      1.11    0.903834
agro_deale~t |      1.03    0.968883
  used_labor |      1.12    0.891675
-------------+----------------------
    Mean VIF |      1.16
```

Appendix 2: Propensity Score Graph



Appendix 3: Pearson correlation coefficient results

```
             | treatm~s hh_mem~s respo~ge educat~n income~2 drough~s impro~ce
-------------+---------------------------------------------------------------
treatment_~s |   1.0000 
  hh_members |  -0.0149   1.0000 
responden~ge |   0.0601   0.0815   1.0000 
   education |  -0.0589   0.0816   0.0893   1.0000 
income_sha~2 |  -0.0209   0.0597   0.0045   0.0949   1.0000 
drought_ye~s |  -0.0128   0.0380  -0.0464  -0.0001  -0.1752   1.0000 
improved_~ce |  -0.0031   0.0460   0.0253   0.0394  -0.0126  -0.0219   1.0000 
primary_area |  -0.0263   0.2142   0.1288   0.1455   0.1365  -0.0842   0.0763 
      credit |   0.0122  -0.0008  -0.0639   0.0044   0.0447  -0.0098   0.0323 
    exp_insu |   0.0069   0.1084  -0.0504  -0.0031  -0.0607   0.0777  -0.0179 
      gender |   0.0147   0.1777   0.0027   0.1989   0.0904   0.0162   0.0461 
        info |   0.0364   0.1087   0.0166  -0.0045   0.0626  -0.2243  -0.0962 
DTM_awaren~s |  -0.0167   0.0352   0.0297   0.0019  -0.0171  -0.1412   0.0261 
fertilizer~e |  -0.0124   0.0711   0.0284   0.0297   0.0313  -0.0828  -0.0334 
      saving |  -0.0043   0.0698   0.0300   0.0266   0.0870  -0.1022  -0.0727 
agro_deale~t |  -0.0120   0.0331   0.0277  -0.0111  -0.0609  -0.0872   0.0130 
  used_labor |  -0.0313   0.0847   0.0719   0.0440   0.0450  -0.0489   0.1160 

             | p~y_area   credit exp_insu   gender     info DTM_aw~s fertil~e
-------------+---------------------------------------------------------------
primary_area |   1.0000 
      credit |   0.0993   1.0000 
    exp_insu |   0.1418   0.0500   1.0000 
      gender |   0.1458   0.0925   0.0600   1.0000 
        info |   0.1212   0.0900   0.1352  -0.0168   1.0000 
DTM_awaren~s |   0.1061  -0.0490   0.0951   0.0320   0.1420   1.0000 
fertilizer~e |   0.1482   0.0492   0.0411   0.0158   0.0775   0.0826   1.0000 
      saving |   0.1449   0.0718   0.1057   0.0187   0.2449   0.0725   0.0853 
agro_deale~t |   0.0086   0.0727   0.0561  -0.0114   0.0801   0.0669  -0.0217 
  used_labor |   0.2632   0.0716   0.1005   0.0546   0.1124   0.1038   0.0859 

             |   saving agro_d~t used_l~r
-------------+---------------------------
      saving |   1.0000 
agro_deale~t |   0.0107   1.0000 
  used_labor |   0.0957  -0.0030   1.0000 
```

Appendix 4: Logit results for estimation of the propensity scores.

```
Logistic regression                                     Number of obs =  1,051
                                                        LR chi2(8)    = 253.27
                                                        Prob > chi2   = 0.0000
Log likelihood = -473.26952                             Pseudo R2     = 0.2111

------------------------------------------------------------------------------------
      adopted_DTM_II | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
---------------------+--------------------------------------------------------------
    treatment_status |
       Voucher Only  |   2.422293   .2696693     8.98   0.000     1.893751    2.950835
     Education Only  |  -.1546414   .3644343    -0.42   0.671    -.8689195    .5596368
Voucher and Education  |   2.406165   .2695019     8.93   0.000     1.877951    2.934379
                     |
       drought_years |   .0672217   .0402318     1.67   0.095    -.0116312    .1460747
                info |  -.3422765   .1945385    -1.76   0.079     -.723565     .039012
       DTM_awareness |   .5050841   .1802842     2.80   0.005     .1517336    .8584347
      fertilizer_use |   .9390586   .4041525     2.32   0.020     .1469343    1.731183
              saving |   .7263244   .1722456     4.22   0.000     .3887293     1.06392
               _cons |  -3.236258   .3152624   -10.27   0.000    -3.854161   -2.618355
------------------------------------------------------------------------------------
```