SCHOOL OF
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# From Cash to Crop

## How Can Financial Inclusion Create a Sustainable Cereal Production in Tanzania?

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## Abstract

This study explores the nexus between financial inclusion and agricultural productivity in Tanzania, where agriculture is a key sector for the nation's economy and inclusive growth. Vulnerable to climate change, the sector faces productivity challenges due to rain anomalies and rising temperatures. Previous studies have highlighted financial inclusion as crucial for reducing vulnerability at the household level, but its impact on climate adaptation in agriculture is unclear. Using multiple linear regressions, this research examines the effect of access to various financial services on agricultural productivity, measured as cereal yields. Despite overall weak results, the study concludes that mobile money and informal savings groups are microfinancial services tend to increase crop yields, other formal microfinance institutions show negative effects. Access to commercial banks also increases cereal yields. These nuanced, yet inconclusive findings provide empirical evidence on the role of financial inclusion for climate adaptation, offering valuable insights and for future research aimed at enhancing agricultural productivity and climate adaptation in Tanzania.

**Key words:** Agricultural productivity, Climate Change, Environment-Poverty Nexus, Financial Inclusion, Food Security, Microfinance, Sub-Saharan Africa (SSA), Tanzania

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# 1. Introduction

With the rapid increase in global warming is causing severe challenges in many Sub-Saharan African countries, including droughts, biodiversity loss and higher levels of food insecurity among other challenges. Tanzania is no exception and faces large issues primarily in handling irregular rain. Climate change hinders agricultural productivity and threatens the livelihood for many households that depend on small-scale, rainfed agriculture (Trisos et al., 2022, pp.1289-1290, 1350). Unreliable rain has led to both crop failures and livestock diseases undermining food security in Tanzania (Chirambo, 2016; Zougmore et al., 2018), despite being the host for many different biomes and growth possibilities (Jafo, 2021; Ministry of Foreign Affairs and East African Cooperation, 2024) . Investments in agriculture to better handle these shocks remain limited when access to the financial markets and credits are limited. Productivity may stagnate or even decline as global temperatures continue to rise. Despite the pressing needs, the available climate finance are not near the required levels, (Jafo, 2021; Trisos et al., 2022, p.1289 ; Zougmore et al., 2018). A majority of international climate finance towards countries in Sub-Saharan Africa is focused on climate mitigation rather than adaptation, despite Africa being the smallest contributor of greenhouse gas emissions (GHG) (Chirambo, 2016, p.198; Trisos et al., 2022, p.1305-1306).

Many scholars have identified inclusive access to financial services as a possible solution to unlock the much-needed climate finance and help rural communities adapt to climate change (Hammill et al., 2008; Lobell et al., 2013; Prabhakar, 2017). Climate adaptation is defined as the adjustment in natural or human systems that moderates harm or exploits beneficial opportunities from climate stimuli or their effects (Lobell et al., 2013). Expanded financial services like microfinance institutions, informal saving's groups or mobile money agents allows for better investment and savings opportunities for climate vulnerable individuals and rural communities as they are more accessible and offer services that reflect their needs. It has the potential to create pro-poor growth to benefit the broader economy (Klapper et al., 2016; Lyons et al., 2020; Polloni-Silva et al., 2021). Several papers (Abiona & Koppensteiner, 2022; Lyons et al., 2020; Mhlanga, 2022) report on the recent digitalisation wave that increased the number of financial services and innovations that reduce the barriers even further for financial inclusion and socio-economic improvement in Sub-Saharan Africa, and East Africa in particular. Including those who are financially excluded could increase climate adaptation funding as demands for climate adaptation investments increase for those who are most climate vulnerable. (Chirambo, 2016 p.198, 2017; Hammill et al., 2008; Prabhakar, 2017). Microfinance institutions and other financial institutions are seen as an important tool for eradication of poverty and small business development and has been promoted by various policies by the Tanzanian government in the 21st century (UN Capital Development Fund, 2022).

While there is extensive literature on how financial inclusion could lead to reduced vulnerability for people in poverty, there is no empirical evidence on how it could help communities to adapt to climate related issues at larger scale. Previous studies focus on how vulnerability is affected by access to financial services at the micro level and for individuals. When studying traditional measurements of financial inclusion, such as access to ATMs, possession of credit or debit cards, increased financial inclusion leads to higher GHG emissions, which could enhance future climate risks and pose a dilemma for developing countries (Liu et al., 2022; Lyons et al., 2020; Renzhi & Baek, 2020; Zaidi et al., 2021). Additionally, Nyiwul (2021) finds that the correlation between increased economic activity and GHG emissions are especially strong in places where inequality levels are high. As the nature-dependency is high in Tanzania (Fedele et al., 2021) it is vital to make policy decisions that develop financial services and economic activity in a way that does not deplete natural resources. Unsustainable agricultural practices could increase the risk of rural households leading to unsustainable indebtedness and worsened prospects for economic development (Awad & Warsame, 2022). The agricultural sector is the most important sector in Tanzania while simultaneously being the most vulnerable sector to climate change (IMF, 2023). Basing the empirical analysis on the Microfinance-Climate framework (Chirambo, 2016, pp. 201-204 , 2017; Hammill et al., 2008), this study will investigate multiple financial institutions and connect it to our current knowledge of climate change and its effect on the agricultural sector to answer the main research question:

*How can access to financial institutions increase cereal productivity in Tanzania?*

The purpose of this thesis is to empirically test how different financial institutions and services can affect climate adaptation mainly through investment in the 21st century. The crop group cereals includes many important staple crops with a positive impact on both poverty alleviation and food insecurity(Chepng'etich et al., 2015; Ngailo et al., 2016; Rowhani et al., 2011). The productivity is measured in yields which is a good measurement for agricultural productivity that also reflects the capacity of climate adaptation (Arslan et al., 2016; Rowhani et al., 2011). By investigating several financial services at the sub-national level, the study contributes to a more nuanced presentation on the dynamics of different financial institutions. In contrast to previous studies that have focused on vulnerabilities at the micro level without assessing the impact at large scale, this study shifts the focus towards the potential spillover effect access to financial institutions have at the sub-national level. This contributes to our understanding on the role of financial institutions to increase agricultural productivity in a low-income setting that is negatively affected by climate change.

Section 2 gives background information on Tanzania's economy and geography, the agricultural sector, and the development of financial institutions during the 21st century. Section 3 presents the theory of this study, including a literature review, presentation of the theoretical framework and the hypothesis statement. Section 4 describes the methodology, the empirical model and shows descriptive statistics used for the analysis. Section 5 presents the results and discuss how it relates to the theoretical framework and previous literature. Section 6 concludes the main points of the study.

# 2. Background

Located in Eastern Africa, the United Republic of Tanzania is one of the largest countries in the region with approximately 63 million habitants, a total area of 945,087 km$^2$, and a coastline of 1,424km towards the Indian Ocean. In addition, there are two major islands by the east coast with tropical and humid climate, Unguja and Pemba (Ministry of Foreign Affairs and East African Cooperation, 2024; World Bank Open Data, 2024). Most of Tanzania lies in the tropical climate zone, yet there is great variation of the climate within the country. From hot and humid coastal regions to semi-arid zones in the central plateau, to temperate highland areas in the south. The vast landscapes hosts biodiversity hotspots and globally significant ecosystems that attract many tourists and the sector that is a major component of Tanzania's economy (Ministry of Foreign Affairs and East African Cooperation, 2024). However, both of these sectors are at risk with the increase of average temperatures and climate change, and with the recent reduction in tourism due to the Covid-19 pandemic, reliance on agricultural output have become more important than previously (World Bank, 2020). The transportation sector, tourism and export market were the worst affected by the pandemic, other sectors fared better and Tanzania showed the strongest economic resilience of the Eastern African countries (World Bank, 2020). Despite the challenges and high levels of poverty in Tanzania today, the share of the population living on less than 2.15 US$ per day has reduced rapidly during the from 84 percent in 2000 to 45 percent in 2018 as the result of the high economic growth (World Bank Open Data, 2024). As of 2019, Tanzania is a lower-middle income country, surpassing the threshold of gross national income (GNI) per capita levels of 1035 US$ after a long period of robust high-income growth.

Figure 1 shows the net adjusted GNI in Tanzania between 1995-2021, reflecting this positive trend (World Bank, 2023). The net adjusted GNI subtracts the investments in fixed capital and natural resource depletion similar to depreciation costs in fixed assets to account for the decline in natural assets. While the economy as a whole avoided a recession during the Covid-19 pandemic in 2020, the growth rates lowered to levels that decreased the per capita income level to 1009 US$ (constant 2015 US$, World Bank, 2020; 2024). In comparison, the adjusted GNI per capita showed 881 US$ during 2020 (World Bank, 2023). Despite high deforestation rates during the 20$^{th}$ century for new agricultural lands (Jafo, 2021), the adjusted GNI per capita have  shows positive growth rates in Tanzania, with the exception of 2006-2012 where the trend stagnated and even retracted which recovered quickly. This trend indicates a more sustainable use of natural resources in the country while still generating increased incomes.

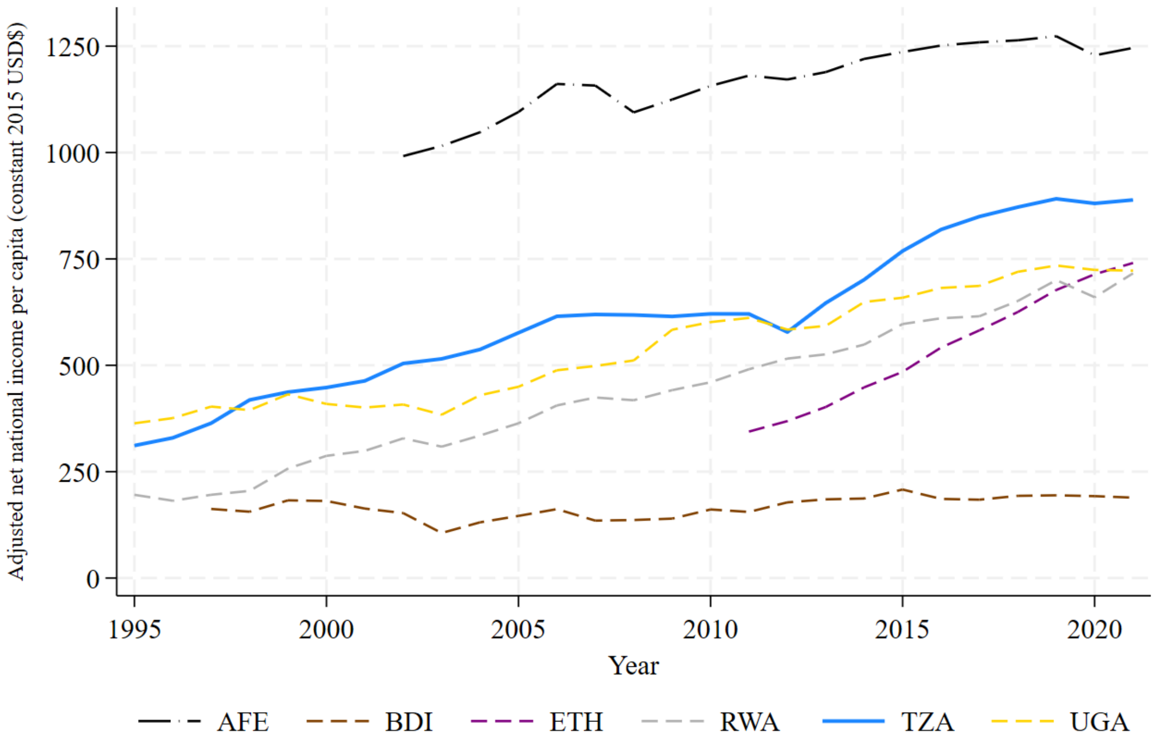


Figure 1 - Adjusted net national income per capita in Tanzania between 1995-2021.
Note: AFE = Eastern and Southern Africa, TZA = Tanzania
Source: World Bank Open Data, 2023

## 2.1 The agricultural sector in Tanzania

Figure 2 shows that the agricultural sector in Tanzania is the most important sector as it absorbs a majority of the labour force in the country (World Bank, 2023). The negative trend reflects a very slow transition to other sectors between 1991-2021, from 85 percent to 66 percent. Compared to other regions, the employment share in the agricultural sector in East African countries is higher than the average employment share in Sub-Saharan Africa and much higher than the world average. In contrast to manufacturing and capital-intensive industries, like mining or constructing, the agricultural sector is labour intensive and foundational to drive structural transformation and increase primarily rural incomes (Andersson & Palacio Chaverra, 2016; Chirambo, 2016, p.198). However, the agricultural sector has not led to increased income and development in Africa during the 20th century same way frontier growth led to development in the US and Asia previously (McMillan et al., 2014). Many are forced to stay or even return to low productivity sectors due to the lack of job opportunities in high productivity sectors, reversing the labour flows to low productivity sectors in many developing countries. Frontier growth in manufacturing and industry have been focusing on capital deepening and depletion of natural resources rather than labour intensive manufacturing. Furthermore, the increase in global food prices and commodities have made agriculture an attractive sector to engage in, giving rise to numerous agribusinesses serving the agricultural sector (Andersson & Palacio Chaverra, 2016). Several developing countries that have encouraged natural resource-based development like agriculture and mining have also encouraged land expansion into fragile lands. Fragile lands are areas that are crucial for the rural communities sustainability, pastures, forests and other natural resources simultaneously constraining for intensive agriculture (Barbier, 2012). These lands usually have lesser soil quality and low yield rates that reduce profits and land rents with possible spillover effect to other sectors. Therefore, there are needs to increase incomes in agricultural production without causing land expansion into fragile land and depletion of natural resources.

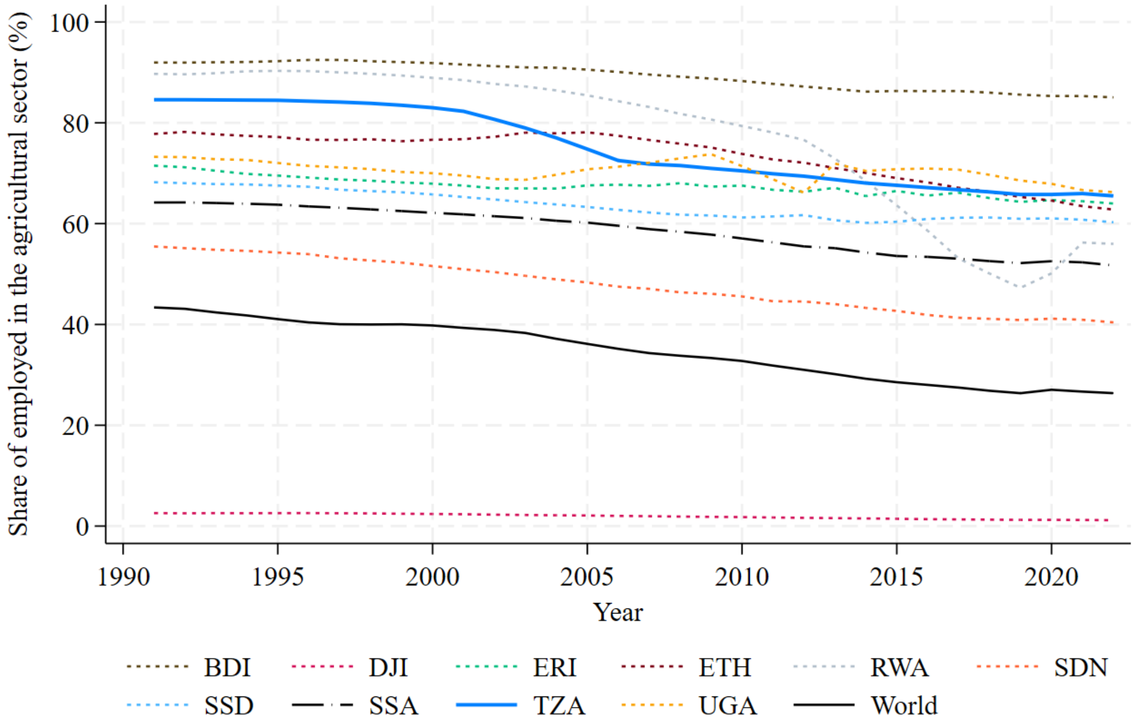


Figure 2 – Employment in the agricultural sector in nine East African countries.
Note: SSA = Sub-Saharan Africa, World = Worldwide average employment share.
Source: World Bank Open Data, 2023.

The most common agricultural activity in several Sub-Saharan African countries is small-scale subsistence farming, mixing both crop production, fishery and livestock (Trisos et al., 2022, p.1350). The varying landscapes and climate zones create a large and diverse agricultural sector, including cash-crops, horticulture for exports and commercial production of staple crops. Besides being an important source of employment, Tanzania GDP is to a large extent reliant on agriculture, making the overall growth levels sensitive to climate change, which is why climate adaptation is the main focus in Tanzania's Nationally Determined Contribution (NDC). Both Pauw & Thurlow (2011) and Rowhani et al. (2011) raise that cereal production is important to reduce vulnerability and food insecurity as it includes many staple crops, maize being the most important crop among cereals. Approximately 45 percent of cultivable land is growing maize, which makes it one of the major crops to improve food security in particular. It is furthermore the main economic driver for many households (Arslan et al., 2016; Rowhani et al., 2011). Improved seeds, maize-legume intercropping, and fertilisers improve maize yields. These effects are enhanced when combined with soil and water conservation practices (SWC). However, as these inputs are expensive, many farmers are limiting their use of sustainable practices which lowers overall productivity and crop yields (Arslan et al., 2016; Gerber et al., 2024).

Rice is an important crop in the southern highlands and is usually grown together with other cash crops, like tea leaves, to increase household income (Ngailo et al., 2016; Pauw & Thurlow, 2011). In addition, there are several initiatives to increase productivity as rice is seen as an important crop to eradicate hunger and food insecurity. Rice productivity is low despite that these regions have the most favourable climate for growing rice. Primarily due to poor soil quality, monocropping, low use of fertilisers and other poor agricultural practices. Other barriers are limited access to markets, unreliable rainfall, diseases and pests, and inadequate capital to invest and receive agricultural inputs. Sorghum is especially important in the semi-arid areas in the central regions as it is a drought resistant crop and has good nutritional value. Sorghum is another important cereal crop with strong growth-linkages for inclusive growth. Therefore, increasing yields in sorghum have strong impacts in food insecurity and poverty alleviation (Pauw & Thurlow, 2011; Rowhani et al., 2011). Regardless of the cereal crop, many farmers face market constraints to successfully maximise all types of cereal yields. Improvements in market access, reduced costs of inputs and development of upstream linkages are important to increase production of cereals (Pauw & Thurlow, 2011).

## 2.2 Financial Inclusion in Tanzania

With increased optimism of the impact on financial institutions already in 1991, the Tanzanian government decided to reform the financial sector drastically to increase the private sector involvement and competitiveness in production. By 2000, the government adopted the National Microfinance Policy to increase efficient financial institutions and to eradicate poverty through better access to financial services. This led to the expansion of Microfinance Institutions (MFI), with the main objective to supply small enterprises and low-income households with affordable financial services. By 2021, there were five tier 1 MFIs, 578, tier 2 MFIs and 369 licensed Savings and Credit Cooperatives Societies (SACCOs) (UN Capital Development Fund, 2022). Other informal institutions are local informal savings groups that do not require licence, registration, or supervision from the government. These institutions are non-deposit microbanks solely dependent on the savings from the members. They can include Rotating, Savings and Credit Associations (ROSCAs), Accumulated Savings and Credit Associations (ASCAs), or Village Savings and Loans Associations (VSLAs) (National Microfinance Policy, 2017). Both MFIs and SACCOs are formal non-bank institutions that need a licence to operate and can offer deposit-taking services. The main difference is that SACCOs are cooperatives owned by their own member, while MFIs could be owned by both profit and non-profit organisations. In contrast, Informal saving's groups are usually dependent entirely on their member's pooled savings. While recent policies have made these institutions better at assessing risk, ensuring smooth business operation and filtering out less serious creditors over time, there are still challenges in outreach and accessibility. Most of these MFIs are concentrated in certain urban regions (UN Capital Development Fund, 2022). Hammill et al. (2008) report this pattern when studying microfinance institutions and discuss how MFIs are still not serving those who are most climate vulnerable due to geographical placement, limited education, management capacity or collateral.

The increased uptake of mobile money in East Africa has created better opportunities to underserved group to get access to financial services. The expansion of mobile money has decreased transaction costs and can facilitate risk sharing across larger distances and more diverse senders, increasing the potential outreach to rural people that are vulnerable to climate change more than other microfinance institutions (GSMA, 2023). In Tanzania, the majority of people who have an account at a financial institution have an account with a mobile money agent. While Kenya has been the leading country in the rapid expansion of mobile money in Sub-Saharan Africa, the development in Tanzania as an early adopter has been similar since the first launch in 2009. By 2015, 38 percent of adults had a mobile money account and 36 percent of all money transfers were through mobile money services (Abiona & Koppensteiner, 2022), by 2021 the share of the adult population with a mobile money account was 45 percent according to the Findex database, an increase with 18 percent in six years which is a faster adoption rate than other financial services (Demirgüc-Kunt et al., 2022). The FinScope 2017 reports that on average 55 percent of households had access to mobile money, indicating a larger increase of uptake (FSDT, 2023).

# 3. Theory

This section presents the current research gap in the nexus of financial inclusion and climate adaptation and states the theoretical framework than can shed new light in the research area. Section 3.1 presents a literature review with current knowledge in agricultural production, access to finance and climate vulnerability and lesson from all three disciplines are combines to present the conceptual framework in section 3.2 and the hypothesis in section 3.3.

## 3.1 Literature Review

While there is a growing amount of literature regarding financial inclusion and its impact on poverty, inequality and the development goals, there is little knowledge of how it affects climate related risks. There is even less literature reviewing the macroeconomic impact from access to financial services as many studies focus on microlevel effects and vulnerabilities for households. Hammill et al. (2008) report that the empirical evidence that do exist in the literature is spread too thin to draw any firm conclusions. The Intergovernmental Panel on Climate Change (IPCC) sixth assessment report also highlights the scarce literature on the subject as of today (Trisos et al., 2022, p.1303). Whether the net effect from financial inclusion on climate adaptation is positive or negative at the sub-national level is still unknown. Therefore, lessons from both the literature on financial inclusion and from agricultural development are needed to understand the relation between microfinance and climate vulnerability in Tanzania.

### 3.1.1 Climate Vulnerability

Sub-Saharan Africa (SSA) is one of the most vulnerable regions due to their high exposure to extreme weather, heavy reliance on rain-fed agriculture, and scarce water resources (Trisos et al., 2022, p.1350; Zougmore et al., 2018). Tanzania face issues regarding irregular precipitation and increased number of floodings despite that droughts are the primary issue in East Africa. Between the years 1980-2022, approximately two thirds of all natural disasters were due to flooding and the recurrence is increasing for each decade (International Monetary Fund (IMF), 2023). Together with droughts, storms and epidemics, Tanzania has become one of the top ten countries in Sub-Saharan Africa with the highest frequency of natural disasters. Food insecurity remains a concern as much of the agricultural production and climate change is set as the primary driver for increased food insecurity (IMF, 2023). The IPCC sixth assessment report confirms that extreme events such as droughts and flooding continue to negatively impact food production, water security and economic growth. 63 percent of farmers in East Africa have reported that weather conditions have worsened the opportunities for growing crops (Trisos et al., 2022, p.1316). Other studies have also shown that temperature and rain anomalies have had a negative impact on production and growth rates in the agricultural sector (Brown et al., 2011; Meehl et al., 2000; Rowhani et al., 2011). However, Rowhani et al. (2011) finds that some crops seem to benefit from the increased rain levels when studying the effect of climate variability on different crop yields in Tanzania. Both maize and sorghum are predicted to increase yields even at rain anomalies at 20% above normal levels. However, they also note that while increased precipitation levels are favourable to some major crop groups in Tanzania, extreme high levels of both rain and temperature have a negative impact on yields. In addition, extreme fluctuations in precipitation have large negative impacts on growth despite the initial positive effect on some crop yields from higher annual rain (Arslan et al., 2016; Brown et al., 2011).

Agricultural productivity and food security will be a greater issue in the future due to the lack of climate finance to handle the increasing climate variability as the global temperature continue to rise according to IPCC predictions. This enlarges the already great finance gap for Tanzania. The financial needs for Tanzania to be able to respond to climate change between 2020-2030 is estimated to be 3.4 billion US$ a year. This can be compared to the financial needs of 20 billion US$ stated by the government in their NDC as of 2021 (Jafo, 2021) to address both adaptation and mitigation issues without hampering the economic development in other sectors. The average per capita emissions in Tanzania were approximately 0.22 tCO2e in 2014 compared to the global average of 7.58 tCO2e (Jafo, 2021). Tanzania state high ambitions of climate mitigation despite low emission levels, yet the NDC highlights that the main priority for the government is to reduce the impact of climate change (Jafo, 2021). Nonetheless, the government needs to find ways to catalyse finance flows into order to achieve their goals in the NDC. Lobell et al. (2013) focus on agricultural productivity and total factor productivity increases from investments in agricultural R&D. Their findings show that investments in R&D leads to higher productivity in the agricultural sector which decreases vulnerability through both climate mitigation and adaptation. Investments in drought-resistant seeds or irrigation systems increase yields as farms become less dependent on weather patterns and face less damage costs due to extreme weather. Additionally, areas with higher crop yields have lower demand for further farmland expansion. In some regions where the frequency and severity of droughts have increased, many farmers have been forced to change their agricultural practices and the crops they are growing (Pauw & Thurlow, 2011). Therefore, agricultural productivity might also be dependent on which crops farmers choose to grow that in turn is endogenous to long-term average rain levels. This might lower production levels for some crops yet increase the overall level for agriculture. Abdelzaher et al. (2020) studies the reverse causality between climate risk and R&D investments by investigating how climate vulnerability affects the share of innovations dedicated to climate adaptation and mitigation. Their results show that more vulnerable countries dedicate a larger share of investments into climate adaptation, which reduce climate vulnerability the following year. Despite the possible improvements in agricultural productivity, an increase of investments and innovation in the agricultural sector will most likely still lead to farmland expansion and deforestation in Sub-Saharan Africa due to the rapid population growth and prevailing food insecurity, yet to a lower extent that what is projected without innovation and investments in the agricultural sector (Lobell et al., 2013).

### 3.1.2 Nature Dependency and the Environment-Poverty Nexus

Nature-dependency is defined as those who have direct dependency on natural resources to maintain their livelihood and well-being. For example, it includes those who the use rivers as a source of drinking water instead of water pumps, or collect biomass fuel directly from the forests. Fedele et al. (2021) use worldwide surveys between 2010 to 2018 to identify areas of high nature-dependency and to what extent people depend on their surrounding nature. The surveys include in total over 5 million households. Their results show that 48 percent of people in Africa are highly nature-dependent, a much higher compared to other regions, like tropical Asia-Pacific (27 percent) and the Americas (9 percent). In Tanzania, no sub-national region had less than 40 percent of the population being nature-dependent in any way and a total 80 percent of the population were highly nature dependent. Almost 35 percent out of these 80 percent are dependent on nature across all areas listed in the study: water, housing, occupation, and energy. Moreover, over 80 percent in all regions are dependent on biomass energy sources. Fedele et al. (2021) state that nature-dependent people are particularly vulnerable to climate change as climate variability impacts the resources available for those who depend upon them. This implies that many in Tanzania are highly vulnerable to climate change and its impacts.

Following the implications of nature dependency, Awad and Warsame (2022) studies the environment-poverty nexus and the environmental Kuznets curve in developing countries. According to the environmental Kuznets curve, alleviating poverty will lead to more engagement in economic activities and energy intensive industries that depletes the limited natural resources. This development worsens the opportunities for future generations or other marginalised groups that depend on these natural resources for future production. As a majority of poor people in Africa is reliant on agriculture and other natural resources, it is vital that developmental strategies incorporate environmental concerns to make poverty alleviation sustainable in the long run (Awad & Warsame, 2022; Fedele et al., 2021). However, these policies are usually costly for the economy which presents the Environment-Poverty nexus dilemma. The strongest correlation between economic growth and environmental degradation is found in Sub-Saharan Africa. With limited technology, rapid population growth and a large portion of smallholder farmers depending on rainfed agriculture, many expand their farm areas into more arid areas and cope with low productivity. This feeds into further soil degradation and overgrazing that require more land expansion (Awad & Warsame, 2022; Barbier, 2012). Although more resources are needed in both climate adaptation and mitigation in Sub-Saharan Africa, Lobell et al. (2013) conclude that in the long-run it is more profitable to focus investments on climate adaptation as investments in climate mitigation would have little impact on the global trends in temperature and precipitation. The previous rapid deforestation and overgrazing is a major concern in Tanzania and restoration of these forests are a priority in their NDC plan to address climate mitigation (Jafo, 2021). Nevertheless, protecting forests also provides benefits like flood protection for communities and better soil, which makes reforestation a good adaptation strategy as well (Fedele et al., 2021; IMF, 2023).

### 3.1.3 Financial Inclusion

Financial inclusion expands on the term financial development and includes targets towards financial services that are accessible, affordable, and safe for all, in particular for people living in poverty. Financial inclusion is seen by many scholars as a powerful tool to reduce poverty, vulnerabilities, and income inequality in the long term. Additionally, financial inclusion has shown to increase food security and improve health. It has therefore the potential to create pro-poor growth and economic development. The empirical evidence is strong and consistent across different regions globally (Klapper et al., 2016; Lyons et al., 2020; Polloni-Silva et al., 2021). Expanded financial services allows better investments and savings opportunities and improved financial control that better reflects the needs of people living in poverty. Lyons et al. (2020) and Mhlanga (2022) write that the recent digitalisation in Sub-Saharan Africa has increased the number of financial services and innovations further, reducing the barriers for financial inclusion and catalysed socio-economic improvement in rural communities more efficiently. More households and companies can successfully use financial instruments to make investments for better agricultural production. This also steers the market towards innovation that are better adjusted for the needs of the rural poor as those who are financial excluded in rural communities might have the knowledge of how to address climate adaptation, but lack the capital (Mhlanga, 2022). Various services for microfinance have been effective in increasing the uptake of financial services (Chirambo, 2016; Hammill et al., 2008) as they ease credit-constraints for those with low income and no collateral. Most importantly has been the increased use of mobile money (Abiona & Koppensteiner, 2022; Lyons et al., 2020; Mhlanga, 2022). GSMA (2023) latest report confirms previous literature on the socio-economic impacts of increased mobile money services, mobile money has led to higher economic growth in a similar way as increased access to traditional financial services. With lower transaction and operational costs, mobile money agents become an even more attractive option for those outside the financial market.

Unfortunately, there is evidence that increased financial inclusion leads to more greenhouse gas emissions in compliance with the implications of the Environment-Poverty Nexus dilemma (Awad & Warsame, 2022). As more people become economically active, their increased consumption and production leads to more pollution and accelerates climate change, which in turn amplifies climate risks in the long run. Several scholars have shown that financial inclusion is positively correlated with higher CO2 emissions, both globally (Renzhi & Baek, 2020) as well as regionally in Asia, OECD and Sub-Saharan Africa (Liu et al., 2022; Lyons et al., 2020; Zaidi et al., 2021). On the contrary, Renzhi & Baek (2020) show results that indicates that the correlation follows an inverted U-shape of the Environmental Kuznets Curve, and that the CO2 emissions can decouple from increased financial activity at very high levels of access to financial institutions. Nyiwul (2021) adds another nuance to the pattern and finds that in countries where social inequality is high, efforts in climate adaptation and mitigation are lower at higher levels of economic activity. Those who are emitting greenhouse gas emissions are not affected by climate change which lowers the incentives to change production into sustainable economic activities.

### 3.1.4 Microfinance and Climate Adaptation

To realise the potential benefits from financial inclusion in reducing climate vulnerability, it is important to understand that different climate adaptive mechanisms are needed in different settings. Castells-Quintana et al. (2018) state that microfinance in the form of cash-transfers and insurance programs through various financial institutions are effective in areas where more severe weather conditions occur but with lower frequency. Cash-transfers also shows promising results in poverty alleviation as it helps those who are most vulnerable and might not have the means to make any investments (Hammill et al., 2008; Prabhakar, 2017). Studying Tanzania in particular, Abiona and Koppensteiner (2022) show that the introduction of mobile money has made households able to smooth out their consumption over temporal shocks and rain anomalies. They use a linear probability model and state that the risk of households getting pushed into poverty during rain anomalies is lower for those that have a mobile money account. These household were also less likely to diversify their incomes and use child labour to compensate for the climate change damage. Despite a reduction in the probability of falling into poverty with mobile money, the effect is outweighed by the general effect rain anomalies have on poverty. Implying that access to mobile money might not always cover for the entire loss during weather shocks.

According to Chirambo (Chirambo, 2016, p.205, 2017), climate adaptation investments have the potential for positive spill-over effects that can create more dynamic markets and better job opportunities as production increases. In Kenya, access to agricultural credit and membership in farmer’s groups have shown to be important drivers to increase productivity for sorghum (Chepng’etich et al., 2015) a crop that has become increasingly important in Tanzania (Rowhani et al., 2011). These associations increase information sharing between members, reduce price of inputs through purchases in bulk and better investment decisions through support of the association in addition to pooling savings and loans. Similar positive effects are observed when studying fish farmers in Madagascar, where support for managerial and technical skills further enhance the positive effects of cooperatives for both food security and incomes (Angermayr et al., 2023). In areas where extreme weather is more frequent it is better to aim for microfinance services that foster investments and innovation for climate-resilient technology and infrastructure. Tanzania which is one of the countries with the highest frequency of natural disasters in Sub-Saharan Africa (IMF, 2023) could benefit from better investment environment to secure the resources for adaptation for vulnerable and nature-dependent people.

Hammill et al. (2008) point out that even if microfinance has the potential to alleviate poverty and reduce risk from climate change, they also have the potential to enhance climate vulnerability. The main source of risk is unsustainable indebtedness without a secure source of income. Using financial instruments to invest in a deteriorating agriculture sector only leads to maladaptation, and credits are better used to either diversify the household’s income in other sectors or to reduce risk through e.g. investments in irrigation systems or other climate resilient seeds (Castells-Quintana et al., 2018; Hammill et al., 2008). Furthermore, they note that microfinance institutions also have limited outreach, and those with the lowest income are still unable to benefit from microfinance. This is also reported in the FinScope 2017 report, stating that the main barriers for formal microfinance institutions like MFIs and SACCOs are due to high membership fees, interest rates or income requirement (FSDT, 2023). They also argue that there is not enough evidence to understand if financial inclusion and the use of microfinance provides a pathway out of poverty or if it is only a tool to handle climate damage costs smooth out consumption over time. Furthermore, as financial inclusion leads to higher carbon dioxide emissions and land degradation, the exposure to climate risks increase when more people engage in economic activities (Hammill et al., 2008; Liu et al., 2022; Renzhi & Baek, 2020). This poses higher risks and vulnerability on top of the increased risks that arise due to the negative externalities of others engagement into the financial markets, especially in countries with high inequality levels (Nyiwul, 2021). Therefore, financial deepening and more engagement into economic activity might also increase climate vulnerability and deepen environmental concerns for those who are still excluded from the financial market. Without access to formal financial institutions of any kind, some resorts to informal, non-efficient and expensive financial institutions as an alternative to pool risks related to the climate, like moneylenders (Chirambo, 2016, p.200). These instruments might still have a positive effect for the household's income yet to a lesser extent than regulated microfinance institutions due to the insecurity of such services.

## 3.2 Conceptual framework

Building on the current knowledge of microfinance, financial inclusion and climate vulnerability, Chirambo (2016, p.201-204) presents a Microfinance-Climate Finance framework that focus on the impact of revolving loan funds, similar to how MFIs and other informal savings groups operate. In formal banking, the credit constraint sets barriers to facilitate investments among the rural poor that are both unable to fulfil the demands of collateral and too risk aversive to take credits for investments at the offered interest rates. Due to underinvestment, communities are trapped into low productive agricultural practices (Castells-Quintana et al., 2018). However, microfinance institutions emerge where commercial banks are missing and can provide loans at lower rates and ease financial constraints for risk-aversive households who lacks collateral. Since they provide loans and not grants, the institutions are sustainable through recycling of resources, simultaneously as they are pooling risks in the community. The conceptual framework that outlines the foundation of this study can be summarised in figure 3, which highlights the potential benefits from all forms of microfinancial services. The framework is to a large extent based on the theories presented in Chirambo (2016, pp.201-204; 2017) but also draws lessons from Hammill et al. (2008). Microfinance institutions, mobile money and informal savings groups have the potential to increase climate resilience and adaptation in local communities, as long as they provide a range of different services to rural communities (Castells-Quintana et al., 2018; Chirambo, 2016, p.200). The main benefit of microfinance is that they are more accessible as these institutions are spread out geographically, have efficient transaction costs and lower demand for collateral in comparison to commercial banks as they can operate at smaller scales and face lower operational costs themselves. While this paper focuses on factors that increase agricultural productivity directly, microfinance can also indirectly impact climate resilience and adaptation in agriculture, like women empowerment and better education, that in turn improve financial literacy and land management.

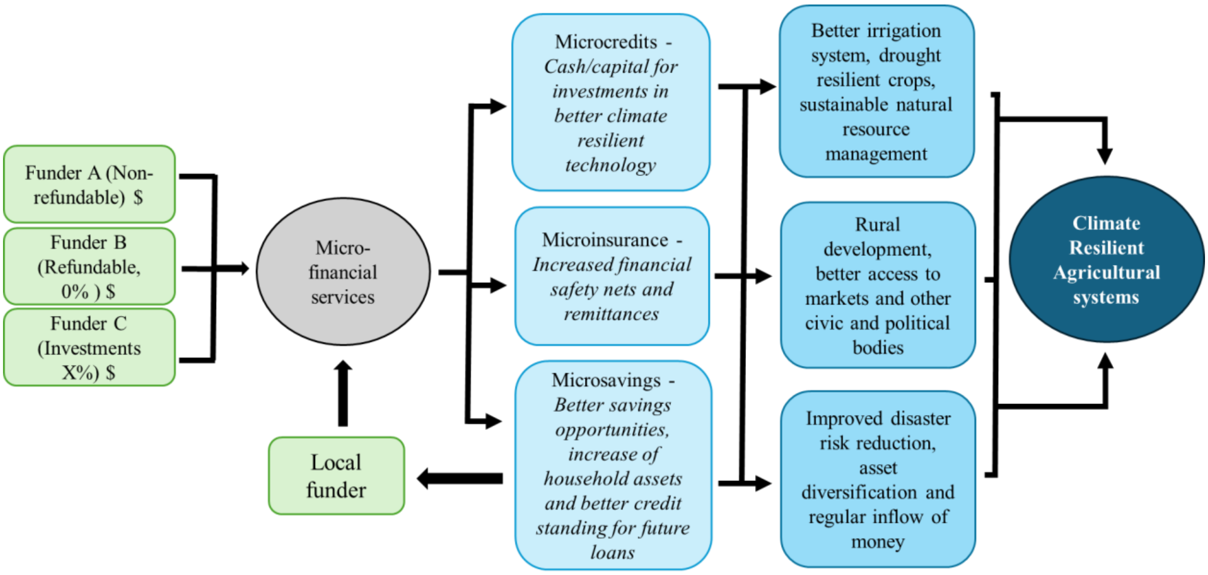


Figure 3 - Microfinance-Climate Framework for increased agricultural productivity.
Source: Authors own, based on Chirambo (2016, pp. 201-204) and Hammill (2008)

The various microfinancial services collect funds from a variety of investors to raise money for important investments or recovery of climate variability damage. This includes individuals, local organisations, banks, governments, and both multilateral and bilateral development aid organisations. These organisations could also be operating non-profit microfinancial services themselves, which lowers costs even further for creditors. Funder A are the entities that make donations to microfinance and other development projects and require no refunds, the mobile money agent, savings group, or MFI only becomes the intermediaries between private investors and the creditors. Funder B are mostly development banks, government and local communities that support MFIs and mobile money with refundable loans, yet to an almost zero percent interest rate. At last, Funder C are different institutions and private investors who supports development projects through microfinance with an expected return to their investments. This can become a powerful development tool that can mobilise more resources and narrow the climate finance gap in many Sub-Saharan African countries as more risk aversive lenders are pooled together with development agencies and donors (Chirambo, 2017).

When loans become more accessible, investments in climate resilient technologies and systems are expected to increase, which also creates jobs in rural areas and scale-up agricultural production. Together with technological developments in telecommunication, better sharing of information and transfer of money, the crowdfunding and peer-to-peer lending can be cheaper and hence offered at lower rate which increase the number of individuals who can participate (Chirambo, 2016, p. 202-204; Hammill et al., 2008; Mhlanga, 2022). Hammill et al. (2008) show the importance of other microfinancial services, like insurance or beneficial loans for education, to increase incentives for investments in the agricultural sector and small enterprises, as different contexts require different services. All three channels, investments, savings and insurance contribute to better agricultural systems that can withstand weather shocks and keep productivity at a higher level. Mainly through investments and instruments that decrease incentives to use saved money for consumption during crises. Other scholars (Lobell et al., 2013; Mhlanga, 2022) who have studied on the same topic have made similar conclusions that complies with the Microfinance-Climate Framework.

### 3.2.1 Defining Climate Adaptation in the Agricultural Sector

Lobell et al. (2013, p.2) states that climate adaptation, "is often defined as 'adjustment in natural or human systems in response to actual or expected climatic stimuli or their effects, which moderates harm or exploits beneficial opportunities". With this vague description, climate adaptation could imply a variety of mechanisms that are context specific and difficult to quantify. Usually, climate adaptation involves the interdependence in several sectors to move resources where they are most needed. A community that is climate vulnerable will experience negative disturbances in productivity during rain anomalies and face difficulties returning to the original level of well-being. Whereas a resilient community might be quicker to recover to earlier productivity levels. Adaptive communities have the infrastructure and technology to withstand weather shocks with little impact on the productivity levels and can focus on increasing productivity. Therefore they can handle reoccurring weather shocks without hampering the economic development (Prabhakar, 2017).

Climate adaptation and vulnerability could be measured in several ways. Abdelzaher et al. (2020) uses the ND-GAIN index that includes 36 indicators in multiple areas[1] to measure climate vulnerability. The many indicators that compile the ND-GAIN capture a holistic perspective of climate vulnerability and adaptive capacity, and has been useful for descriptive purposes in reports (IMF, 2023). The main fallbacks is that the index risk of being skewed due to missing data in the different components of the index, an issue for developing countries in particular and most likely contains measurement errors making it less suitable for a case study of Tanzania (Abdelzaher et al., 2020). Other ways of measuring climate resilience and adaptation is the change of agricultural output and productivity. For Tanzania that is reliant on the agricultural sectors, these measurements are more relevant. Some scholars have used the crop yield per hectare to measure productivity levels and how they are affected by climate change (Lobell et al., 2013; Pauw & Thurlow, 2011; Prabhakar, 2017). Measuring the yield controls for any small-scale farmers who tries to expand their land to increase production and incomes, as large farms with high production could still show low yield per hectare and low productivity. High productivity would therefore imply good agricultural practices that are resilient to these shocks.

Another common measurement is the prevalence of food insecurity, which focus more on climate vulnerability (Angermayr et al., 2023; Chirambo, 2017; Pauw & Thurlow, 2011). Regions with better diets implies better agricultural productivity which reflect the adaptive capacity to some extent. Food insecurity is an important indicator where a significant share of farming is subsistence farming (IMF,

[1] Water, food, health, ecosystems, human habitat, and coastal, energy and transport infrastructure.

2023) and production might not be reflected in sales data or GDP per capita. At last, some scholars have used a measurement for agricultural yield gap to measure productivity. Either defined as the difference between attainable yield and actual yield (Gerber et al., 2024), or as the annual difference in crop yields from the long term average trend (Caballero et al., 2016). While other factors, such as conflicts and institutional environment also affects the productivity levels in agriculture (Chirambo, 2017), much of the variability in productivity levels are due to climate change and extreme weather which is why it is widely used as an indicator for climate vulnerability, resilience and adaptation (Trisos et al., 2022. p.1349). Fluctuations in productivity captures to what extent different districts can handle climate variability. Important insights could be retrieved from the alternative measurements. However, to capture climate adaptation and both capture production used for household consumption and commercial sales, this study will base the empirical models on crop yields, focusing on cereals and important staple crops within this category.

## 3.3 Hypothesis

While all financial instruments are expected to increase agricultural productivity due to better access to investments opportunities, institutions that do not reach nature-dependent people and rural communities are expected to be inefficient in increasing agricultural investments. Therefore, institutions that increase assess to microfinance, such as MFIs, mobile money agents, SACCOs and informal savings groups are expected to increase yields more than commercial banks. These have better outreach in rural communities and therefore responds to the needs of nature-dependent people and small-scale farmers (IMF, 2023). Districts with higher access to commercial banks might instead reflect inequalities of opportunities, where production might expand through depletion of natural resources that other groups are dependent on. This development might increase production levels, yet the crop yields remain unaffected. Based on the Microfinance-Climate framework and the literature review, the following two hypotheses are tested:

$H_1$: Increased access to financial institutions increases cereal yields.

$H_2$: Microfinancial services have a stronger positive effect on cereal yields compared to commercial banks.

The null hypothesis is that access to financial institutions has no effect on cereal yields and there is therefore no difference between the effect on cereal yields from commercial banks and microfinance. These two hypotheses draw attention to the role of microcredits as the primary channel for increased productivity in the Microfinance-Climate framework. Both Chirambo (2017) and Hammill et al. (2008) write that increased access to savings and insurances have an indirect effect on climate adaptation as better financial security increase investments level. Nonetheless, the expected channels that microsavings and microinsurance increase productivity happens through investments where access to credits is crucial.

Different studies show different results regarding how long the benefits from certain investments take to develop. The return to investments could vary greatly as access to financial institutions could facilitate both long term investments, such as innovation or education, and short-term investments like fertilisers, improved seeds or seeds for intercropping/crop rotation. Dallimer et al. (2018) show that investments in sustainable land management practices in Kenya increased maize yields to some extent at least from year 2 after investment and forward. Investments in manure and fertilisers realised the full benefits after three years with the first increase of maize yields already within a year of the investment. However, the investments into agroforestry took up to ten years to fully develop the benefits in maize yields, although some benefits were received already after the second year. In contrast, Raitzer and Kelley (2008) make a cost-benefit analysis of investments in agricultural R&D and conclude that the profitability from investments in innovation could take up to a decade to develop once the technology is adopted, in compliance with Lobell et al. (2013) who conclude that a 20 year lag is necessary when measuring the benefits of R&D investments. A three-year lag from when household received access to financial services to the benefit of the adoption of certain agricultural investments is therefore considered enough time to generate positive results in this study. Especially as it might be more relevant to farmers with low productivity and low input to focus on adoption of climate adaptive technology rather than R&D expenses (Mhlanga, 2022). Those who are most urgently in need for agricultural investments are more likely to adopt existing technology than to invest in innovation (Chirambo, 2016, pp.196-197, 2017; Mhlanga, 2022) which should shorten the return to investment period to the lower bound in Dallimer et al. (2018). The positive effects might increase when observing a longer time period and going back to explore the effect over a longer time period might show stronger results once data is available.

# 4. Methodology

Due to data limitations, this study will perform a multiple linear regression at the district level for crop yields in 2020 and 2017 for access to financial institutions. The data is of good quality and each observation at the district level consists of multiple aggregated observations from the either the household survey or detailed geospatial data. This section describes the methodology of performing the quantitative analysis to test this hypothesis. It includes a presentation of the data, the empirical model, and the limitations of the study.

## 4.1 Data

A compilation of cross-secional survey datasets is needed to investigate the effect of financial inclusion on agricultural climate adaptation in Tanzania, as there is no single dataset that contains information in both fields. The datasets are from multiple organisations that collaborates with the Tanzanian National Bureau of statistics with funding from either the Tanzanian government or other UN agencies, with the purpose to enhance knowledge based development strategies (FSDT, 2023; International Food Policy Research Institute (IFPRI), 2024; WFP & Climate Hazards Center UC Santa Barbara, 2024). A great part of data cleaning involved harmonising the name of districts and regions to make comparisons across the different datasets and years possible each data source is presented in this section.

### 4.1.1 FinScope Dataset

Data on both access to financial institutions and usage of these services are retrieved from the FinScope 2017 Surveys (FSDT, 2023). The main objective of the FinScope is to gather demand side data on usage, access, and attitudes among Tanzanian households and how it changes over time and there is a significant portion of variables that captures access to a various range of financial services. This study will focus access to commercial banks, MFIs, SACCOs, mobile money and informal savings groups. Since 2006, a total of five waves of FinScope surveys have been conducted. However, only the dataset from the 2017 survey and onwards includes district-level information for the 9,549 respondents in Tanzania. The data is aggregated for each district and shows the weighted average share of the population that have access to different financial institutions. The household weights are provided in the dataset to adjust for potential skewness and bias in the sampling (FSDT, 2023) which is important as the FinScope 2017 survey have an oversampling of respondent in five districts in mainland Tanzania to allow for in-depth analysis in these areas.

Access to these services is defined as a household owning at least one active account that has been used at least once in the past year (or in the past six months for mobile money). Accounts that have not been used within the timespan are treated as dormant accounts and excluded from the relevant financial institution. This can be compared to the definition in the 2021 Findex report (Demirgüc-Kunt et al., 2022, pp.9-10) that uses account ownership as the foundational factor for financial inclusion. The advantage of using the definition used in FinScope is that it captures the share of people that actually benefits from certain financial services as they have successfully used it. Many low-income individuals report that they need help from friends or family to use digital financial services. Some have experienced unexpected costs after using certain financial service which has limited their active usage of their account. Both lack of financial and digital literacy and safety sets up barriers for individuals to benefit from different financial services despite having an account (Demirgüc-Kunt et al., 2022). In addition to information about financial access at different institutions, the survey also includes information about other socio-economic variables, such as household size, educational level, land ownership and main source of income. This information is useful as controls for the analysis in this thesis.

### 4.1.2. Agriculture and Food Insecurity

Data on agricultural yields at the district level is retrieved from the Spatial Production Allocation Model (MAPSPAM, International Food Policy Research Institute (IFPRI), 2024). MAPSPAM calculates the total production of certain crops within a geographic area, using a combination of geospatially satellite data in 0.05 degrees grid cells and production statistics from administrative local units. It includes a total of 42 crops where production is calculated under the assumption that each crop grows by itself in one plot. The authors note themselves that this is seldom the case in tropical areas where multiple crops can be harvested within a year, usually either through intercropping where there are two or more crops grown simultaneously, or through growing different crops during different harvest seasons. To account for this, the dataset is computed using a cropping intensity parameter that equals 1 or more if there are multiple crops or harvests in the same plot, making the calculations more accurate. Another source of measurement error might occur if data from administrative local authorities count harvests from these types of plots incorrectly. There is a risk that some plots are counted twice as separate plots during intercropping or multiple harvests when in practice the same plot have been used for multiple crops (You et al., 2014). However, since the MAPSPAM weights in both geospatially retrieved data on physical area of cropland within each area and production data from administrative units, the potential measurement error is reduced.

In compliance with Pauw & Thurlow (2011) and Rowhani et al. (2011), the study focus on cereal yields in the models. Cereals have been highlighted as important crops for both poverty alleviation and food security and studying such staple crops gives insights to how communities have adapted to climate change and improved production to secure growth. Furthermore, additional regressions are estimated using three of the most important crops in Tanzania; Maize, Sorghum and Rice. The crop group “cereals” includes all of the three crops and other types of cereals that is included in the MAPSPAM dataset that furthermore follows the crop categorisation of FAO (IFPRI, 2020). As different crops are affected differently by precipitation (Dell et al., 2012; Pauw & Thurlow, 2011), precipitation data on both long term average precipitation and annual rain anomalies are retrieved from the CHIRP dataset (WFP & Climate Hazards Center UC Santa Barbara, 2024). The long-term average could be a deciding factor to what type of crops a farmer will cultivate and is therefore an important factor to include in the analysis. The long-term average is calculated on the average precipitation per year based on data between 1989 and 2018. The rain anomaly variable acts as a disturbance to agricultural production as it shows the deviation from the long-term average that farmers might base their agricultural practices on. Similar to the MAPSPAM, the data for precipitation is aggregated to administrative districts from satellite data at the 0.05 degrees grid cells.

## 4.2 Descriptive statistics

Table 1 shows summary statistics for both the usage of different financial institutions and for the average crop yields in 154 districts in Tanzania, some districts were excluded due to missing data or change in the administrative district borders between 2017-2020, the full list of districts is presented in appendix A. Tanzania has 195 districts as of 2020 (The National Bureau of Statistics, 2020). While it might seem like that many districts are excluded, a large share of the total area that is covered by the datasets. The main reason why there are fewer data points compared to total number of districts is that many of the regions have been split into rural and urban areas since the 2017 survey. This is most likely as a result of rapid urbanisation and population growth that requires some areas to be divided. When observing which areas that are entirely excluded, the selection seems random and is not expected to create a bias. However, the FinScope 2017 survey mentions that a possible bias from the sampling within each district might occur due to language barriers and accessibility to travel to some communities (Financial Sector Deepening Trust, 2023).

The data from the FinScope dataset shows the weighted aggregates in each household. The lowest share of people who are using one category of financial institution is zero in all types of services except for mobile money. This is also the financial institution that is most widely used as it presents the highest mean, median and maximum share compared to other institutions. The last row for financial access shows the share of the population with access to at least one financial institution. This includes commercial banks, formal MFIs and SACCOs, mobile money and informal saving groups. In addition, this variable also adds the share of the population who might have access to capital through national insurance programs or pensions. It therefore captures a larger group of people in the financial market than what the individual institutions do together. All microfinance and show similar numbers as all financial institutions yet excludes access to commercial banking.

Table 1 – Summary statistics of access to financial services and average yields

| | Mean | Standard dev. | Min. | Median | Max. | Obs. |
|---|---|---|---|---|---|---|
| *Usage of financial services 2017 per district – Share of total respondents* | | | | | | |
| Banked (%) | 12.7 | 11.7 | 0.0 | 8.9 | 57.4 | 154 |
| MFI (%) | 4.6 | 5.6 | 0.0 | 3.1 | 38.7 | 154 |
| Mobile Money (%) | 55.3 | 18.9 | 8.5 | 55.7 | 95.9 | 154 |
| SACCO (%) | 1.7 | 3.2 | 0.0 | 0.0 | 19.3 | 154 |
| Savings Group (%) | 16.4 | 10.5 | 0.0 | 14.2 | 49.1 | 154 |
| **All microfinance (%)** | 59.7 | 18.2 | 15.8 | 60.6 | 98.0 | 154 |
| **All financial institution (%)** | 60.1 | 18.2 | 15.8 | 61.4 | 96.3 | 154 |
| *Yields 2020 per district – Average kg/ha* | | | | | | |
| Maize | 1,717 | 1,214 | 48.2 | 1,559 | 14,740 | 154 |
| Rice | 2,051 | 1,395 | 566* | 1,903 | 9,105 | 154 |
| Sorghum | 1,247 | 831 | 627* | 1,155 | 4,264 | 154 |
| **Cereals** | 7,554 | 3,043 | 48.2 | 7,785 | 16,938 | 154 |

Source: IFPRI, 2024 for crop yields, FSTD, 2023 for access to financial institutions. * The number shows the minimum value of yields in those districts that had any production of the crop. The real minimum crop yields in the sample is zero (0.0).

The district with the lowest share, Kiteto in Manyara, has at least 15 percent of its population connected to at least one financial service, this is also the district with the lowest share with access to microfinance. The district with the highest share connected to any financial service is Urban Moshi in Kilimanjaro where almost all households have access to financial services. Studying financial access in each region shows that some regions have large differences between districts. For example, the district with the lowest share of the population who uses mobile money is the Ngorongoro district in Arusha, a region that otherwise has high access to mobile money with a mean value of 57 percent. Surprisingly, and in contrast to what previous literature have reported, both MFIs and SACCOs report low shares of people who used their services during 2017. The FinScope report shows that the expansion of MFIs and SACCOs have stalled and instead uptake of mobile money have increased drastically as mobile phones have become more affordable, which could indicate a crowding-out effect (FSDT, 2023; GSMA, 2023). It is important to note that both MFIs and SACCOs capture only the formal microfinancial institutions at the upper tiers that are fewer in numbers and have limited geographical outreach (FSDT, 2023). Informal saving's groups operate in similar ways like SACCOs yet are an informal channel for credits and savings. These institutions might be more accessible as the average share who has access and use the services is 16 percent in Tanzania.

The statistics of crops yields in Table 1 shows the great variation in yields across different crops in different regions. All districts grow some cereals, however not all regions grow all individual cereal crops. While Maize is the only crop grown in every region, the differences in productivity are large.

Wete, the most effective district produces 300 times more maize per hectare than the least effective district, Micheweni. The differences might reflect different prioritised crops among farmers due to the varying climate or supply and demand in nearby districts, rather than different agricultural practices. As an example, both Wete and Micheweni are geographically small districts in the Northern Pemba region, the high yields in one district could lead to farmers opting for other crops in the other district to maximise production and trade between the districts. There were 22 districts that did not produce any rice during 2020. The district with the lowest productivity were Moshi in Kilimanjaro, and the highest productivity were observed in Kyela in Mbeya. There were also 22 districts that did not produce any sorghum, most of these districts are urban or in Zanzibar. The lowest sorghum yield is observed in Rural Mtwara, and the highest yield were in Mkinga in Tanga. The regions that report the highest and the lowest yields in both rice and sorghum follow previous literature given the different environmental circumstances that is observed in these districts (Chepng'etich et al., 2015; Ngailo et al., 2016).

Figure 3 shows the development of monthly rain anomalies in each district between the years 2000-2020. It is presented as the percentage of monthly precipitation compared to the long-term average rain levels (marked with a line at 100 percent on the Y-axis). While the variability is large already from the beginning of the 21st century, with several outliers marked, the pattern fluctuates around the long-term average up until 2014. However, with the increased temperatures over the years (Brown et al., 2011; Rowhani et al., 2011; Trisos et al., 2022, p.1327) it is apparent that flooding and heavy rain has become a more urgent issue as almost all districts have recently had higher precipitation levels, with extreme values far outside the normal maximum value. For example, Unguja in Zanzibar reported precipitation levels in 2019 that was 198 percent of the long-term average precipitation level, which is almost twice the amount of rain compared to normal levels. In addition, the aggregated levels of rain anomaly on monthly basis, might cancel out negative and positive rain anomalies across different days. This could imply that short-term rainfall could be at even higher levels if the rest of the month is followed by a "dryer-than-normal-period".

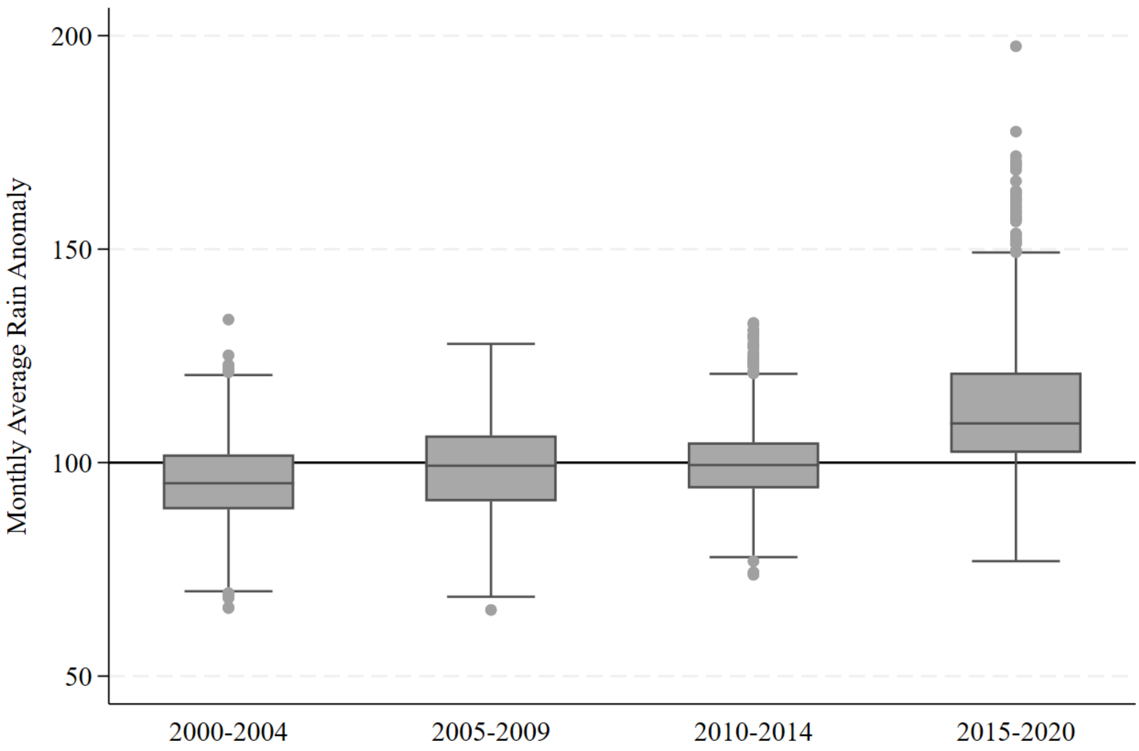


Figure 3 – Development of rain anomalies between 2000-2020.
Source: WFP & Climate Hazards Center UC Santa Barbara, 2024

Table 2 shows summary statistics for both long-term average precipitation and anomalies during 2020. Long-term average for 10-days precipitation, column (1), is the average of the 10-days rolling aggregation of precipitation between 1989-2018 and reflects distribution of rain levels in the districts. In other words, the mean value shows that it rained 28mm per 10 days in average in Tanzania between 1989-2018. Column (2) shows the same variable but based on the monthly rolling aggregation. Column (3) shows the annual average rain anomaly in percentage from the long-term average in column (1). During 2020, the districts had in average 23% more rain during a 10-days period compared to the long-term average rain levels. Column (4) shows the annual average rain anomaly from the monthly long-term values in column (2). Studying the summary statistics in both column (3) and (4), short-term anomalies (10 days) are proportional to monthly anomalies, showing similar minimum and maximum values and standard deviation. Running a correlation test also shows that those observations that have high levels of rain anomalies during the 10-days period also have similar levels of deviation during the monthly period, with a correlation coefficient of 0.98. Using monthly rain anomalies does not impact the climate variability more than when using 10-days rain anomalies.

Table 2 – Summary statistics for precipitation trends and levels 2020

| | (1) Long-term average, 10-days precipitation (mm) | (2) Long-term average, monthly prec. (mm) | (3) Annual average rain anomaly 2020, 10 days (%) | (4) Annual average rain anomaly 2020, monthly (%) |
|---|---|---|---|---|
| Mean | 28.25 | 118.34 | 123.63 | 127.72 |
| Standard dev. | 6.98 | 33.28 | 15.99 | 19.20 |
| Min. | 16.39 | 64.72 | 88.89 | 89.02 |
| Median | 28.01 | 109.47 | 121.37 | 123.18 |
| Max. | 52.79 | 245.23 | 160.84 | 177.53 |
| No of obs. | 167 | 167 | 167 | 167 |

Source: WFP & Climate Hazards Center UC Santa Barbara, 2024

## 4.3 Empirical model

The regression models are primarily based on the empirical models presented in Arslan et al. (2016) who use, among other models, a pooled Ordinated Least Squares (OLS) model to determine the productivity function of maize yields in Tanzania. They are running regressions based on panel data of household surveys to mainly determine the adoption of sustainable agricultural practices. Yet, they also test the underlying production function to measure productivity, which is what this study will follow. Their method is also similar to Angermayr et al. (2023) who use cross-sectional data to study small-scale aquaculture in Madagascar and determinants of fish income from fish, another possible measurement of productivity at the household level.

(1) $$\ln\left(Yields_{j,t}\right) = \alpha + \beta_1 Banked_{j,t-3} + \beta_2 Microfinance_{j,t-3} + \sum\beta_k X_{j,t-3} + \varepsilon_j$$

(2) $$\ln\left(Yields_{j,t}\right) = \alpha + \beta_1 Banked_{j,t-3} + \beta_2 MFI_{j,t-3} + \beta_3 MobileMoney_{j,t-3} + \beta_4 SACCO_{j,t-3} + \beta_5 Savings\ group_{j,t-3} + \sum\beta_k X_{j,t-3} + \varepsilon_j$$

Equation 1 specifies the main model for this study. To see the total effect of microfinance, the model includes one variable for all microfinancial services. This is a common way of measuring financial inclusion and reduces the number of constraints in the model (Lyons et al., 2020; Renzhi & Baek, 2020; Zaidi et al., 2021). Combining different institutions into one index reduce the numbers of restrictions in the model which becomes better suited to handle a small dataset. This coefficient can be compared to *Banked* indicate the share of population with access to a commercial bank in district *j* and is used to compare the effect of in relation to the effect of microfinance. $\sum\beta_k X_{j,t-1}$ is a vector of control variables and $\varepsilon_j$ is the error term. Equation 2 shows the individual financial services to differentiate their individual effect on crop yields. All variables indicate the level of access to different financial institutions in each district *j, MFI, SACCO* and *Savings group* indicate the share of the population with access to a MFI, a SACCO, or a Savings group in the past 12 months in district *j*. *MobileMoney* indicates the share of population with access that have used a mobile money agent in the past 6 months. The models are estimated using OLS-regressions, like the models presented in Arslan et al. (2016). Standard errors are clustered at the regional level as districts within the same region have more integration through shared regional offices who provide technical and administrative assistance that affects the efficiency of financial institutions and crop yields (Ministry of Foreign Affairs and East African Cooperation, 2024). The variables and the control variables are lagged with three years to the main dependent variable cereals yield.

The data on financial access is derived from household survey data, each datapoint consist of a dummy variable to mark if a household have access to a certain financial institution. The financial institutions dummy variables are then aggregated into district level with weighted average of the population share with access to financial institutions, to represent the actual population at a 95 percent confidence level (FSDT, 2023). The weights are calculated according to probability sampling weights, that takes the inverse probability of a single observation (household) being included in the sample based on rural-urban split or the number of adults in one single household. This way of adjusting weight is the recommended use of the data according to the launch report of the FinScope dataset and the weights together with the sampling design minimise the risk of skewness or extreme outliers in the aggregated data (FSDT, 2023). Each financial institution is calculated according to equation 3. The variable is computed for each *k* financial institution, e.g. access to MFI or SACCO, in each *j* district. *w* is the weight provided in the waw data for each household *i* in district *j*.

$$Financial\ Access_{k,j} = \frac{\sum w_{k,i,j} x_{k,i,j}}{\sum w_{k,i,j}} \tag{3}$$

### 4.3.1 Control Variables

A number of control variables are included in the models to reduce potential bias due to endogeneity. Assuming that the same mechanisms that affect productivity and income levels at household level also affect productivity at the district level, the main model use the same control variables as Angermayr et al. (2023) and Arslan et al. (2016). This also complies with literature on the determinants other cereal yields in East Africa (Chepng'etich et al., 2015; Ngailo et al., 2016). The list of all control variables include:

$Farmers_{j,t-1}$ = Share of population who has farming as the main income in 2017 in district *j*.

$Educ.level_{j,t-1}$ = Share of population who has at least some secondary education or more in 2017 in district *j*.

$Age_{j,t-1}$ = Average age of the household head in 2017 in district $j$

$HH\ Size_{j,t-1}$ = Average household size 2017 in district *j*.

$Female_{j,t-1}$ = Share of population in a household who have a woman as the household head 2017 in district *j*.

$Landowner_{j,t-1}$ = Share of population who owns their own agricultural land in 2017 in district *j*.

$Average\ precip._j$ = Long-term average monthly precipitation levels in district *j*, between 1980-2018.

$Rain\ anomaly_{j,t}$ = Annual average of the monthly rain anomaly from the long-term average during 2020 in district *j*. Expressed as the percentage of normal precipitation.

$\varepsilon_j$ = Error term for district $j$

The variable for farmers also partly controls for urban and rural districts as a larger share of the population in urban areas engage in other sectors where there is better infrastructure and market access (Hammill et al., 2008; Prabhakar, 2017). Similar to the variables on financial inclusion, the control variables show the weighted average of the share of population who corresponds to a specific group. The full model is shown in equation 4 and 5.

$$(4)\quad \ln\left(Yields_{j,t}\right) = \alpha + \beta_1 Banked_{j,t-3} + \beta_2 Microfinance_{j,t-3} + \beta_3 Farmers_{j,t-3} + \beta_4 Educ.\ level_{j,t-3} + \beta_5 Age_{j,t-3} + \beta_6 HH\ Size_{j,t-3} + \beta_7 Female_{j,t-3} + \beta_8 Landowner_{j,t-3} + \beta_9 Average\ precip._j + \beta_{10}\ Rain\ anomaly_{j,t} + \varepsilon_j$$

$$(5)\quad \ln\left(Yields_{j,t}\right) = \alpha + \beta_1 Banked_{j,t-3} + \beta_2 MFI_{j,t-3} + \beta_3 MobileMoney_{j,t-3} + \beta_4 SACCO_{j,t-3} + \beta_5 Savings\ group_{j,t-3} + \beta_6 Farmers_{j,t-3} + \beta_7 Educ.\ level_{j,t-3} + \beta_8 Age_{j,t-3} + \beta_9 HH\ Size_{j,t-3} + \beta_{10} Female_{j,t-3} + \beta_{11} Landowner_{j,t-3} + \beta_{12} Average\ precip._j + \beta_{13}\ Rain\ anomaly_{j,t} + \varepsilon_j$$

## 4.4 Data limitations

The main drawback in this study is that once the data is aggregated, it includes very few observations which limits the statistical power. However, despite the small number of observations the statistical precision is improved due the well-constructed sampling design and weights in the original household level data. Therefore, the probability of the sample mean representing the true mean in each district is increased and the effect of extreme outliers reduced (FSDT, 2023; Gelman, 2007). Despite the good quality of the data. There might still be issues with endogeneity and unobserved heterogeneity that cannot be controlled in cross-sectional data. Usually, expertise and thorough research in the literature is needed to assess which control variables are needed to isolate the causal effect Even when there is knowledge, it is often difficult to achieve in reality due to data limitation (Gelman, 2007). The development of microfinancial services is new and much of the data is limited at the sub-naional level to a short time period (Mhlanga, 2022; Trisos et al., 2022, p.1303). While the models in this study use a good number of control variables to reduce this bias, it is important to interpret the results cautiously. Therefore, while this thesis can give indications of the effect, the results presented here cannot be seen as the final estimation to how financial inclusion and crop yields are related in Tanzania.

As a robustness check, regression models will be estimated using Weighted Least Squares regressions (WLS). Similar to Angermayr et al. (2023) household weights are used as the weighting variable. WLS is in general a more efficient estimator compared to robust OLS-estimators when there is heteroscedasticity in the residuals, as it gives different weights to different observations that might be extreme outliers or disturbed by an error variance that increases with one or more of the independent variables in the model. However, it requires a known conditional variance function of the residuals to assign the correct weights for each variable. The standard errors becomes invalid in a WLS-regression if the wrong function is specified in the regressions, as the statistical tests will have the wrong size (Gelman, 2007; Mendenhall & Sincich, 2014, pp.446-450). The dataset provides household weights, yet the results might be misleading and should be interpreted with caution as it is uncertain how the sampling of the household affects the heteroscedasticity and how the model should be specified using this variable. Other model specifications are presented in the appendix B-D as robustness checks. These include estimations on individual cereal crops and alternative OLS-models based on residual analysis.

# 5. Analysis

The following section presents the results from the regressions and discuss how it relate to the stated hypotheses. Section 5.2 provides a discussion of the results in relation to existing literature to identify possible channels where financial institutions affect crop yields. Both sections briefly mention and weight in results into the discussion from the robustness checks in appendix, while the appendices themselves include an elaborated discussion of the method for the robustness checks.

## 5.1 Results

Table 3 shows the estimated effect of increased financial access on cereals. Model (1)-(3) are based on equation 1, whereas model (4)-(6) are based on equation 2. Each coefficient shows the increase of yields in percentages. Following the residual analysis in appendix B, models (3) and (6) that controls for districts that deviates from the normal distribution. Despite sensitive coefficients and weak results throughout the table, some patterns can be identified. When observing all the microfinance, the overall effect is positive and significant for all models, except for when controlling for outliers. Model (3) is yielding positive yet statistically insignificant results, with a p-value of 17 percent. Model (3) displays a 0.52 percent increase in cereal yields per percentage point increase of the share of population who have access to any microfinancial service. The highest estimate shows a 1.48 percent increase in cereal yields in model (2). Alternative models in the appendix consistently shows positive results yet differ in magnitude and statistically significance. While the magnitude of the effect is difficult to estimate, it is clear that access to microfinancial services have a positive impact on cereal yields. The effect of having access to a bank shows ambiguous results across all models. In some models the effect is negative, and in some models the effect is positive. The most robust models with the highest F-statistic show a positive result. In contrast to model (3) and (5) model (6) presents a coefficient with statistically significant effects. A one percentage point increase of access to banks increases the cereal yields with approximately 0.95 percent.

The most important financial institutions are the informal savings groups, with positive estimates throughout all model specifications. While the estimates are statistically insignificant in model (4) and (5) with a p-value of 19 and 14 percent, the estimate become statistically significant when outliers are controlled for in model (6). The estimated effect of access to informal savings groups is 0.46 percent increase of cereal yields. Given the size of the estimate in other models, this number is likely to be on the lower bond. Mobile money is also an important channel for increasing cereal productivity. Model (4) and (5) shows the strongest positive effects on cereal yields. However, when controlling for outliers, the effect is well decreased with large standard errors. This implies that the effect might be somewhat overestimated yet still positive. Surprisingly, both MFIs and SACCOs seem to have a large negative effect on crop yields. This negative effect is consistent throughout almost all models, including the robustness checks. In some models the effect is statistically significant and very large compared to other financial institutions. Model (5) shows that a one percentage point increase of access to SACCOs decrease cereal yields by 4.5 percent. In models where the negative effects of MFIs are statistically significant, the negative effects from SACCOs are heavily reduced. This might imply that the variables are subject to multicollinearity. A simple correlation test yields the correlation coefficient of 31 percent that is statistically significant at the five percent level, indicating an issue of multicollinearity. However, the VIF test in appendix B reassures that the standard errors are not inflated due to multicollinearity. Nonetheless, it might be difficult to disentangle the individual effect of MFIs and SACCOs if they are closely correlated.

Table 3 – The effect on access to financial institutions on cereal yields.

| | *Dependent variable is cereal yields* | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Banked (%) | **-1.871**** | -1.033 | 0.468 | -1.052 | 0.102 | **0.953**** |
| | **(0.884)** | (0.785) | (0.332) | (1.037) | (0.920) | **(0.469)** |
| Microfinance (%) | **1.171**** | **1.482***** | 0.523 | | | |
| | **(0.567)** | **(0.415)** | (0.372) | | | |
| MFI (%) | | | | -1.701 | -1.520 | **-1.137**** |
| | | | | (1.290) | (1.282) | **(0.519)** |
| Mobile Money (%) | | | | **1.283**** | **1.188**** | 0.271 |
| | | | | **(0.614)** | **(0.579)** | (0.408) |
| SACCO (%) | | | | **-5.685**** | **-4.463*** | -0.466 |
| | | | | **(2.558)** | **(2.448)** | (1.202) |
| Saving's Groups (%) | | | | 0.646 | 0.787 | **0.462**** |
| | | | | (0.487) | (0.527) | **(0.225)** |
| Share of farmers | | **0.855***** | **0.311*** | | **0.737**** | 0.246 |
| | | **(0.240)** | **(0.158)** | | **(0.284)** | (0.165) |
| Share of pop. with secondary education | | -0.118 | **0.328*** | | -0.156 | **0.299*** |
| | | (0.282) | **(0.193)** | | (0.258) | **(0.177)** |
| Share of pop. with female HH-head | | -0.618 | 0.231 | | -0.589 | 0.180 |
| | | (0.382) | (0.250) | | (0.499) | (0.285) |
| Age of the HH-head | | 0.004 | 0.000 | | 0.010 | 0.003 |
| | | (0.013) | (0.010) | | (0.015) | (0.008) |
| HH Size | | 0.024 | -0.002 | | -0.003 | -0.014 |
| | | (0.038) | (0.023) | | (0.034) | (0.020) |
| Share of landowners | | 0.522 | 0.144 | | 0.606 | 0.202 |
| | | (0.437) | (0.250) | | (0.431) | (0.230) |
| Average monthly precipitation | | **-0.010***** | -0.001 | | **-0.009**** | -0.001 |
| | | **(0.003)** | (0.003) | | **(0.004)** | (0.003) |
| Rain anomaly, monthly (%) | | -0.006 | 0.001 | | -0.003 | 0.002 |
| | | (0.004) | (0.002) | | (0.004) | (0.002) |
| Control for outliers | No | No | Yes | No | No | Yes |
| Observations | 154 | 154 | 154 | 154 | 154 | 154 |
| R-squared | 0.06 | 0.28 | 0.75 | 0.13 | 0.31 | 0.76 |
| Adj. R-squared | 0.04 | 0.23 | 0.74 | 0.10 | 0.25 | 0.73 |
| F-stat | 2.95 | 3.93 | 27.48 | 4.76 | 2.96 | 20.52 |
| P-value | 0.068 | 0.002 | < 0.001 | < 0.001 | < 0.001 | < 0.001 |

Note: Robust standard errors in parentheses, clustered at the regional level. *** p<0.01, ** p<0.05, * p<0.1.

Many of the control variables are showing the expected values according to previous studies and literature. Districts with a higher share of farmers have better opportunities to exchange knowledge, farming inputs and commodities which increase average cereal yields. Moreover, farmers are more concentrated in rural areas where there are more incentives to invest in agriculture in lack of other job opportunities. Household heads with higher education and land ownership also increase yields, as there is both knowledge and collateral to makegood investments decisions. However, educational level displays a negative yet insignificant coefficient when controlling for outliers. Similar patterns but reversed are seen when studying the sex of the household head, the effect of more female household heads switches signs when controlling for outliers. While both age of the household head and household size have signs of the coefficients that complies with previous literature, the size of the estimates are very small and display a null result. Rain anomalies show very small coefficients, indicating that it does not affect crop yields. While rain might have an impact on individual crops, the total effect on cereals might be more diverse and cannot be explained by one linear coefficient. Average monthly precipitation has a small negative impact on cereal yields, indicating that cereals grow better in Tanzania's dryer climates. It might also be that farmers grow vegetables or other cash crops in humid tropical climates where soil fertility is better.

The weak coefficients as well as the low F-statistic can to some extent be explained by few observations in the sample. Nonetheless, all models still yield statistically significant models. When including controls, the lowest $R^2$-value increase to 23 percent. The models F-statistic and $R^2$-value increase drastically when controlling for outliers, this indicates that model (3) and (6) are most reliable. Robustness checks appendix B and C support the strongest results reported in table 3. Appendix D presents additional regressions on three individual crops within the cereal crop group; maize, rice and sorghum. The estimates are similar to table 3 yet show that different institutions have varying effects on different crops. For example, rice yields are negatively affected by mobile money while commercial banks have a strong positive effect. However, models on individual crops are non-robust and the results of total cereals yields are more reliable. The inconsistent result of financial institutions on individual crops might be due to practices of intercropping and crop rotation, which might lower the crop yield for one specific crop yet increase total yields for all crops grown into one hectare of land.

The results suggest some evidence that support hypothesis $H_1$, yet the null hypothesis cannot be rejected due to the uncertainty of the coefficients and their value. Having access to commercial banks and to microfinance increase cereal yields somewhat. While the magnitude is uncertain, the estimates do point towards small positive impacts on cereal yields. The weak results are both due to the small dataset and due to the different effects, each individual financial institution have on cereal yields. This becomes apparent when observing the individual financial institutions and their diverse effect on cereal yields. This shows that $H_1$ might only be true when studying access to informal savings groups, mobile money, and commercial banks. The positive effect of access to microfinance in total on cereal yield is larger than access to commercial banks in all models which indicates that hypothesis $H_2$ is true. However, these results are not robust either. In model (1) and (2), the coefficients for access to banks and access to microfinance are significantly different from each other with a 95 percent confidence interval. However, model (3) that presents the most robust model shows no statistically significant coefficients with similar values for both variables. In fact, A Wald test reveals that there is a 92 percent probability that these coefficients have the same value. The evidence is not strong enough to reject the null hypothesis that there are no differences between access to microfinance and access to commercial banks as the strongest models in table 3 yields results of statistical insignificance.

## 5.2 Discussion

Despite the proposed benefits of the Microfinance-Climate framework and the potential of microfinance to increase adaptive capacity, the quantitative analysis fails to provide evidence of the positive impact of microfinance at the district level in Tanzania as the null hypothesis cannot be rejected. Given the available data, it is notable that any coefficients show statistically significance, which implies that there might be strong effects of financial inclusion to cereal yields that should be investigated further with more data in the future. Therefore, even if it is not possible to make any definitive conclusions, a further analysis of the results could still give important insights. Access to MFIs and SACCOs have consistently shown strong negative effect on yields. Access to informal savings groups show consistently positive, yet statistically insignificant results. Mobile money has a positive impact on crop yields, where most models also display statistically significant results. Access to commercial banks have a more ambiguous impact on cereal yields. Some regressions show either no or negative effects on cereal yields from access to commercial banks. In other models the effect of access to banking is positive and statistically significant yet does not differ from the effect of microfinance. Expansion of formal banks into rural areas of Tanzania have been difficult and expensive, which limits the potential to expand and lower costs for farmers and rural agricultural development. While they can offer services that are needed for increased productivity, the use of these services might still be too limited to increase productivity at the district level.

What seems to matter the most for a positive impact of financial institutions is the outreach of certain services. Table 1 displays that mobile money has the best outreach among the districts, which also yields strong evidence for a positive impact on cereal yields. Access to informal savings groups are also important institutions that is widespread in Tanzania. Access to mobile money might increase agricultural productivity for some, although it requires both digital and financial literacy to fully benefit from the services (GSMA, 2023; Lyons et al., 2020). When controlling for outliers in urban areas that have better access to mobile money agents or other networks to receive advice (GSMA, 2023), the significance of mobile money becomes less apparent. Instead, informal savings groups and access to commercial banks become more important. Savings groups are small, local institutions that are numerous in Tanzania and can with financial services satisfy the needs of the farmers in a specific context to a greater extent than more centralised institutions (Chirambo, 2016, pp.203-204). Their offices might therefore be more accessible for creditors in rural areas to receive technical assistance and other benefits (Angermayr et al., 2023). In contrast, MFIs and SACCOs have the lowest share with access and these institutions display the strongest negative impact on cereal yields. MFIs at the higher tiers were also reported to have limited geographical outreach and are mainly situated in urban areas, where access to commercial banks are better as well they provide more secure credits (UN Capital Development Fund, 2022). This might both lower the share of people who use it and limit the potential to increase productivity in agriculture where many in urban areas might diversify their economic activities in other sectors entirely. This follows both the climate-microfinance framework and the arguments of Hammill et al. (2008) who raise that MFIs still do not include enough of the rural and vulnerable people to improve climate adaptation where it is most needed.

Due to the high membership fees or the requirement to open an account or too high interest to increase incentives for investment into cereal productivity, many farmers report that they face barriers to use formal microfinancial institutions which is a possible explanation to the limited outreach. They also report that their knowledge of how MFIs and SACCOs operate are limited and perceive these services as unreliable (FSDT, 2023). In contrast, smaller groups face lower costs of monitoring and evaluation as well as in administration, which could lower interest rates and membership fees, making credits more accessible for farmers. Similarly, the widespread use of mobile money and innovative financial technology have also reduced costs even further to facilitate more efficient microcredits and savings for the most vulnerable farmers (GSMA, 2023; Mhlanga, 2022). These farmers, who might not have the resources to scale up farming operations and increase their farming size, could use smaller investments for intercropping, irrigation systems or fertilisers. Much of small-scale agricultural production is for household consumption and the monetary gains from increased yields might be limited. Therefore, it is vital that access to credit is affordable and mobile money and informal savings groups might be the institutions that can provide financial services at the lowest cost.

While the limited outreach might explain why there is no positive effect of access to MFIs and SACCOs, it does not explain the negative effect observed. The negative effect of MFIs might reflect the potential risks both Awad & Warsame (2022) and Nyiwul (2021) raise in their studies. When inequality increase, efforts in climate adaptation decrease and expansion takes place at the cost of other natural resources. The low yield might reflect how the incentives to increase productivity and sustainable agricultural practices are lowered when there are inequal opportunities for financial access. When only a smaller group get access to credits and investment opportunities, they might increase production at the cost of the environment which results in land degradation and pollution. This worsens the prospect of production for neighbouring farmers and nature-dependent individuals which could reduce total crop yields in a district (Awad & Warsame, 2022; Nyiwul, 2021). Another possible explanation to the strong negative effect of MFIs and SACCOs is that climate vulnerable individuals risk falling into a negative spiral of indebtedness (Hammill et al., 2008; UN Capital Development Fund, 2022). Farmers who use MFI might be worse off after taking a loan through an MFI as they struggle with pay back loans during losses in a volatile and climate sensitive agricultural sector, especially in Tanzania that faces increased numbers of both floods and droughts. To be able to pay back to MFIs and SACCOs, farmers have to sell off important assets for productivity which lowers average crop yields.

Another reason behind the ambiguous results might be that these services might be used other purposes than increase agricultural productivity. Despite strong evidence in earlier studies of the impact of access to financial services to vulnerability and poverty alleviation (Lobell et al., 2013; Lyons et al., 2020; Polloni-Silva et al., 2021), there is no guarantee that this development occurs through the increase of agricultural investments and increased crop yields as the Microfinance-Climate framework implies. The report from GSMA report and other empirical studies (Abiona & Koppensteiner, 2022; GSMA, 2023; Lyons et al., 2020) on financial inclusion state that financial services are primarily used for consumption smoothing over time and savings for emergencies rather than for investments. Food insecurity is often handled through an increase of remittances which have increased with mobile money (GSMA, 2023; Mhlanga, 2022). Moreover, respondents in FinScope 2017 state that they use financial services primarily for savings, not investments. This has the potential to increase investment indirectly as strengthened safety nets and insurance for vulnerable people make them less likely to sell assets for consumption during crises. Additionally, the maintained consumption and demand during extreme weather secure safe profits for agriculture that stimulates further investments. This relates more to climate resilience and strengthens the channels of microsaving and microinsurance in the Microfinance-Climate framework. The effect of financial inclusion to crop yields become more uncertain, as the effect take place in several steps that in turn are affected by other factors. The effect would be dependent on how these microfinancial institutions are used. If some members only use it for safe storage of savings, they will still to a large extent be nature-dependent and engage in low productivity farming yet have access to credits and food supplies in times of crisis.

As data were only available for one point in time, there might be unobserved heterogeneity that creates noise and uncertainty in the models. A possible disturbance affecting the regression models is the impact of the Covid-19 pandemic. Although the restrictions in Tanzania were very modest in comparison with other Eastern African countries and the world as a whole, the pandemic slowed the economic growth in 2020. Export markets and the tourist sector were the hardest hit, yet growth in other sectors were also limited due to lower demand, reduced levels of foreign direct investment and stringent credit constraints. The transportation sector was also significantly affected (World Bank, 2020), which potentially limited farmers' access to agricultural inputs regardless of their credit access or access to other financial instruments. While this might pose a greater issue for new investments and productivity gains in the future, the impact from previous investments up until 2020 is expected to be limited, especially in the cereal production that is driven by domestic consumption (Arslan et al., 2016; Pauw & Thurlow, 2011). The main channels in how the pandemic might have affected crop yields are the lower labour productivity and lower incentives keep up production when supply chains are disrupted. This could partly explain why urban areas much lower cereal yields, as more populous areas chose to limit mobility more extensively despite no strict mobility restrictions from the government (World Bank, 2020). Previous research has shown that different types of investments into agricultural productivity have different time lags to yield returns to investments. In areas where innovation and more research are needed, the investments might take longer time to show productivity gains (Lobell et al., 2013; Raitzer

& Kelley, 2008). Investments into agroforestry has also shown to require long periods for investments to pay off (Dallimer et al., 2018). Inconclusive results might entail that the effect of access to financial services needs longer time, especially since financial literacy is limited and there might take time to learn and navigate the financial markets before making well performing investments.

# 6. Conclusion

In an effort to understand the impact of financial access to climate adaptation and increased agricultural productivity in Tanzania, this study utilised previous knowledge from both agricultural productivity and financial inclusion to empirically test the arguments and implications of the Microfinance-Climate Framework in the case of Tanzania. This offers unique insights as it investigates how different financial institutions impact macroeconomic measurements, while still allowing for the in-depth analysis when focusing on one single country. The literature review consistently show the negative impact of climate change to agricultural productivity and the need to increase investments and innovation to the sector to secure future production. The Microfinance-Climate framework is the primary conceptual framework in the study, highlighting the importance of microfinance and local initiatives to create sustainable revolving fund loans that can increase investments and other financial services that make communities better at climate adaptation. Furthermore, agricultural productivity is an important channel to generate higher income and inclusive growth as a majority of Tanzanians are dependent on agriculture for their livelihood. The study tested the effect of access to financial institutions in 2017 on average cereal yields in 2020 in Tanzania, using a multiple regression model. Cereal yields are an important crop group that includes many staple crops that have the potential to increase food security and to reduce vulnerability in Tanzania. The regression analysis indicates that the financial institutions that had the best outreach in the country were the most efficient institutions to increase productivity in cereal production, these were mobile money agents and informal savings groups. Commercial banks have also a positive impact on yields, which shows that it offers beneficial services for those who have access to banks. However, while the results show some consistency across different models and different financial institutions, the evidence for this is not strong enough to reject the null hypothesis that access to financial services do not have any impact on crop yields.

The null result might not necessarily indicate that better access to financial services have no impact on vulnerability for nature-dependent individuals and the rural poor. It rather implies that more is needed than simply access to financial services to increase agricultural productivity. Financial literacy, knowledge of sustainable agricultural practices, access to other markets, coordination within farmers' associations and competitive interest rates might be equally important for agricultural productivity. The positive effect of financial institutions to crop yields might increase if these things improve to increase well performing investments that stimulate further supply of credits, less land degradation, and a more inclusive economic development. While investments might still be limited, the literature review reveals that climate adaptation might be achieved through other channels of the Microfinance-Climate Framework. Better savings opportunities and remittances can maintain consumption levels during times of crises as there are more financial means for households. This can lower food insecurity and thus climate vulnerability, although the savings might not be enough to stimulate productivity enhancing investments. Financial inclusion could therefore still be a mechanism to achieve climate resilient communities where growth in agriculture is sustained. However, the evidence does not support that financial inclusion could be a way out of poverty and climate vulnerability, as agricultural productivity needs to increase for incomes to increase in the rural communities.

In a time where rising global temperatures and their impact on developing countries are inevitable, it is crucial to find efficient ways to mitigate damages from climate change. This study provides a first step in collecting and analysing empirical data at the sub-national level for climate adaptation on one area of climate adaptation that is relevant for Tanzania, increased agricultural productivity and cereal yields. Using the novel Finscope 2017 dataset and geospatial data from MAPSPAM a more nuanced analysis was conducted to highlight the varying effects different financial institutions have on cereal yields with the financial technology available today. However, the small dataset raises concerns of the robustness and uncertainty of the results. When more data becomes available over time, more thorough regression models can more precisely measure the magnitude of the impact of financial inclusion. Furthermore, future research can expand the scope to other crops and sectors, such as cash-crops or livestock, by using the same theoretical framework. At last, this study has focused on the demand side of financial inclusion. Future research should also investigate the supply side of investments and financial services to understand how the financial sector can unlock important climate funding for both Tanzania and other developing countries as a whole. This presents a promising and important research area as more empirical evidence is needed to assess how effective financial inclusion can improve agricultural productivity and climate adaptation at larger scale.

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# Appendix A

Table A1 - List of regions and districts in Tanzania.

| Region | District |
|---|---|
| Arusha | Arusha Rural |
| | Arusha Urban |
| | Karatu |
| | Longido |
| | Meru |
| | Monduli |
| | Ngorongoro |
| Dar-es-salaam | Ilala |
| | Kinondoni |
| | Temeke |
| Dodoma | Bahi |
| | Chamwino |
| | Chemba |
| | Dodoma Urban |
| | Kondoa |
| | Kongwa |
| | Mpwapwa |
| Geita | Bukombe |
| | Chato |
| | Geita |
| | Mbogwe |
| | Nyang'hwale |
| Iringa | Iringa Rural |
| | Iringa Urban |
| | Kilolo |
| | Mafinga Urban |
| | Mufindi |
| Kagera | Biharamulo |
| | Bukoba Rural |
| | Bukoba Urban |
| | Karagwe |
| | Kyerwa |
| | Missenyi |
| | Muleba |
| | Ngara |
| Kaskazini Pemba | Micheweni |
| | Wete |
| Kaskazini Unguja | Kaskazini A |
| | Kaskazini B |
| Katavi | Mlele |
| | Mpanda Rural |
| | Mpanda Urban |
| Kigoma | Buhigwe |
| | Kakonko |
| | Kasulu Rural |
| | Kasulu Urban |
| | Kibondo |
| | Kigoma Rural |
| | Kigoma Urban |
| | Uvinza |
| Kilimanjaro | Hai |
| | Moshi Rural |
| | Moshi Urban |
| | Mwanga |
| | Rombo |
| | Same |
| | Siha |
| Kusini Pemba | Chake Chake |
| | Mkoani |
| Kusini Unguja | Kati |
| | Kusini |
| Lindi | Kilwa |
| | Lindi Rural |
| | Lindi Urban |
| | Liwale |
| | Nachingwea |
| | Ruangwa |

| Region | District |
|---|---|
| Manyara | Babati Rural |
| | Babati Urban |
| | Hanang |
| | Kiteto |
| | Mbulu |
| | Simanjiro |
| Mara | Bunda |
| | Butiama |
| | Musoma Rural |
| | Musoma Urban |
| | Rorya |
| | Serengeti |
| | Tarime |
| Mbeya | Chunya |
| | Kyela |
| | Mbarali |
| | Mbeya Rural |
| | Mbeya Urban |
| | Rungwe |
| Mjini Magharibi | Magharibi |
| Morogoro | Gairo |
| | Kilombero |
| | Kilosa |
| | Morogoro Rural |
| | Morogoro Urban |
| | Mvomero |
| | Ulanga |
| Mtwara | Masasi |
| | Mtwara Rural |
| | Mtwara Urban |
| | Nanyumbu |
| | Newala |
| | Tandahimba |
| Mwanza | Ilemela |
| | Kwimba |
| | Magu |
| | Misungwi |
| | Nyamagana |
| | Sengerema |
| | Ukerewe |

| Region | District |
|---|---|
| Njombe | Ludewa |
| | Makambako Urban |
| | Makete |
| | Njombe Rural |
| | Njombe Urban |
| | Wanging'ombe |
| Pwani | Bagamoyo |
| | Kibaha |
| | Kibaha Urban |
| | Kisarawe |
| | Mafia |
| | Mkuranga |
| | Rufiji |
| Rukwa | Kalambo |
| | Nkasi |
| | Sumbawanga Rural |
| | Sumbawanga Urban |
| Ruvuma | Mbinga |
| | Namtumbo |
| | Nyasa |
| | Songea Rural |
| | Songea Urban |
| | Tunduru |
| Shinyanga | Kahama Urban |
| | Kishapu |
| | Shinyanga Urban |
| Simiyu | Bariadi |
| | Busega |
| | Itilima |
| | Maswa |
| | Meatu |
| Singida | Ikungi |
| | Iramba |
| | Manyoni |
| | Mkalama |
| | Singida Urban |
| Songwe | Ileje |
| | Mbozi |
| | Momba |
| | Tunduma |

| Region | District |
|---|---|
| Tabora | Igunga |
| | Kaliua |
| | Nzega |
| | Sikonge |
| | Tabora Urban |
| | Urambo |
| | Uyui |
| Tanga | Handeni |
| | Kilindi |
| | Korogwe |
| | Korogwe Urban |
| | Lushoto |
| | Mkinga |
| | Muheza |
| | Pangani |
| | Tanga Urban |

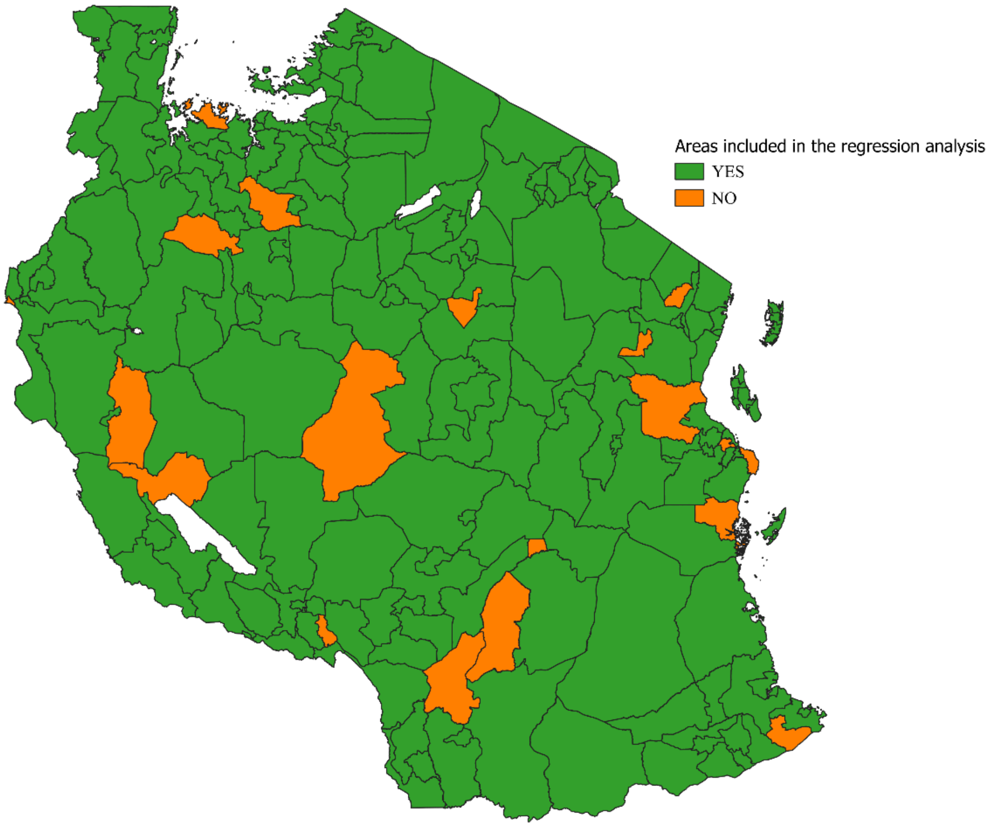
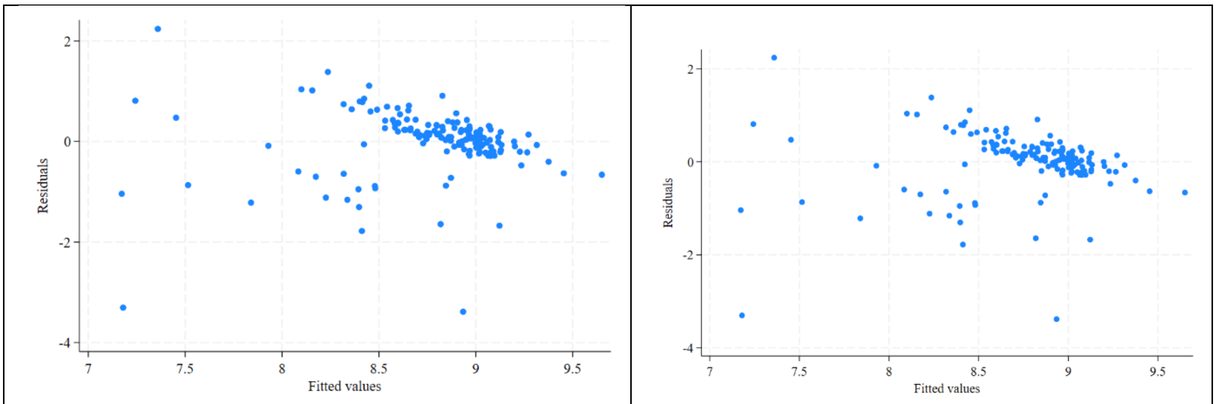



Figure A1 – Map of Tanzania and areas included in the analysis. Source: Authors own, based on data from the National Bureau of Statistics (2020). Note: The borders are based on administrative units from 2020, one data point from 2017 could therefore represent several districts in this map as some have been divided between 2017-2020.

Appendix B

A residual analysis is necessary when running regressions to secure that internal validity. However, as the empirical model are robust and clustered at the regional level, the Breush-Pagan/Cook-Weisberg test for heteroscedasticity is not applicable. Some insights are retrieved from the scatterplots in figure B1 that shows the residuals against predicted values of cereal yields from the model (2) and (5) in table 3. Due to some outliers in the dataset in panel a), the estimates might be biased based on the distribution of the residuals. Even though the F-statistic yielded significant values, one should be cautious of the implications of the model due to this potential biasedness and violation of the assumption $E(\varepsilon) \neq 0$ for OLS-regressions. Panel b), c) and d) have residuals that are constant across different values of $\hat{y}_j$.




a) Cereals only including microfinance

b) Cereals including all individual financial institutions

Figure B1 – Residual plot vs. fitted values for the OLS regression

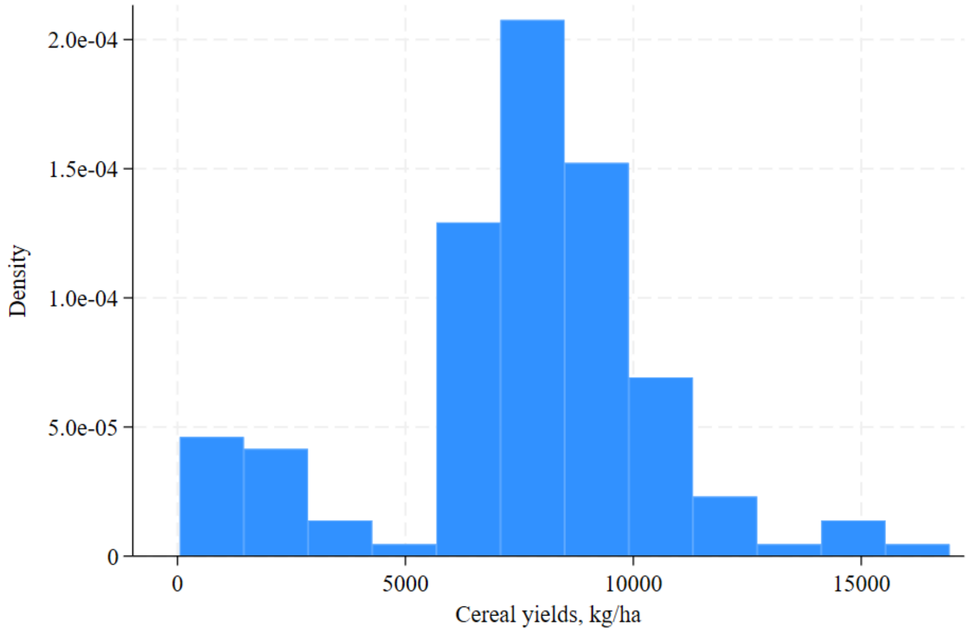



Figure B2 – Distribution of cereal yields across different districts.

To adjust for the bias observed in panel b), an alternative regression model is estimated after either the removal of potential extreme outliers or an added control variable. The outliers were identified based on the distribution of cereal yields. As figure B2 shows, there is no normal distribution among the cereal yields. Instead, it seems that there are two separate groups of cereal yields, one of low productivity and one of high productivity districts. Table B1 displays the list of the districts that have an average cereal yield of less than 5000kg/ha and belongs to the low productivity district. Almost all of the districts are in urban areas which could be systematically differ in crop yields compared to the more rural districts. For example, limited access to agricultural land, and better opportunities to invest in other sectors might crowd out initiatives to increase productivity in urban settings.

Table B1 – List of districts that does not follow the normal distribution of cereal yields.

| Region | District | Cereal Yields |
|---|---|---|
| Dar-es-salaam | Ilala | 1759.617 |
| Dar-es-salaam | Kinondoni | 1784.325 |
| Dar-es-salaam | Temeke | 1310.458 |
| Kaskazini Pemba | Micheweni | 48.23183 |
| Kaskazini Unguja | Kaskazini A | 3147.102 |
| Kaskazini Unguja | Kaskazini B | 2767.379 |
| Katavi | Mpanda Urban | 4301.215 |
| Kigoma | Kasulu Urban | 1902.173 |
| Kilimanjaro | Hai | 2885.823 |
| Kilimanjaro | Moshi Urban | 3461.887 |
| Kusini Pemba | Chake Chake | 771.2462 |
| Kusini Pemba | Mkoani | 460.6583 |
| Kusini Unguja | Kusini | 2154.221 |
| Kusini Unguja | Kati | 1709.604 |
| Mbeya | Mbeya Urban | 1984.892 |
| Mjini Magharibi | Magharibi | 2551.781 |
| Morogoro | Morogoro Urban | 1224.592 |
| Mtwara | Mtwara Urban | 1204.641 |
| Njombe | Makambako Urban | 1305.675 |
| Ruvuma | Nyasa | 1716.913 |
| Songwe | Tunduma | 758.689 |
| Tanga | Korogwe | 257.0534 |
| Tanga | Pangani | 753.1069 |

Table B2 shows the adjusted estimates for cereal yields once. Model (1) and (2) have excluded the district listed in table B1 entirely whereas model (3) and (4) have added a dummy variable to control for the effect of these districts. When removing the outliers entirely, the effect from both mobile money and SACCO is removed entirely. While they are still showing the same sign, the statistically significance is removed. Instead, the effect of increased access to commercial banks has a significant positive effect which increases in both statistical and economic significance when all of the observations are included but controlled for in model (3) and (4).

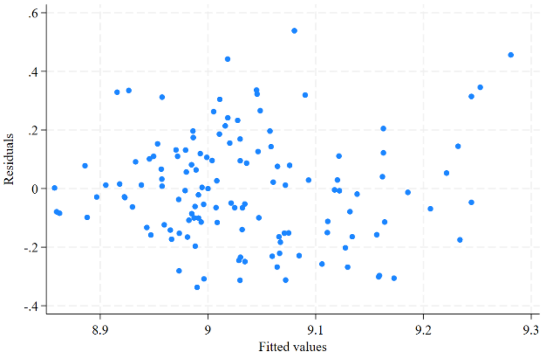
Table B2 – Effect of financial institutions on cereal yields, adjusted for outliers.

| | *Dependent variable is Cereals* | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Banked (%) | 0.372 | **0.502*** | 0.468 | **0.953**** |
| | (0.278) | **(0.293)** | (0.332) | **(0.469)** |
| Microfinance | 0.082 | | 0.523 | |
| | (0.161) | | (0.372) | |
| MFI (%) | | **-0.941**** | | **-1.137**** |
| | | **(0.461)** | | **(0.519)** |
| Mobile Money (%) | | 0.031 | | 0.271 |
| | | (0.176) | | (0.408) |
| SACCO (%) | | -0.103 | | -0.466 |
| | | (0.674) | | (1.202) |
| Saving's Groups (%) | | 0.162 | | **0.462**** |
| | | (0.167) | | **(0.225)** |
| Share of farmers | 0.061 | 0.034 | **0.311*** | 0.246 |
| | (0.104) | (0.104) | **(0.158)** | (0.165) |
| Share of pop. with secondary education | 0.102 | 0.121 | **0.328*** | **0.299*** |
| | (0.098) | (0.094) | **(0.193)** | **(0.177)** |
| Share of pop. with female HH-head | 0.232 | 0.196 | 0.231 | 0.180 |
| | (0.182) | (0.174) | (0.250) | (0.285) |
| Age of the HH-head | 0.004 | 0.004 | 0.000 | 0.003 |
| | (0.005) | (0.005) | (0.010) | (0.008) |
| HH Size | -0.010 | -0.018 | -0.002 | -0.014 |
| | (0.013) | (0.014) | (0.023) | (0.020) |
| Share of landowners | -0.033 | -0.036 | 0.144 | 0.202 |
| | (0.149) | (0.150) | (0.250) | (0.230) |
| Average monthly precipitation | **0.002*** | **0.002*** | -0.001 | -0.001 |
| | **(0.001)** | **(0.001)** | (0.003) | (0.003) |
| Rain anomaly, monthly (%) | **0.003***** | **0.004***** | 0.001 | 0.002 |
| | **(0.001)** | **(0.001)** | (0.002) | (0.002) |
| Low productivity district | | | **-1.895***** | **-1.889***** |
| | | | **(0.188)** | **(0.188)** |
| Observations | 131 | 131 | 154 | 154 |
| R-squared | 0.19 | 0.22 | 0.75 | 0.76 |
| Adj. R-squared | 0.12 | 0.14 | 0.74 | 0.73 |
| F-stat | 2.81 | 6.02 | 27.48 | 20.52 |
| P-value | 0.004 | < 0.001 | < 0.001 | <0.001 |

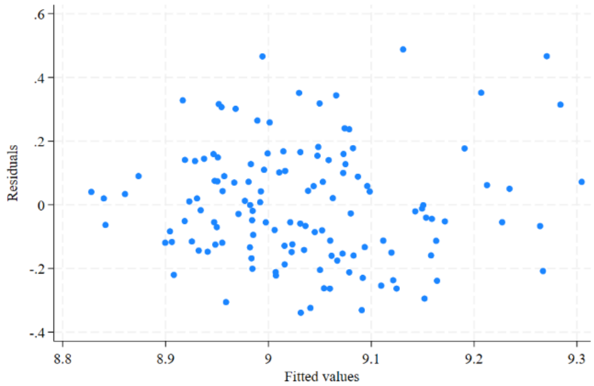
Note: Robust standard errors in parentheses, clustered at the regional level *** p<0.01, ** p<0.05, * p<0.1

The F-statistic and $R^2$-values increase drastically in model (3) and (4) which indicates that these models have the best fit. Figure B3 shows the scatterplot for fitted valued on residuals from all the regressions in Table B2. The distribution of residuals proves that the previous bias is reduced. However, the variance is somewhat heteroscedastic despite being adjusted for clustered standard errors. Therefore, the standard errors for each coefficient should be interpreted with caution.

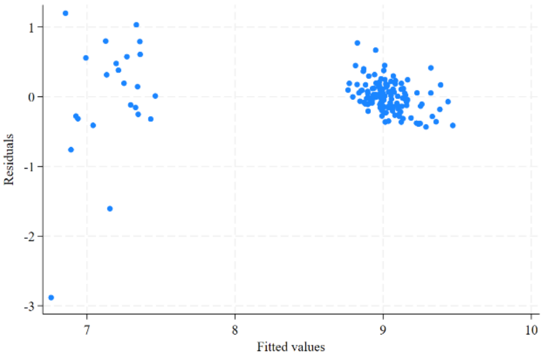
Table B3 presents a Variance Inflation Factor (VIF) test for multicollinearity among the control variables in the different regression models in table 3. The VIF indicates how many times the variance of a regressor is inflated due to correlation with the other regressors. Each column shows which model from table 3 the VIF is estimated on. The models that do not include any control variables are therefore excluded. None of the regressors show a high VIF-value in table B3. As a rule of thumb, VIF values below 10 is considered acceptable and the regressors do not pose any significant issues for the regression model (Mendenhall & Sincich, 2014).



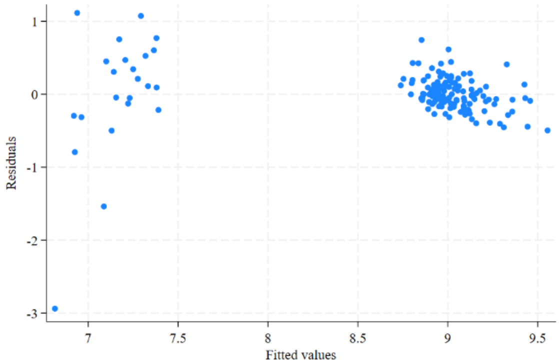

a) Residuals from model (1)




b) Residuals from model (2)




c) Residuals from model (3)




d) Residuals from model (4)

Figure B3 – Fitted values vs. residuals for the adjusted model for cereal yield

Table B3 – Variance Inflation Factor (VIF)

| *Regression model*<br>*Variable* | Table 3<br>(2) | Table 3<br>(3) | Table 3<br>(5) | Table 3<br>(6) |
|---|---|---|---|---|
| Banked (%) | 2.53 | 2.62 | 3.09 | 3.15 |
| Microfinance (%) | 2.24 | 2.35 | | |
| MFI (%) | | | 1.99 | 1.99 |
| Mobile Money (%) | | | 2.53 | 2.64 |
| SACCO (%) | | | 1.39 | 1.45 |
| Saving's Groups (%) | | | 1.32 | 1.32 |
| Share of farmers | 2.38 | 2.42 | 2.37 | 2.41 |
| Secondary education of HH head | 1.46 | 1.49 | 1.48 | 1.52 |
| Share of female HH head | 1.22 | 1.25 | 1.24 | 1.27 |
| Age of HH head | 1.46 | 1.43 | 1.49 | 1.49 |
| Size of HH | 1.42 | 1.43 | 1.45 | 1.45 |
| Share of landowners | 1.41 | 1.43 | 1.45 | 1.47 |
| Average monthly precipitation | 1.15 | 1.25 | 1.19 | 1.29 |
| Rain anomaly, monthly (%) | 1.34 | 1.39 | 1.47 | 1.27 |

# Appendix C

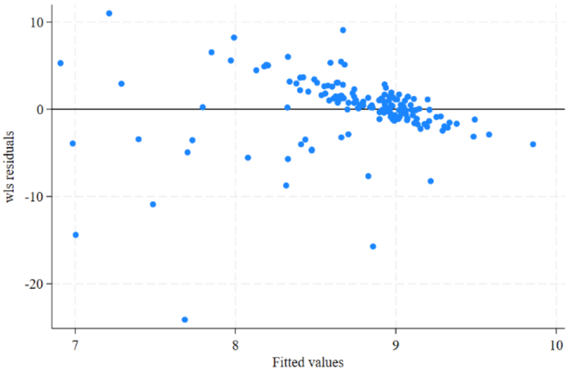
Table C1 shows the regression output when using WLS-regressions. The weighting variable is the sum of the household weights in the district. The reason to use the sum of the household weights is that the weight for each household is based on the sampling design for the entire dataset across all districts and regions, taking the sum of their weight will therefore show the total impact each district should have in relation to other districts. The results show similar estimates as the OLS-regressions when control variables are included. The main difference is that the F-statistic and $R^2$-value is dramatically increased for model (2)-(4). Microfinance as a whole show somewhere between 0.6 - 1.5 percent increase in cereal yields for each percentage point increase of microfinance. Whereas access to banking shows ambiguous results with both negative and positive values, both statistically significant depending on the model specification. When using WLS-regression, the strongest positive effect on cereal yields is mobile money. The strong effect on mobile money is reduced substantially when controlling for extreme outliers. The positive effect on cereal yields from access to informal savings groups is still positive yet low and show no significant result when using WLS-regressions. Both MFIs and SACCOs still show negative results, in similar size as the OLS estimates.

Based on the scatterplots in figure C1, the different distributions of the residuals do not seem to be affected by the WLS-regression in comparison with the residuals in appendix B. The main difference is that the residuals are much smaller compared to OLS-regressions for all models except for model (1). The bias remains in panel a) and b). Furthermore, the regression seems to show a slightly biased result as panel c) and d) show correlation between the fitted values and the residuals. The bias is very small given the low scale on the Y-axis and should not pose major issues as long as the regression is not extrapolated. Despite the high F-statistic and $R^2$-value, both the internal and the external validity is limited.

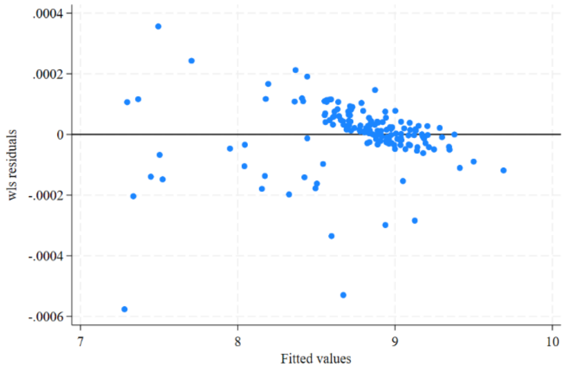
Table C1 – WLS-regressions on the effect of financial inclusion on cereals

| | *Dependent variable is cereals* | | | |
|---|---|---|---|---|
| | | | Controlled for outliers | Controlled for outliers |
| | (1) | (2) | (3) | (4) |
| Banked (%) | **-1.599**** | -0.857 | 0.422 | **0.844*** |
| | **(0.693)** | (0.731) | (0.411) | **(0.448)** |
| Microfinance (%) | **1.508***** | | **0.626**** | |
| | **(0.460)** | | **(0.256)** | |
| MFI (%) | | **-2.746**** | | -0.962 |
| | | **(1.287)** | | (0.753) |
| Mobile Money (%) | | **1.163**** | | **0.453*** |
| | | **(0.445)** | | **(0.257)** |
| SACCO (%) | | **-3.361*** | | -0.877 |
| | | **(1.980)** | | (1.161) |
| Saving's Groups (%) | | 0.865 | | 0.437 |
| | | (0.612) | | (0.352) |
| Share of farmers | **0.771*** | 0.551 | 0.329 | 0.280 |
| | **(0.406)** | (0.395) | (0.215) | (0.224) |
| Share of pop. with | -0.042 | -0.053 | **0.286**** | **0.272*** |
| secondary education | (0.289) | (0.273) | **(0.139)** | **(0.153)** |
| Share of pop. with | -0.620 | -0.632 | 0.244 | 0.190 |
| female HH-head | (0.620) | (0.579) | (0.293) | (0.322) |
| Age of the HH-head | 0.005 | 0.010 | -0.001 | 0.002 |
| | (0.016) | (0.016) | (0.009) | (0.009) |
| HH Size | 0.011 | -0.016 | -0.000 | -0.015 |
| | (0.046) | (0.045) | (0.026) | (0.026) |
| Share of landowners | 0.474 | **0.787***** | 0.058 | 0.031 |
| | (0.360) | **(0.298)** | (0.190) | (0.180) |
| Average monthly | **-0.011***** | **-0.013***** | -0.001 | -0.001 |
| precipitation | **(0.003)** | **(0.003)** | (0.002) | (0.002) |
| Rain anomaly, | **-0.008**** | **-0.007**** | 0.001 | 0.003 |
| monthly (%) | **(0.003)** | **(0.003)** | (0.002) | (0.002) |
| Observations | 154 | 154 | 154 | 154 |
| R-squared | 0.33 | 0.65 | 0.85 | 0.94 |
| Adj. R-squared | 0.28 | 0.62 | 0.84 | 0.93 |
| F-stat | 6.91 | 20.14 | 72.10 | 157.98 |
| P-value | < 0.001 | < 0.001 | <0.001 | <0.001 |

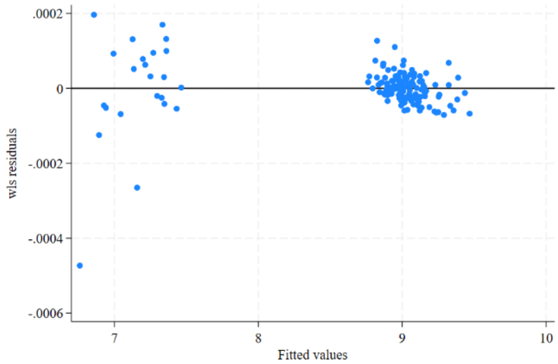
Note: Weighted variable is the district sum of household weights *** p<0.01, ** p<0.05, * p<0.1



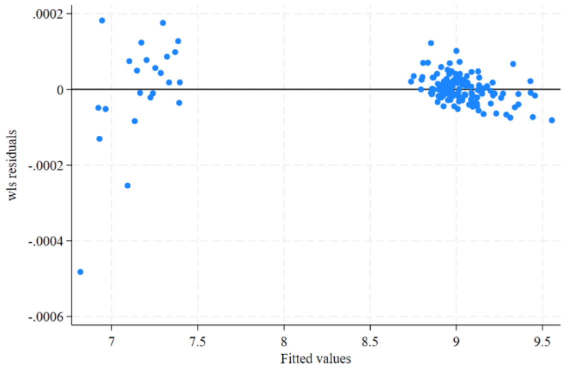

a) Residuals for model (1)




b) Residuals for model (2)




c) Residuals for model (3)




d) Residuals for model (4)

Figure C1 – Residual plot vs. fitted values for the WLS-regressions

## Appendix D

Table D1 shows the estimated effect of access to financial services on one single crop at a time, focusing on maize, rice and sorghum. These crops have been highlighted as three of the most important crops for small-scale farmers and poverty alleviation. The models are comparable across different crops as the coefficients are expressed as the relative change in crop yields. When examining all three crops, it's evident that no financial institutions consistently present the same results across all crop types, yet there are some identifiable patterns. The total effect of microfinance is less robust and shows both positive and negative results, and both statistically insignificant and significant results. The sign and size of the coefficient follows the signs and magnitude of the effect of increased access to mobile money. This reflect that microfinance might not offer services that suits for all crops, it could also be that microfinancial services are used to diversity away from climate sensitive crops, which would lower average yields from some crops while increase for others. Having access to a commercial bank shows positive results in all models, yet they are statistically insignificant with large standard errors in many cases. The exception is when studying rice in model (4) that display a strong positive coefficient for access to bank services.

Mobile money seems most important to increase sorghum yields. However, increased access to mobile money seems to lower rice yields. For rice yields, access to informal savings groups are more important, and show a stronger positive effect compared to the effect on total cereals in table 3. Similar to all other models, access to MFIs decreases crop yields for all three crops. Maize yields decrease with 1.9 percent for each percentage point increase of access to MFI. However, in contrast to other models, SACCOs display positive coefficient, these coefficients have very large standard errors and therefore there is no evidence that SACCOs have any effect on crop yields based on the results in table D1. It is important to note that the F-statistic is low, with somewhat higher p-value compared to other models, Furthermore, the difference between $R^2$ and adjusted $R^2$ is in some models large. All this indicates that these regressions are performing worse when estimating yields for individual crops and not entire crop groups.

Regressions for each crop is also estimated using Weighted Least Squares, the results are presented in table D2. The sign of each coefficient is consistent with the results in D1. However, the size of each coefficient is somewhat larger and several of them are statistically significant. This strengthens the result in table D1 despite their low F-statistic. The effect of microfinance as a whole has a positive and statistically significant result for both maize and sorghum, and negative yet insignificant effect on rice yields. It becomes evident that different financial services are more or less important for different individual crops when studying access to mobile money. As mobile money is statistically significant and positive for both maize and sorghum yet remains negative for rice. Access to a commercial bank is also more significant when estimating with WLS compared to OLS, which indicates that the effect is greater than what first appears in table 3 and table D1.

Table D1 - OLS-regressions for the three important cereal crops

| *Dependent variable* | Maize | | Rice | | Sorghum | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Banked (%) | 0.157 | 0.654 | 0.654 | **0.920*** | 0.122 | 0.282 |
| | (0.395) | (0.511) | (0.542) | **(0.520)** | (0.347) | (0.353) |
| Microfinance (%) | 0.564 | | -0.281 | | **0.489*** | |
| | (0.344) | | (0.314) | | **(0.249)** | |
| MFI (%) | | **-1.955***** | | -1.398 | | **-1.397***** |
| | | **(0.589)** | | (0.963) | | **(0.487)** |
| Mobile Money (%) | | 0.446 | | **-0.737*** | | **0.627***** |
| | | (0.402) | | **(0.364)** | | **(0.171)** |
| SACCO (%) | | 0.258 | | 1.440 | | -1.556 |
| | | (1.406) | | (1.497) | | (1.529) |
| Saving's Groups (%) | | 0.387 | | **0.757**** | | 0.053 |
| | | (0.270) | | **(0.330)** | | (0.283) |
| Share of farmers | 0.205 | 0.144 | 0.231 | 0.160 | -0.038 | -0.066 |
| | (0.200) | (0.194) | (0.191) | (0.176) | (0.191) | (0.181) |
| Share of pop. with secondary education | 0.244 | 0.225 | 0.161 | 0.244 | **-0.306**** | **-0.296*** |
| | (0.189) | (0.174) | (0.308) | (0.303) | **(0.135)** | **(0.146)** |
| Share of pop. with female HH-head | 0.117 | 0.018 | 0.047 | 0.032 | 0.195 | 0.119 |
| | (0.334) | (0.277) | (0.297) | (0.269) | (0.315) | (0.309) |
| Age of the HH-head | 0.002 | 0.003 | 0.002 | 0.004 | -0.002 | -0.002 |
| | (0.010) | (0.008) | (0.006) | (0.007) | (0.011) | (0.011) |
| HH Size | 0.015 | 0.004 | **-0.067*** | **-0.080**** | 0.030 | 0.019 |
| | (0.028) | (0.024) | **(0.035)** | **(0.031)** | (0.023) | (0.023) |
| Share of landowners | 0.038 | 0.065 | -0.073 | -0.058 | 0.466 | 0.461 |
| | (0.258) | (0.242) | (0.392) | (0.350) | (0.350) | (0.364) |
| Average monthly precipitation | -0.000 | -0.001 | 0.001 | 0.001 | 0.004 | 0.004 |
| | (0.003) | (0.002) | (0.003) | (0.003) | (0.003) | (0.003) |
| Rain anomaly, monthly (%) | **-0.005*** | -0.004 | **0.006**** | **0.009*** | 0.007 | 0.007 |
| | **(0.003)** | (0.003) | **(0.002)** | **(0.005)** | (0.005) | (0.004) |
| Observations | 154 | 154 | 132 | 132 | 132 | 132 |
| R-squared | 0.09 | 0.20 | 0.12 | 0.20 | 0.21 | 0.25 |
| Adj. R-squared | 0.03 | 0.04 | 0.04 | 0.11 | 0.15 | 0.17 |
| F-stat | 1.73 | 2.65 | 1.71 | 9.92 | 2.62 | 7.09 |
| P-value | 0.119 | 0.014 | 0.138 | < 0.001 | 0.026 | < 0.001 |

Note: Robust clustered standard errors by regions in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table D2 – Regressions estimated with Weighted Least Squares for the three main crops in cereals

| | Maize | Maize | Rice | Rice | Sorghum | Sorghum |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Banked (%) | 0.158 | **0.958*** | 0.649 | **0.933*** | 0.122 | 0.394 |
| | (0.532) | **(0.544)** | (0.529) | **(0.546)** | (0.458) | (0.463) |
| Microfinance (%) | **0.564*** | | -0.274 | | **0.491*** | |
| | **(0.323)** | | (0.330) | | **(0.286)** | |
| MFI (%) | | **-2.421***** | | -1.421 | | **-1.685*** |
| | | **(0.862)** | | (0.999) | | **(0.872)** |
| Mobile Money (%) | | **0.575*** | | **-0.747**** | | **0.673**** |
| | | **(0.305)** | | **(0.368)** | | **(0.277)** |
| SACCO (%) | | 0.796 | | 1.452 | | -1.192 |
| | | (1.392) | | (1.428) | | (1.278) |
| Saving's Groups (%) | 0.205 | 0.407 | 0.237 | **0.762**** | -0.037 | 0.272 |
| | (0.288) | (0.415) | (0.260) | **(0.340)** | (0.226) | (0.329) |
| Share of farmers | 0.244 | 0.339 | 0.178 | 0.153 | -0.306 | -0.068 |
| | (0.209) | (0.239) | (0.211) | (0.212) | (0.186) | (0.216) |
| Share of pop. with secondary | 0.117 | **0.390***** | 0.041 | 0.222 | 0.188 | **-0.345*** |
| education | (0.448) | **(0.139)** | (0.404) | (0.251) | (0.354) | **(0.180)** |
| Share of pop. with female HH- | 0.002 | -0.347 | 0.001 | 0.042 | -0.001 | 0.146 |
| head | (0.012) | (0.292) | (0.010) | (0.363) | (0.009) | (0.341) |
| Age of the HH-head | 0.015 | 0.005 | **-0.067**** | 0.005 | 0.029 | -0.002 |
| | (0.033) | (0.010) | **(0.030)** | (0.009) | (0.026) | (0.009) |
| HH Size | 0.038 | 0.025 | -0.068 | **-0.080***** | **0.462**** | 0.035 |
| | (0.264) | (0.031) | (0.255) | **(0.027)** | **(0.222)** | (0.026) |
| Share of landowners | -0.000 | 0.014 | 0.001 | -0.063 | **0.004*** | **0.500**** |
| | (0.002) | (0.231) | (0.002) | (0.287) | **(0.002)** | **(0.218)** |
| Average monthly precipitation | **-0.005**** | 0.000 | **0.006**** | 0.001 | **0.007***** | 0.002 |
| | **(0.002)** | (0.002) | **(0.003)** | (0.002) | **(0.002)** | (0.002) |
| Rain anomaly, monthly (%) | 0.205 | -0.003 | 0.237 | **0.009***** | -0.037 | **-0.010*** |
| | (0.288) | (0.002) | (0.260) | **(0.002)** | (0.226) | **(0.006)** |
| Observations | 154 | 154 | 132 | 132 | 132 | 132 |
| R-squared | 0.09 | 0.40 | 0.11 | 0.20 | 0.21 | 0.31 |
| Adj. R-squared | 0.03 | 0.34 | 0.05 | 0.11 | 0.14 | 0.23 |
| F-stat | 1.46 | 7.08 | 1.64 | 3.88 | 3.29 | 3.73 |
| P-value | 0.159 | < 0.001 | 0.103 | <0.001 | <0.001 | <0.001 |

Note: Weighted variable is the district sum of household weights *** p<0.01, ** p<0.05, * p<0.1