Food and Agriculture Organization of the United Nations

Smallholder productivity under climatic variability:

Adoption and impact of widely promoted agricultural practices in Tanzania

ESA Working Paper No. 16-03

April 2016

Agricultural Development Economics Division
Food and Agriculture Organization of the United Nations

Recommended citation

FAO, 2016. *Smallholder productivity under climatic variability: Adoption and impact of widely promoted agricultural practices in Tanzania*, by Aslihan Arslan, Federico Belotti and Leslie Lipper. ESA Working Paper No. 16-03. Rome, FAO.

Smallholder productivity under climatic variability: Adoption and impact of widely promoted agricultural practices in Tanzania[1]

Aslihan Arslan
FAO-ESA

Federico Belotti
CEIS Tor Vergata

Leslie Lipper
FAO-ESA

March 18, 2016

[1]We are grateful to William Settle, Senior Technical Officer at the Plant Production and Protection Division (AGP) of FAO for facilitating funding from the European Commission to conduct this research. We also thank to Giulio Marchi, Geospatial Analyst at the Agricultural Development Economics Division (ESA) of FAO, for his valuable support during the extraction process and subsequent merge of rainfall data, and David Roodman for his useful comments on the identifiability of a fully observed and recursive mixed-process system of equations. Any views expressed or remaining errors are solely the responsibility of the authors. Please contact `aslihan.arslan@fao.org` or `federico.belotti@uniroma2.it` for questions and comments.

Abstract

Food security in Tanzania is projected to deteriorate as a result of climate change. In spite of the Government's efforts to promote agricultural practices that improve productivity and food security, adoption rates of such practices remain low. Developing a thorough understanding of the determinants of adoption and updating our understanding of the impacts of these technologies under the site-specific effects of climate change are crucial to improve adoption. This paper addresses these issues by using a novel data set that combines information from two large-scale household surveys with geo-referenced historical rainfall and temperature data in order to understand the determinants of the adoption of sustainable and productivity improving practices and their impacts on maize productivity in Tanzania. The specific practices analyzed are: maize-legume intercropping, soil and water conservation practices, the use of organic fertilizers, inorganic fertilizers and high yielding maize varieties. We find that farmers located in areas where the cropping season's rainfall has been highly variable have 15 percent lower maize yields. Similarly, farmers located in areas where maximum temperatures during the growing season exceed 30 degrees Celsius have approximately 25 percent lower yields. Both rainfall variability and hotter temperatures are expected to increase under climate change, underlining the importance of policies to buffer food security from the estimated effects of climate change. Our analysis identifies policy entry points both to improve maize productivity and the adoption of practices to do so through careful empirical analysis. This paper contributes to evidence base to support policies for climate smart agriculture and underlines the importance of integrating site-specific analyses of climatic variables in policy targeting to foster adoption of appropriate practices to improve food security under climate change.

Keywords: Technology adoption, productivity analysis, climate change, panel data, Tanzania.

Contents

List of Figures

List of Tables

Introduction

Climate change is expected to have significant impact on food security in Sub-Saharan Africa (SSA), where most livelihoods heavily depend on rain-fed smallholder agriculture (Ziervogel et al., 2008; Barrios et al., 2008; TZG, 2009). Rising temperatures and changes in rainfall patterns have direct effects on crop yields, as well as indirect effects through changes in irrigation water availability, thus exacerbating the impacts of droughts, soil degradation and decline in biodiversity. In the absence of a policy agenda to increase economic growth and decrease poverty while maintaining the natural resource base, the negative effects of climate change on crop production will be especially pronounced in SSA. Forecasts for SSA show that *ceteris paribus*, rice, wheat, and maize yields are likely to decline in the next thirty years by 15%, 34%, and 10%, respectively (Nelson et al., 2009).

An estimated 90% of the Tanzanian population depends on rain-fed crop production and pastoralism to meet its basic food needs (Patt and Winkler, 2007). Country-specific climate models predict an average decrease in maize yields of 33%, with a wide variation (10-84%) across the the country (NAPA, 2007). Given that maize is the main staple in rural Tanzania, productivity decreases at this scale will affect the most vulnerable households that have high exposure to climate shocks as well as low adaptive capacity. Therefore, understanding the factors that influence rural households' decisions to adopt (or not) adaptive and productivity-increasing agricultural practices in response to long run changes in temperature and rainfall, as well as the impact of these practices on productivity is of paramount importance for food security.

The goal of this study is to provide a comprehensive analysis of the factors that influence the adoption of a set of agricultural practices that have the potential to improve farmers' adaptive capacity, including maize-legume intercropping, soil and water conservation measures (SWC), organic fertilizer, inorganic fertilizer and high yielding maize varieties, as well as their impacts on productivity in rural Tanzania. To this aim, we use the first two waves (2008/2009 and 2010/2011) of the Tanzania National Panel Survey (TZNPS), a nationally representative household survey that assembles information on a wide range of topics, with a strong focus on agriculture and rural development. We merge this data with geo-referenced historical rainfall and temperature variables to control for the effects of the levels and historical variations in climate variables on adoption and productivity. Given the overwhelming importance of maize for food security and the economy as a whole, we focus on maize farmers only.

Overall, this paper contributes to the literature by combining the technology adoption and agricultural adaptation literatures with rigorous empirical analysis. The specific contributions of the paper are threefold. First, although there is a well-developed literature investigating the determinants of technology adoption, research that explicitly accounts for climate risk in this literature is still nascent (Deressa and Hassan, 2009; Di Falco et al., 2011; Kassie et al., 2013; Arslan et al., 2014; Asfaw et al., 2014). We provide a comprehensive and rigorous analysis based on a two-period panel data combined with novel climate and bio-physical data to model farmers' adoption of five different practices simultaneously using a multivariate probit model, which captures the complementarities and/or substitutabilities among different agricultural practices while controlling for household-specific time-invariant unobserved heterogeneity. Second, we study the impact of these practices on maize productivity taking explicitly into account the potential endogeneity of adoption. Third, by exploiting exogenous variation in weather outcomes over time and between administrative areas, we investigate the impact of climate shocks on both technology adoption and productivity.

We find evidence that different practices are affected by different factors and that they are not mutually independent, suggesting the existence of complementarities between different practices. There is a very strong negative relationship between the historical variability in growing season rainfall and the adoption of organic and inorganic fertilizers, while this relationship is strongly positive and significant for improved seeds. This finding suggests that farmers may be decreasing the use of fertilizers the more variable the rainfall becomes, and that they perceive improved seeds as an adaptation strategy to variable rainfall. We also find that access to government extension services significantly increases the likelihood of adoption of all practices but legume intercropping, highlighting the key role of extension services in governing the adoption decisions of farmers. Another significant finding related to institutions is the positive and significant relationship between land tenure and the adoption of organic fertilizers and SWC, both of which are expected to bring longer term benefits to farmers underlining the importance of tenure security in long term investments in land. On the other hand, practices with more immediate benefits, i.e. fertilizer and improved seeds, are more likely to be adopted if credit is available. In terms of household characteristics, we find that in general the probability of adoption increases with household head's years of education and household size, as expected, underlining the role of information and labor constraints in adoption of agricultural technologies.

As for the determinants of maize productivity; maize-legume intercropping, SWC and inorganic fertilizers all have a positive and statistically significant impact on maize yields, suggesting the existence of synergies between these practices and food security. We find evidence of a strong negative relationship between maize productivity and both the variation in rainfall and the maximum temperatures during the growing season, indicating a lack of adaptive capacity to these shocks that are expected to increase in frequency under climate change. Policies to improve farmers' adaptive capacity are needed to improve food security given climate change projections.

The rest of this paper is organized as follows. Chapter 2 provides a discussion of the macroeconomic context, agricultural production and climate variability, as well as an overview of agricultural policy and promotion of various practices in Tanzania. Data sources, sample composition and descriptive statistics are presented in Chapter 3. Chapter 4 presents the conceptual framework and analytical methodology with emphasis on the empirical model. The main empirical results are presented and discussed in Chapter 5. Chapter 6 concludes by presenting the key findings and policy implications.

Background

2.1 Macroeconomic context, agricultural production and climate variability

Located in southern Africa and bordered by Kenya, Uganda, Rwanda, Burundi, the Democratic Republic of the Congo, Zambia, Malawi, and Mozambique, Tanzania is a large sparsely populated country with population density of 51 persons/Km^2 with a large variation across regions (Tanzania National Bureau of Statistics, 2013).[1] The last census reports that the population of Tanzania (around 45 million in 2012) is four times that of 1967 and that it has grown by about 30 percent in the last decade.

As for the state of the economy as a whole, Tanzania has made impressive economic gains in the last decade reaching an annual GDP growth rate close to 7 percent. The growth rate in the agricultural sector has been about 4 percent. As reported by the World Bank (2013), this steady-state economic growth has been mainly driven by *i*) the rapid growth of a small number of economic sectors (communication, financial services, construction, manufacturing and retail); *ii*) the fact that volatility has been confined to sectors with a limited overall impact on GDP; *iii*) the constant, although quite low, growth rate of the agricultural sector which accounts for a large share of the GDP; *iv*) the resilient domestic demand and *v*) the country's limited exposure to external shocks mainly related to the limited dependence on net external trade.

However, the reported macroeconomic performance has not translated into a similarly strong reduction in poverty. An assessment of income-poverty levels in Tanzania shows that the percentage of population below the basic-needs poverty line decreased from 38.6 in 1991 to 33.6 in 2007, while trends in other welfare indicators are mixed. Even though consumer durables owner-

[1] The population is concentrated in Dar es Salaam and Zanzibar Urban regions with population densities of 3,133 and 2,581 persons/Km^2, while Lindi and Katavi regions are those with the lowest population densities with 13 and 15 persons/Km^2, respectively.

ship and access to education and public health services have increased, ownership of agricultural assets and access to clean water showed some deterioration. Hence, despite the aforementioned improvements, Tanzania is lagging in its progress towards its targets on reducing poverty and food insecurity and in achieving the Millennium Development Goals (MDGs) target of halving poverty by 2015.

The agricultural sector remains the largest sector in the economy and hence its performance has a significant effect on output and corresponding income and poverty levels. According to the economic outlook of the World Bank (2013), the sector contributes to almost one quarter of Tanzania's overall GDP, provides 85 percent of exports, and employs about 80 percent of the work force. Growth is largely driven by the expansion of cultivable land rather than by increasing productivity. The major constraints facing the agriculture sector are the decreasing labor and land productivity due to application of poor technologies, as well as the dependence on unpredictable weather conditions. Both crops and livestock are indeed adversely affected by periodical droughts (World Bank, 2013).

Tanzania's agriculture is largely based on smallholders. Smallholder farmers account for about 84% of cultivated land with an average farm size of about 2.4 ha (Fischer, 2003).[2] Among those that grow maize, the average area allocated to the crop is about 0.8 ha (0.86 ha in our sample). The Government of Tanzania owns most of the large-scale farms (i.e. greater than 5 ha), which accounts for the remaining 16% of cultivated land (about 1% of maize farmers cultivate more than 5 ha in our sample). The most prevalent staple crops include maize, cassava, rice, sorghum, and millet, while the main exported crops are sugar, coffee, cotton, tobacco, and tea.

According to the 2002-03 National Sample Census of Agriculture (NSCA), maize is the most widely cultivated crop in Tanzania, produced by 4.5 million farm households representing about 82% of all Tanzanian farmers covering 45% of total cultivated land (USAID, 2010). The regions with the largest total production, according to the NSCA, are Mbeya and Iringa, followed by Shinyanga, Ruvuma, Tanga, Rukwa, and Mwanza. Unlike other staple crops like paddy rice and sorghum, maize production is geographically dispersed throughout the country. As for trade, maize imports over 2005-07 averaged 116 thousand tons, while maize exports averaged 70 thousand tons, representing about 2% of maize production.[3]

[2] Average farm size also varies depending on gender; men are more likely to cultivate greater than 1 ha, while women are more likely to cultivate plots less than 0.3 ha.

[3] Tanzania exports maize to Zambia and Malawi in the south, and to Kenya in the north.

As far as climate variability is concerned, most of Tanzania is characterized by a unimodal rainy season, which occurs between December and April. The northern and northeastern parts of the country, however, show a bimodal rainfall pattern, with a shorter *vuli* rainy season from October to December and a longer *masika* rainy season from March to May. Projections from General Circulation Models reported by Arndt et al. (2012) show that, relative to a no climate change baseline and considering domestic agricultural production as the principal channel of impact, food security in Tanzania appears likely to deteriorate as a consequence of climate change in the next 30 years. The authors pointed out that climate change will affect households differently based on their income and consumption patterns; will produce regional-specific shocks; affect crops differently, thus implying that the extent of the potential negative effect on income and consumption will depend on the smallholder farmers' cropping patterns and their ability to reallocate farm resources between activities. Moreover, as reported by Morton (2007), the socio-economic impact of climate change on smallholder farmers will depend on their adaptive capacities. Tanzania's National Adaptation Plan of Action ranked agriculture and food security as the most vulnerable sector affected by climate change and prioritized activities to improve the understanding of the impacts of climate change on agriculture and food security (NAPA, 2007). The agricultural practices analyzed in this study have the potential to contribute to these adaptation efforts by improving productivity and its resilience to shocks through improvements in soil health and water retention capacity. These practices also form an integral part of agricultural policy of the country as detailed in next next sub-section.

2.2 Overview of agricultural policies for food security and productivity

The agricultural policy in Tanzania has focused on increasing output and efficiency of agricultural production at the village level since the 1980s.[4] In its 1997 revised form, this policy has also focused on enhancing environmental awareness through education extension services, and undertaking further research on the promotion of agricultural practices aimed to enhance food security and increase smallholder farmers' productivity and income while avoiding nega-

[4]The complete set of agricultural policy priorities were: *i*) increase output and efficiency of agricultural production at the village level; *ii*) increase efficiency in the use of energy inputs; *iii*) increase the use of tractors and/or animal-drawn implements for farming; *iv*) introduce village-level transportation and the use of small scale human or draught-animal-powered technologies and, in general, *v*) increase the use of renewable energy resources.

tive environmental externalities, nutrient depletion, soil degradation and erosion (TZG, 1997). In particular, soil conservation and land use planning through fertilizer, animal manure and mulching techniques have been promoted through extension and training services. Moreover, a set of regulatory and technical services ranging from quality control and certification of improved seeds to training and promotion for water-harvesting technologies have been used as policy instruments.

The National Land Policy reinforces the objectives of the agricultural policy especially in the treatment of "shifting cultivation", considered as one of the main drivers of land and soil degradation, through the allocation of land to rural farmers on a tenure basis. An improved tenure security is expected to increase the incentives to adopt practices that increase productivity and improve soil health in the long run.

One of the important agricultural policies is fertilizer subsidies that were discontinued from 1990 to 2002. The Government reintroduced fertilizer subsidies in the 2003/04 season and by 2008/09 they reached the amount of TShs 32 billion (TZG, 2010). In 2008/09 about 700,000 farmers were targeted to receive 155,000 metric tons of subsidized fertilizer and 65,000 tons of seeds. In 2009/10, 1.5 million beneficiaries received 4.5 million input vouchers, which are viewed as a tool to increase yields for maize and other crops. The subsidy program, in which the Ministry of Agriculture, Food Security and Cooperatives (MAFC) has been fully involved through the distribution of the vouchers from the national to the village level, has been largely financed by the World Bank's Accelerated Food Security Project (AFSP) (Minot and Benson, 2009).

While the AFSP continues to target agricultural services to smallholders, the new agricultural development policy "Kilimo Kwanza" (KK) introduced in 2008 gives priority to large-scale farming based on a more private sector oriented approach to agricultural development.[5] The most high-profile state interventions in agriculture continued to be small-scale irrigation under the ASDP and input subsidies under the National Agriculture Input Voucher Scheme (NAIVS), which peaked during 2010/11.

It is worth noting that, despite the aforementioned subsidy programs, one of the leading

[5]KK favors national agribusiness companies and joint ventures with foreign investors, some of which are beginning to materialize in the Southern Agricultural Growth Corridor of Tanzania (SAGCOT) launched at the World Economic Forum for Africa in May 2010 as a public-private partnership between the Government and more than 20 agribusiness companies and international organizations (TDRG, 2009).

independent research institutions in Tanzania have reported that 98% of the poorest 20% of farmers (as well as about 69% of the richest ones) had never used chemical fertilizer (REPOA, 2007). The same evidence has been reported by the Tanzania Development Research Group, which pointed out “an upward trend in political corruption financing the continued dominance of the CCM ruling party” (TDRG, 2009). The misuse of public resources by the central government severely reduces the volume of services reaching the majority of the poor, particularly in rural areas (World Bank, 2010). Moreover, evidence of widespread corruption in the National Agricultural Input Vouchers Scheme (NAIVS) suggests that many among the intended target group of smallholders have not received subsidized inputs. Similar evidence has been reported at the local level, where abuses of input distribution procedures are common (TDRG, 2009). We control for the potential implications of these irregularities in our empirical model below.

More recently, cognizant of the negative impacts of climate change on agriculture such as declining yields and increasing pest/disease occurrence, the government of Tanzania has developed strategies to support agriculture for food security (TZG, 2008, 2009). These policies include the promotion of drought tolerant and pest-resistant crop varieties, early warning systems to inform farmers about rainfall anomalies, as well as improving access to credit for smallholders to facilitate technology adoption (TZG, 2008; MAFAP, 2013). In spite of government’s efforts the use of various adaptation strategies remain low (MAFAP, 2013).

Against this background, understanding the determinants of the adoption and the productivity implications of practices promoted to improve food security and productivity is critical in improving the targeting and the effectiveness of agricultural development policies in Tanzania. Enhancing this understanding with a detailed analysis of the effects of climatic variables on farmer decisions and productivity, as we do in this paper, would help further strengthen agricultural policies under climate change.

Data and variables description

3.1 Data

The Tanzania National Panel Survey (TZNPS), implemented by the Tanzania National Bureau of Statistics (TZNBS), is part of the Living Standards Measurement Study-Integrated Surveys on Agriculture, a series of nationally representative household panel surveys that assembles information on a wide range of topics, with a strong focus on agriculture and rural development. The survey collects information on socio-economic characteristics, production activities in agricultural, livestock and fisheries sectors, non-farm income generating activities and consumption expenditures. It currently consists of two waves, the first conducted over twelve months from October 2008 to September 2009 and the second over the same period of 2010-11. Both waves make use of three main questionnaires to collect data: a Household Questionnaire (HQ) collecting information on household composition, educational attainment, health, labor market participation, non-farm and social activities[1]; an Agriculture Questionnaire (AQ), administered to any household that has engaged in any farming or livestock activities, in which data are collected at both the plot and crop levels on inputs, production and sales; a Community Questionnaire (CQ) administered to a group of local leaders determined by the field supervisors and designed to collect information about the community where the selected households are located.[2]

The TZNPS, designed to be representative at the national, urban/rural, and major agro-ecological zone levels, is based on a stratified, multi-stage cluster sample design recognizing explicitly four analytical strata: Dar es Salaam, other urban areas in mainland, rural areas in mainland, and Zanzibar. Within each stratum, clusters were randomly selected as the primary sampling units, with the probability of selection proportional to their population size. In urban

[1]Data on labor, education, and health status are collected at the individual level.

[2]The second wave has seen the introduction of a forth household questionnaire dedicated to collect information on fisheries (fishing, processing and trading), which provides much richer data on fisheries compared to the first wave.

areas, clusters match census Enumeration Areas (EAs)[3], while in rural areas, clusters match villages. In the last stage, 8 households were randomly chosen in each cluster (Tanzania National Bureau of Statistics, 2012).

The first wave's original sample consists of 3,265 households in 409 Enumeration Areas (2,063 households in rural areas and 1,202 urban areas). About 74.5 percent of these households (2,429) are agricultural households[4]. In this study, we focus on the 1,296 households which have cultivated and harvested maize during the main cropping season, which captures about 85% of the total annual maize production in Tanzania.[5]

The second wave has tracked almost all households originally interviewed during the first round with an attrition rate of only 3%. If a household has moved from its original location, the members were interviewed in their new location.[6] If a member of the original household had split from their original location to form or join a new household, information was recorded on the new location of this member.[7] The second wave's original sample consists of 3,924 households in 409 EAs (2,629 households in rural areas and 1,295 urban areas), 1,515 of which are maize farmers (out of 2,769 agricultural households).

The final sample, consisting of both waves, is an unbalanced panel of 1,833 households and 2,810 observations. The breakdown by household status and wave of the selected sample as well as of the original sample is reported in Table 1. It is worth noting that the unbalanced nature of the panel stems from both the selection of maize farmers and the presence of about 20% of the households who had split in the second waves.[8] Figure 1 shows the selected sample representativeness, reporting the number of households in each EA by AEZ. The final sample covers

[3]Tanzania is divided into thirty regions (mkoa), twenty-five on the mainland and five in Zanzibar. 169 districts, also known as local government authorities, have been created. Of the 169 districts, 34 are urban units, which are further classified as 3 city councils, 19 municipal councils, and 12 town councils. The census EAs are the smallest operational areas established for the the 2002 Population and Housing Census, more specifically, the National Master Sample Frame.

[4]We consider as agricultural households those with at least one cultivated plot in the main rainy season

[5]This information comes from the USDA website for Tanzania: http://www.fas.usda.gov/pecad2/highlights/2003/03/tanzania/i (accessed June, 2013).

[6]When the location was within one hour of the original location, the interview has been conducted by the field team at the time of their visit to the EA, while if the new location was more than an hour from the original one, details were recorded on specialized forms subsequently passed to a dedicated tracking team for follow-up.

[7]Households are identified in the first wave by a fourteen-digit number that is constructed from the district, ward, locality, enumeration area, and household number. The second wave household identifier is represented by that of the first wave plus two digits representing the identification number for the tracking target with the lowest individual identifier from the first wave.

[8]As an intermediate output we also constructed a balanced panel of 977 households.

261 EAs and 9 AEZ. We use the TZNPS to create variables that represent the determinants of household's adaptive capacity, such as the adoption of agricultural practices to maintain or increase incomes, financial and human capital, as well as access to markets and information.

In order to control for the effects of rainfall and temperature variations on farmers' adoption decisions and maize productivity, we merge the TZNPS with historical rainfall and temperature at the EA level. Rainfall data come from the daily Africa Rainfall Climatology version 2 (ARC2) of the National Oceanic and Atmospheric Administration's Climate Prediction Center (NOAA-CPC) summed at decadal (10-days) values and corrected for possible missing daily values. The ARC2 rainfall database contains raster data at a spatial ground resolution of 1/10 of degree for African countries for the period 1983-2012. Our temperature data are decadal surface temperature measurements for the period of 1989-2010 obtained from the European Centre for Medium-Range Weather Forecasts (ECMWF). [9]

Using this data, we construct variables to define exposure to risk including indicators of climatological variability (characterized by spatial and time variation) as well as short-run indicators of weather conditions (characterized by spatial variation only). As for the former type of indicators, we consider the between-years rainfall's Coefficient of Variation (CoV) (σ/μ from the distribution of annual rainfall totals) and the average rainfall shortfall (the average of the annual totals departures from the long run average), both computed for the 1983-2012 period at EA level.[10] Being proxies of the climate uncertainty in a specific area, we expect these indicators to be key determinants of adoption. As for short-run weather conditions, we consider the total rainfall, the seasonal maximum temperature and the ratio of the within-year CoV over the average of within-year CoVs of the previous 25 years. We expect these indicators to be key determinants of the maize productivity.

We also control for bio-physical sensitivity that forms part of the definition of vulnerability in climate adaptation literature (Smit and Wandel, 2006). We merge our sample with indicators of soil nutrient availability and soil pH extracted from the Global Agro-Ecological Zones (GAEZ)

[9]Through our procedure, we extracted the mean rainfall and temperature for the buffer zones with 10 km and 50 km radius, respectively, around the EAs centroids.

[10]One of the major advantages of the CoV in our context is that, for a given level of standard deviation, it changes as the mean changes reporting a lower level of variability for those EAs with higher level of average rainfall. On the other hand, CoV is scale-invariant. In our context this property is non desirable. This is because an area in which the rainfall distribution over the reference period is characterized by $\mu = 5$ and $\sigma = 10$ will show the same CoV of an area in which the distribution is characterized by $\mu = 2$ and $\sigma = 4$. This looks like a very strong assumption since the shape of these two distributions is very different.

database and the Harmonized World Soil (HWS) database, respectively.[11] These two variables allow to control for the effects of bio-physical characteristics on both adoption and productivity. Finally, we use the information available in the FAO crop calendar to construct an indicator of the main Agro-Ecological Zones (AEZ).[12]

3.2 Variables and descriptive analysis

3.2.1 Dependent variables

As already mentioned, the agricultural practices considered in this study include maize-legume intercropping, soil and water conservation practices, organic fertilizer, inorganic fertilizer and high yielding maize varieties. We define as adopters the households who have treated at least one plot with these practices, irrespective of the area covered. Thus, the non-adopters are households who did not use these practices at all. Figures from 2 to 6 show the geographic distribution of the considered practices by survey year.[13]

The maize-legume intercropping system has the potential to alleviate the binding constraints of poor soils, helping to maintain productivity under climate change characterized by unreliable rainfall and drought. In fact, when intercropped with maize, legumes help to produce larger quantities of better quality organic matter inputs (such as nitrogen and soil organic carbon) leading to greater productivity benefits compared with mono-cropped maize plots (Schmidt et al., 2003; Rusinamhodzi et al., 2012). Summary statistics indicate that maize-legume intercropping is the most prevalent practice in our sample practiced by about 33% of households both in 2008 and 2010. This practice is especially widespread in western Tanzania (agro-ecological zone IX), where adoption rates are about 64% and 60% in 2008 and 2010, respectively.

The use of organic fertilizer is one of the most important sustainable agricultural practices, since it harmonizes agricultural production with the natural environment, improving soil permeability and water holding capacity as well as soil chemical properties (such as N, P, K) and other fundamental mineral nutrients. Moreover, it may contribute to the reduction of the use

[11] Soil nutrient availability has been extracted as the more frequent value of the 15 Km radius buffer areas around the EAs centroids, while soil pH has been extracted as the average value of the 15 Km radius buffer areas around the EAs centroids.

[12] Detailed descriptions of the nine Tanzania AEZ can be found at http://www.fao.org/agriculture/seed/cropcalendar/welcome.do.

[13] Table 11 in the Appendix reports the same information reported in Figures from 2 to 6 adding the standard deviation of adoption variables within each AEZ.

of chemical fertilizer, which has been causing environmental problems such as eutrophication in water system or land degradation (Marenya and Barrett, 2007). As pointed out by Reganold et al. (1987), the impact on productivity of chemical fertilizer is higher than that of organic fertilizer, at least in the short run. On the other hand, organic fertilizer appears to be more effective in reducing soil erosion and maintaining soil productivity in the long run. As shown in Table 2, about 17% of farmers report the use of organic fertilizer, with an average quantity of about 660 and 497 Kg/ha in 2008 and 2010, respectively (the difference between the two waves is not statistically significant). The adoption rate is highest in the AEZ VII in the first wave (34.2%) and in the AEZ VIII in the second wave (34.7%).

The adoption of SWC measures can provide benefits by reducing water erosion, improving water quality, and promoting the formation of natural terraces over time, all of which have the potential to lead to higher and more stable yields. SWC measures also often provide benefits to neighbors and downstream water users by mitigating flooding, enhancing biodiversity, and reducing sedimentation of waterways (McCarthy et al., 2011). SWCs include erosion control bunds, terraces, gabions/sandbags, vetiver grass, tree belts, water harvest bunds or drainage ditches. Our data shows that about 20% and 14% of households have at least one plot treated with SWC structures in 2008 and 2010, respectively. This figure is highest in the AEZ VIII for both waves (37.1% in 2008 and 26.2% in 2010). Among the adopters, about 63% have used terraces or erosion control bunds.

About 16% of households in 2008 (19% in 2010) have treated at least one of their plots with inorganic fertilizer, which is relatively low given the farm input subsidy program being implemented during the study period. Looking across the different AEZ, adoption appears to be higher in AEZ IV with a peak of 53.4% in 2010. It is interesting to note that the average quantity has increased between the two waves reducing substantially the ratio of organic to inorganic fertilizer use, even though the observed increase in the use of inorganic fertilizer is not statistically significant (Table 2).

The use of improved seeds is another practice that could improve food security by improving productivity (see Feder et al., 1985; Feder and Umali, 1993, and references therein). Nevertheless, there is no a clear cut evidence on the superiority of high yielding varieties with respect to local ones under harsh climatic conditions or climate change. The share of adopters of improved maize varieties is about 18.4% in 2008 (16.6% in 2010) and this figure is a bit larger in the AEZ

I in 2008 (23.9%) and AEZ VII in 2010 (33.6%). It is worth emphasizing that the high-yield potential of the improved seeds can be realized only if at least some inorganic fertilizer are applied (Feder et al., 1985).

Panel (a) of Table 2 reports some descriptive statistics on the complementarity between inorganic fertilizers and improved seeds for the 2008 season. As expected, improved maize seeds on average provide higher yields than traditional varieties: the average yield is 1,855 kg/ha for improved seeds and 1,382 kg/ha for traditional varieties (see also table 5). Organic fertilizer is applied by about 17 percent of farmers and the average application amounts to 660 kg/ha. We also find that more inorganic fertilizer is applied on improved varieties than traditional ones: it is applied by 28 percent and 13 percent of farmers, respectively. Nevertheless, about 75% of households have adopted improved varieties without fertilizer, thus not exploiting the potential benefit from the joint usage of these practices. In terms of the quantity applied, the average amount of organic (inorganic) fertilizer application is about 351 (30) kg/ha for traditional seeds, while it is 6 (14) times higher for improved seeds. This evidence highlights that many farmers are not exploiting the potential benefit of the improved seeds/fertilizer joint usage. The same figures emerge from panel (b) of Table 2 for the 2010 season, with an important exception represented by a reversion in the inorganic fertilizer application rates between traditional and improved varieties.

The descriptive analysis conducted so far does not distinguish between households who adopt one practice from those who use multiple practices in combination. Table 3 shows that the picture changes when we look at the use of multiple practices at the same time.[14] Overall, the extent of multiple adoption is relatively small. Of the 1,296 households who have cultivated at least one maize plot in 2008 (1,515 households in 2010), about 62% (60%) have benefited from one or more practices, while all considered practices were jointly adopted in only 4 (3) cases in 2008 (2010). Maize-legume intercropping is confirmed as the most common practice used by the households in our sample. It is applied on at least one plot as a single technology by the 13.5% (15.5%) of the farmers, in combination with SWC measures by 4.8% (1.0%) of the households and in combination with inorganic fertilizer on 3% (4.4%) of the cases in 2008 (2010). Improved seed alone is adopted by 5.2% (5.3%) of the farmers, in combination with

[14]Note that our definition of multiple adoption does not distinguish between the use of multiple practices in the same plot from the use of multiple practices on different plots.

SWC measures by 1.9% (0.7%) in 2008 (2010). Around 5% used only organic fertilizer in both waves, while inorganic fertilizer alone is adopted only in 3.8% (4.6%) of the cases in 2008 (2010).

The panel nature of our data allows us to analyze the dynamics of adoption and dis-adoption of the practices analysed here. Table 4 reports national transition matrices for the five considered agricultural practices. The most stable technology adoption is for inorganic fertilizer: 83% of adopters in 2008 still used it in 2010. Around 42% of adopters of organic fertilizer dis-adopted the practice in 2010, while the dis-adoption rate for maize-legume intercropping is about 48%. About 23% of non-adopters of this practice in 2008 have adopted it in 2010. The highest dis-adoption rate is observed for SWC practices (72%). Access to improved seeds among farmers who did not use them in 2008 increased and 10% of them had used improved seeds in 2010. Dis-adoption, however, is also rife for this practice at 70.5%.

Figure 7 reports the average maize yield (Kg/ha) by district and wave. The highest productivity districts are located in the south-west and north-east of the country, mainly in the Arusha, Dodoma, Iringa, Mbeya, Rukwa, and Ruvuma, and Kilimanjaro regions. Table 5 reports maize yield in the main cropping season by adoption status and wave. The descriptive statistics show a significant difference in maize yields between adopters and non-adopters. Adopters of inorganic fertilizer in 2008 have harvested about 1,133 Kg/ha more than non-adopters (1,366 Kg/ha in 2010) while adopters of maize-legume intercropping have about 703 Kg/ha more (831 Kg/ha in 2010). The lowest maize yield gain is reported for improved seeds and SWC measures, which are about 473 and 491 Kg/ha in 2008 (649 and 595 Kg/ha in 2010), respectively. Overall, this picture suggests that adoption of any of the farm management practices may have a significant role in increasing maize productivity in Tanzania. [15] The simple averages, however, may be due to other observable and unobservable factors, such as differences in household characteristics and endowments, which in turn may make adoption endogenous. The ways in which we deal with this in our empirical analysis of yields are discussed in detail in Section 4.

3.2.2 Explanatory variables

Our explanatory variables are mainly based on economic theory and past empirical work on the adoption of agricultural practices and productivity (Feder et al. (1985); Feder and Umali (1993);

[15] The statistically significant difference between the adopter groups also remains subjectively the same when we look at disaggregated analysis by AEZ.

Just and Zilberman (1983); Rosenzweig and Wolpin (1993); Doss (2003) among others), as well as the more recent literature on adoption of adaptation measures (Di Falco et al., 2011; Arslan et al., 2014; Asfaw et al., 2014). Summary statistics of the selected explanatory variables by survey year and AEZ are presented in Tables 6 and 7, respectively.

The first set is related to socio-demographics and includes age, gender, marital status and education level of the household head, as well as household size and dependency ratio. The average age of the sample household head is about 47 years old in 2008 (48 years old in 2010) and around 24% were female in both years. As in many SSA countries, women face specific constraints such as less education, inadequate access to land and information, low level of production assets and livestock ownership (De Groote and Coulibaly, 1998). Thus, we expect female headed farmers to be less likely to adopt new practices.

The average years of education of household head is 4.6 (4.7), and about 64.5% (59.3%) of household heads are married. Several empirical studies have shown that farmers with better education are earlier adopters of modern technologies and apply modern inputs more efficiently throughout the adoption process (See Feder et al. (1985) and reference therein). Thus, we expect that more educated farmers are more likely to adopt the practices analyzed here.

The average household size is about 5.35 (5.61) while dependency ratio is about 1.19 (1.13). Household size is a potential indicator of labor supply for production. For instance investments in SWC can be particularly labor demanding and may be too expensive to undertake for households with limited access to labor. Thus, we expect that labour demanding practices are more likely adopted by large households. Looking across the nine AEZ, there seem not to be emerging pattern in terms of socio-demographics, the only exception represented by the households in the first and eighth AEZ which tend to have bigger household and higher dependency ratios compared to the others.

As wealth indicators, we include a wealth index based on durable goods ownership and housing conditions as well as an agricultural machinery index based on access to agricultural implements and machinery.[16] The average wealth index decreased between the two considered waves from 0.16 to 0.07 while we observe a small increase in the agricultural machinery index (from 0 to 0.017). Wealthier households are expected to be more able to finance the purchase

[16]Livestock size (measured in tropical livestock units (TLU) has not been considered because of the high correlation with the agricultural machinery index.

of inputs, such as chemical fertilizer and improved seeds.

We also include several land related characteristics at the household level, such as land size devoted to maize, tenure status, self reported soil quality, self reported land slope and use of irrigation. On average, land devoted to maize is about 0.8 ha with significant differences across AEZ and about 90% of households have a property right on their plots regardless in which area the land is located. While about 55% of the households report having good soil quality, only about 2% use irrigation on their plots in both years. As pointed out by Besley (1995) and Kassie and Holden (2007), tenure security, here proxied by a dummy for land ownership, is expected to increases the probability of adoption. We expect this to be especially true for practices, whose benefits are captured in the long run, such as the use of organic fertilizer and SWC measures.

By facilitating information flow or mitigating transactions costs, access to extension advices is expected to have a positive effect on the adoption decision. It is worth noting that the proportion of farmers who have benefitted from extension advices is halved between the two cropping seasons (from 14% in 2008 to about 7% in 2010). We also include an index capturing the intensity of information about agricultural input prices received by the household. We expect that better prices' information will positively impact the probability of adopting agricultural input such as inorganic fertilizer and improved seeds. Conversely, by increasing travel time and transport cost, the distance from home (4km on average) and markets (10km on average) are expected to have a negative influence on the likelihood of adoption. Access to credit is frequently mentioned as an important determinant technology adoption literature (Feder et al., 1985; Feder and Umali, 1993). In our sample, less than 2% of the households had access to credit in order to procure inputs for the coming season.

As for the main production inputs, we consider the number of workers used by the farmer for weeding, planting and harvesting (the average number of workers for these three activities is about 17 and is quite constant across waves), the number of ox-based machinery (about 0.5 in 2008 and 0.9 in 2010) as well as a dummy for the use of pesticides (about 12% of farmers have reported use of pesticides in 2008 with a slight decrease in 2010). We include one political variable to control for the effects of potential political irregularities in the distribution of inputs such as seeds, fertilizers or information, on adoption and productivity. This variable is a dummy variable equal to one if the community leader is supporting the ruling party, and decreased from 93% to 42% between two survey years.

The last set of variables used in the analysis is related to climatic and bio-physical variables, to control for exposure to climate risk and bio-physical sensitivity, respectively. The indicators of climatological variability and weather conditions are described in Section 3 and include: CoV and average rainfall shortfall for the period 1982-2012, total rainfall and maximum temperature of the growing season in question, and the ratio of the within-year CoV over the average of within-year CoVs (the average computed on the previous 25 years). Bio-physical variables include: severe soil nutrient availability constraints, average soil pH levels and road density (both in the 15km buffer zone of EA centroids). We find that the soils in our sample EAs are moderately acidic with an average pH level of 5.7, which is expected to affect maize productivity negatively. In order to control for subjective external shocks, we include a dummy variable indicating whether less area has been planted on that plot due to drought. We observe that 19% of farmers have been negatively affected by drought in 2008 (about 27% in 2010).

Figure 8 shows the geographic distribution of the average long run rainfall's CoV at district level. As can be seen, there is an increase in the average long run rainfall's CoV as one moves from south-west to north-east across Tanzania. Figure 9 shows the geographic distribution of the long run average rainfall's shortfall. We observe that areas which are more likely subjected to drought are concentrated in the southern and northern Tanzania. As for short-run weather indicators, Figure 10 clearly shows that, from the geographical point of view, weather shocks have affected in very different ways the two considered cropping seasons. Northern Tanzania has experienced a higher within-season rainfall variability with respect to the long run average in 2008, while the same is true for central Tanzania in 2010. On the other hand, Figure 11 shows that no appreciable differences have been experienced in terms of spatial and temporal variations of maximum temperature. Finally, Figure 12 and 13, show the average of soil pH and road density at district level, respectively. The former shows that soils are moderately to strongly acidic in most of the EAs, and the soils most suitable for maize production (i.e. >5.9 pH) are found in the northeast and the central parts of the country ; and the latter reflects the location of the major cities and urban localities.

Conceptual framework and methodology

Agricultural households are utility-maximizing agents involved in both production and consumption decisions. This representation is quite standard in classical agricultural household models in which the most important implication is that when markets are complete and efficient, market prices support a separation (i.e. recursiveness) of household consumption and production decisions. Following Benjamin (1992), rather than going into the details of the general agricultural household model and its extensions, we present a stylized model which underlies the subsequent empirical analysis.[1]

For any production cycle and subject to a budget constraint, each household maximizes a twice differentiable, quasi-concave utility function defined over consumption and leisure

$$u_h = u(c, l; \boldsymbol{a}). \tag{4.1}$$

The vector $\boldsymbol{a}$ summarizes household characteristics, which are treated as exogenous. The household also faces a twice differentiable, convex production function

$$y = F(L, W, K, AD; A), \tag{4.2}$$

which depicts the relation between inputs and output, where L represents the sum of family and hired labor, W is water, K is capital including traditional and more advanced agricultural equipment, and A is the household's (fixed) quantity of land. In this representation we explicitly consider the adoption of 5 practices represented by adoption dummies AD as additional inputs in the production process. It is worth noting that, given a fixed quantity of land, a strictly positive albeit minimal quantity of labor, seeds, water and agricultural equipments is technically

[1]For a detailed presentation of the agricultural household model see Lau et al. (1978), Rosenzweig (1980), Strauss (1982) and Singh et al. (1985).

necessary to produce a given quantity of output, while the adoption of a specific practice is assumed to be strictly related to the expected benefit of its use.

In this framework, the farmer allocates the family time between leisure, on-farm and off-farm work. It can also purchase additional labor and sell its products in a competitive market. The existence of the latter, as well as of a competitive labor market, implicitly ensure exogenously determined prices for inputs and outputs. With fixed prices, production decisions (e.g., those related to the amount of labor and other variable inputs involved in the production process) are not affected by household preferences concerning labor and consumption goods. Indeed, both can be bought or sold to enable the household to achieve the subjective equilibrium position corresponding to the optimal level of production (Delforce, 1994). In other words, the consumption and production decisions are linked only through income and only in one direction, from the production to the consumption side (Singh et al., 1985). This recursiveness does not hold if any prices in the model are affected by production decisions. As Delforce (1994) pointed out, this is generally the case when markets do not exist, they are not competitive and/or if risk (such as for instance climate shocks) and risk aversion are recognized to be significant factors.

For this study, the crucial implication of the separability property is that we can analyze only the production side of the model focusing on adoption decisions and their effects on productivity without simultaneously taking into account consumption decisions. While this strategy would require testing for the separability property, it is worth emphasizing that in the last decade the essential elements of a reasonably competitive markets may often be found even in rural areas (Singh et al., 1985). Evidence for Tanzania suggests that the assumptions at the heart of the separability property are plausible enough to justify the adoption of the separable approach. For instance, although labor market presents imperfections, such as precarity and absence of formal contracts or benefits especially for the youths employed in the agricultural sector, and may not be perfectly competitive, the assumption that farm households are price takers does seem reasonable (See for instance LO-FTF, 2013; Mduma and Wobst, 2005). As for product markets, they exist in the main towns while there is a low availability of village-level markets for staple commodities (about 25% of EAs have its own food market in both considered waves) which imposes considerable costs on sellers, who must travel to a central marketplace (the average distance of the main market for food in the selected sample is about 10 Km). On the other hand, asymmetric information between lenders and borrowers and uncertain conditions in agriculture and financial markets lead to imperfections in the credit market (such as credit constraints, see Abdulai and Huffman, 2005, on this point); As mentioned before, less than 2% of the households in our sample (in both waves) had access to credit.

Even in presence of imperfect product and credit markets, it may be argued that such failures can be overlooked in the interests of model simplicity. Nevertheless, in order to reduce the omitted variable bias that may potentially (negatively) affect the estimates presented in Section 5 to the extent that the separability property does not hold, we include in our empirical analysis most of the explanatory variables that can be used to test the separability hypothesis, i.e. socio-demographic factors that determine consumption decisions (e.g., household size, head's education, etc.) (Benjamin, 1992).

4.1 Econometric strategy

Within this conceptual framework and given the fact that a farmer is more likely to adopt a mix of practices taking into account their complementarities and/or substitutabilities (see the seminal contributions of Feder, 1982; Dorfman, 1996, on this point), we analyze the determinants of adoption using the following multivariate probit model based on the latent variable approach:

$$g^*_{it,j} \quad = \quad \psi_{i,j} + \boldsymbol{z}_{it,j}\boldsymbol{\gamma}_j + \varepsilon_{it,j} \tag{4.3}$$

where

$$g_{it,j} = f(g^*_{it,j}) = \begin{cases} 1 & \text{if} \quad g^*_{it,j} > 0 \\ 0 & \text{if} \quad g^*_{it,j} \leq 0 \end{cases} . \tag{4.4}$$

and

$$\boldsymbol{\varepsilon}|\psi_{i,j}, \boldsymbol{z}_{it} \quad \sim \quad \text{i.i.d.}(\mathbf{0}, \Sigma). \tag{4.5}$$

Equation (4.3) defines the latent variable $g^*_{it,j}$ that captures the expected benefits from the adoption of the jth practice (with $j = 1, \ldots, 5$) for farmer i at time t; $\boldsymbol{z}_{it,j}$ represents a vector of exogenous variables which are hypothesized to affect the adoption decision (see section 3.2), $\psi_{i,j}$ is the farmer specific unobserved time-invariant heterogeneity and $\varepsilon_{it,j}$ is the classical idiosyncratic error term, both specific to the equation of the j-th practice. Finally, the error terms share a multivariate distribution with an unstructured covariance matrix. This assumption explicitly allows for complementarities and/or substitutabilities among different practices. We estimate two versions of model (4.3) - (4.5) using Maximum Simulated Likelihood. The first does not exploit the panel nature of our sample by pooling the available data while the second, through the so-called Mundlak (1978) correction, explicitly controls for the effect of time-invariant unobservable factors ($\psi_{i,j}$ for $j = 1, \dots, 5$) without assuming their independence with the explanatory variables and losing the ability to estimate the effect of time-invariant variables.[2] Our strategy to model the adoption decisions by controlling for both the interdependencies between different practices and unobserved heterogeneity is a novel contribution to the empirical literature, which addresses only one of these challenges if any, due to data limitations.

The second stage of our analysis is estimating the impact of adoption on productivity, which requires the specification of a functional form for equation (4.2). We consider the following *hybrid* production function:

$$y_{it} \quad = \quad \alpha_i + \boldsymbol{x}_{it}\boldsymbol{\beta} + \boldsymbol{g}_{it}\boldsymbol{\delta} + \varepsilon_{it}, \tag{4.7}$$

where y_{it} represents the natural logarithm of the output variable (kg of maize/ha) for farmer i at time t; $\boldsymbol{x}_{it}$ represents a vector of exogenous variables including production inputs as well as those covariates hypothesized to affect productivity (also through consumption) presented in section 3.2, $\boldsymbol{g}_{it}$ is the $J-$vector of observed binary variables indicating the adoption of practices each of which is tied to each latent variable $g^*_{it,j}$ (see equations (4.3)) through the rule specified in equation (4.4), α_i and ε_{it} are the farmer specific unobserved time-invariant heterogeneity and the idiosyncratic error term, respectively.[3]

As Mundlak (2001) points out, input variables are likely to be correlated with unobserved time-invariant farmer characteristics and this makes them endogenous. In order to overcome this issue, one may exploit the longitudinal nature of the data to rule out the main cause of

[2]In a panel data framework, the key issue involving the unobserved effects is whether they are mean independent from the observed explanatory variables. If this is the case the random-effects estimator is both consistent and efficient. On the other hand, when $E(\alpha_i|\boldsymbol{x}_{it}, \boldsymbol{z}_{it}) \neq 0$, only the fixed-effects estimator will be consistent. Unfortunately and unlike in the linear case, the fixed-effects estimation of a mixed- model like (4.3) - (4.5), in addition to being computationally unfeasible, introduces the so-called incidental parameters problem. The Mundlak (1978) correction allows to assume correlation between α_i, the household specific effects and the observed explanatory variables. However, this strategy requires to make an explicit parametric assumption about the distribution of the unobserved heterogeneity, i.e. assuming a conditional normal distribution with linear expectation and constant variance

$$\alpha_i|\boldsymbol{x}_{it}, \boldsymbol{z}_{it} \sim N(c + \phi\bar{x}_i + \xi\bar{z}_i + a_i, \sigma_a^2) \tag{4.6}$$

where $\bar{x}_i$ and $\bar{z}_i$ are the averages of $\boldsymbol{x}_{it}$ and $\boldsymbol{z}_{it}$ for $t = 1, \dots, T$ and σ_a^2 is the variance of a_i in the equation (4.6).

[3]All the continuous variables that can be considered a production input are expressed in log. Together with the output, a log-log specification implies a Cobb-Douglas functional form.

endogeneity, that is using fixed-effects methods to estimate the parameters of the model (4.7).[4] Even if this is the case, this approach might still result in biased estimates for the adoption dummy coefficients (because of the potentially unresolved endogeneity issue). Indeed, as argued by Schultz (1975) in a more general context, the adoption of a new technology, even when it can be considered as a production input, is followed initially by a period of "disequilibrium" characterized by experimentation and learning. It is at this stage of the process that adoption tends to be highly correlated with households' access to information, their ability to find the resource needed to finance the new technology, and their access to markets for primary and complementary inputs. Once the initial learning and experimentation has run its course and informational obstacles vanish, differences in the adoption patterns between farmers should disappear. As Ruttan (1977) pointed out, the endogeneity issue may persist in the case of relevant markets' failure as well as high risk, production uncertainty and households' risk aversion. In these cases, adopters may continue to have systematically different characteristics from non-adopters even in the final stages of the adoption process.

In order to check the robustness of our results to various specifications, we estimate the parameters of model (4.7) by Ordinary Least Squares (Pooled OLS), Generalized Least Squares with and without Mundlak correction (RE Mundlak and RE, respectively) and Instrumental Variables (IV) with Mundlak correction (2SLS Mundlak). The first approach imposes exogeneity of adoption without exploiting the longitudinal nature of the sample to control for the effect of time-invariant unobservable factors, e.g. households' unobserved heterogeneity. The second and third allow to control for unobserved heterogeneity but still assume the exogeneity of adoption. Clearly, these approaches might yield biased results if the exogeneity assumption is violated. The last approach allows to explicitly take into account the potential endogeneity of adoption as well as households' unobserved heterogeneity, thus avoiding the potential aforementioned bias.

The IV estimation of model (4.7) requires a set of at least five instruments to be identified. Unfortunately, we were able to find just four instruments implying that the parameters of model (4.7) cannot be identified. To overcome this issue, we follow Lewbel (2012) who proposed a method for constructing instruments as simple functions of the model's data. This approach may be useful in applications where traditional instruments are weak or the order condition

[4]See Mundlak (2001) for a detailed discussion of inputs' endogeneity in a production function derived, as in our case, starting from a theoretical model of expected profits-maximizing agents.

does not hold, as in our case. Basically, a set of instruments is constructed exploiting the heteroskedasticity of the residuals in the first stage regressions and it is then used, along with the externally available instruments, to increase efficiency and provide testable overidentifying restrictions (otherwise not testable). Since the residuals of the first stages are by construction heteroskedastic, our yield model perfectly fits the prerequisites of the Lewbel (2012) approach.[5]

As far as the selected instruments are concerned, the coefficient of variation and the average shortfall of rainfall computed over the period 1983-2012 at EA level are intended to capture the uncertainty about expected climatic conditions (see Section 3).[6] This choice arose from the consideration that rural households form expectations about the climatic conditions of their area, thus we might expect that they plant crops and use farm practices that are suited to that area according to the uncertainty of climatic conditions. However, in order to increase the probability that these indicators are valid instruments, we include in our specification a set of variables which measure the seasonal rainfall and temperature shocks, as they are likely to be correlated with both coefficient of variation and average shortfall. Our third and fourth instruments are represented by two dummy variables, the first capturing household access to information from extension agents on specific farm management practices, and the second indicating the presence of a community leader which sided for the ruling party during the time of the survey (CCM in both survey years). While the intuition behind using the access to information as instruments for the adoption decision has been discussed in previous section, we argue that, due to the pervasive corruption, the CCM membership of the community leader may be associated with access to subsidized inputs, which in turn affects fertilizer and improved seed adoption (see the last part of section 2.2 on this point).

In terms of diagnostics, we use the Angrist and Pischke (2009) first-stage multivariate F statistics in order to test the relevance of the used set of instruments, the latter including the four aforementioned instruments along with those constructed following Lewbel (2012).[7]

[5]This follows from the fact that IV estimation of model (4.7) is based on a set of linear probability models as first stages.

[6]It is worth noting that the coefficient of variation is just the interaction between the inverse of the mean and standard deviation. As such, it should be included in the model along with its components. However, we are not interested here in disentangling the impact of the inter-annual level and variability of rainfall and, even if including the coefficient of variation alone is likely to mix these effects, it allows to exploit the same information in a parsimonius way.

[7]According to Staiger and Stock (1997), the weak instrument hypothesis will be rejected if the F statistic is greater than 10.

The exogeneity condition (instruments' validity) involves the unobservable error term ε_{it}, and therefore it cannot be tested but only maintained. As part of the assessment of the reliability of IV estimates, we also perform under- (Kleibergen-Paap LM statistic), over- (Hansen J statistic) and weak- (Anderson-Rubin) identification tests. Finally, we test for the endogeneity of adoption using a C statistic (defined as the difference between two Sargan-Hansen statistics) which is robust to various violations of conditional homoskedasticity (see Baum et al., 2007, for more details on the used diagnostics).

When appropriate, we also perform the robust version of the Hausman (1978) test to confirm the appropriateness of the Mundlak correction, i.e. fixed-effects estimation. In all models we also tested for multicollinearity and outliers finding that they are not serious problems for almost all explanatory variables. Estimated standard errors are clustered at household level to allow reliable inference in the case of heteroscedasticity (serial correlation should not be an issue here given that our panel covers 2 time periods only).

Empirical results

5.1 Determinants of agricultural practice adoption

Results from the pooled estimation of the multivariate probit model (4.3) - (4.5) are presented in Tables 8 and 9, while those from the fixed-effects estimation of the same model are presented in the Appendix A (Tables 12 and 13). As expected, even though the fixed-effects estimator (obtained here through the Mundlak correction) is consistent in the presence of dependence between covariates and time invariant unobserved heterogeneity, the estimates are very imprecise because of the very small length of our panel. Since the robust Hausman test rejects the fixed-effects specification for three out of five practices, we will draw our conclusions based on pooled estimates.

Overall, results clearly show that the adoption of different practices is affected by different factors and that they are not mutually independent. The mutual dependency of adoption decisions is supported by the significant estimated correlation coefficients between the error terms of each adoption equation (Table 9). Besides justifying the use of a multivariate probit approach, the signs of these coefficients support the notion of complementarities between practices. Consistent with the findings of Teklewold et al. (2013) for rural Ethiopia and Kassie et al. (2013) for rural Tanzania, we find that improved seeds are complementary to inorganic fertilizer and SWC measures. This result is also coherent with the discussion in Feder et al. (1985) according to which the high-yield potential of the improved seeds can be realized only if at least some inorganic fertilizer is applied. Contrary to our expectations, we also find that inorganic fertilizer is significantly complementary with the use of its organic counterpart as well as with maize-legume intercropping. The latter is not expected given the fact that legumes are supposed to help in fixing nitrogen contributing to improving the fertility of the soil. Adoption of organic fertilizer is also significantly complementary with SWC measure. These results have important policy implications since they suggest that the implementation of a policy promoting one of the practices may result in spillover effects on the others.

We find that uncertainty in the rainfall, as represented by the long run CoV of rainfall, is strongly associated with the adoption of improved seed, organic and inorganic fertilizers, although the effect is heterogeneous. For instance, the higher the variability of rainfall, the lower the probability of organic and inorganic fertilizer adoption. This result is consistent with the findings of Teklewold et al. (2013), who found that the probability of adoption of inorganic fertilizer is higher in areas where rainfall is reliable in terms of timing, amount and distribution. Moreover, coherently with Kassie et al. (2010), we find that the likelihood of inorganic fertilizer's adoption is higher in wetter areas, as the coefficient of the long rung average rainfall shortfall is negative and statistically significant. On the other hand, the likelihood of adopting improved seeds is higher in areas where the historical rainfall variability is high, supporting the hypothesis that farmers perceive the use of improved seeds as a strategy to mitigate the effects of unpredictable climatic conditions and water stress.[1] Contrary to expectations, we do not find a significant positive relationship between rainfall variability and legume intercropping and SWC, both of which are thought to provide long term benefits in the face of climate variability.

As pointed out by Feder et al. (1985), farmers' technology choices are based on their subjective probabilities and hence on their exposure to information regarding a new technology. We find that access to government extension services significantly increases the likelihood of adoption of all practices but legume intercropping. As expected, we also find that access to information on input prices increases the probability to adopt inorganic fertilizer, SWC and improved seeds. These results clearly highlight the key role of rural institutions in governing the adoption decisions of farm households suggesting that improvements in the extension services, both in terms of coverage and efficiency, are essential in helping farmers to overcome barriers to information regarding both new technologies and prices.

Interestingly, we find that the probability of improved seeds adoption is lower when the community leader sides for the ruling party (CCM), thus confirming our expectation about the adverse effect of the pervasive corruption on subsidized input access. On the other hand, the likelihood of adopting maize-legume intercropping and organic fertilizer seems to increase when

[1] Although the TZNPS data does not identify the specific names of improved seeds, a number of improved seed varieties used in Tanzania are specifically bred to be drought tolerant as part of the Drought Tolerant Maize for Africa (DTMA) project of CIMMYT: http://www.cimmyt.org/en/news-and-updates/item/no-maize-no-life

the community leader sides for the ruling party, perhaps because of the non-subsidized nature of these practices. These first 4 variables in Table 8 are the IVs we later use to control for the endogeneity of adoption.

In terms of household characteristics, older farmers are significantly more likely to adopt inorganic fertilizer. We find a significant and differentiated role of marital status in two out of five adoption decisions: being married increases the likelihood of inorganic fertilizer adoption while the opposite is the case for maize-legume intercropping. We also find heterogeneity in the case of household size which appears to have a negative effect on the adoption of inorganic fertilizer while it is positively and related with the adoption of high yielding varieties. Consistent with the discussion in Feder et al. (1985), we find a homogeneous positive and strongly significant association of household's head years of education and the likelihood of adoption, with the exception of maize-legume intercropping. These results are also coherent with those obtained by Lapar and Pandey (1999) in the Philippine highlands and by Tenge et al. (2004) in Tanzanian west Usambara highlands who both observe a positive influence of education on SWC adoption.

Consistent with Besley (1995) and Kassie and Holden (2007), households who hold the ownership of land are more likely to adopt organic fertilizer and SWC measures. Moreover, an increase in the size of land devoted to maize significantly increase the likelihood of inorganic fertilizer adoption. As expected, we find that the household wealth proxies such as the wealth and the agricultural implements indices are important determinants of agricultural technology adoption. With the exception of maize-legume intercropping, the coefficient of the wealth index is positive and strongly significant highlighting the key role of household's wealth in the adoption decision. This result is consistent with those reported in Teklewold et al. (2013) and Kassie et al. (2013). On the other hand, the agricultural implements index appears to be positively and strongly related only to adoption of organic fertilizer. Consistently with the technology adoption literature (Feder et al., 1985; Feder and Umali, 1993), we also find that farmers with access to credit are more likely to adopt practices that involve liquidity, such as inorganic fertilizer and improved seeds. Interestingly, we find evidence of a negative and strongly significant association between the likelihood of adopting maize-legume intercropping and the access to credit on input.

Access to irrigation on the plot has a negative effect on adoption of all practices, although the coefficient is statistically significant only for maize-legumes intercropping. We also find, that farmers who have cultivated very steep plots are more likely to implement SWC measures and use organic fertilizer as Teklewold et al. (2013) and Kassie et al. (2013). As expected, farmers are using SWC to prevent soil erosion. Moreover, severe constraints on soil nutrient availability significantly decrease the probability of organic and inorganic fertilizer adoption as well as that of SWC measures. As expected, the higher is the road density in the area the higher is the probability of inorganic fertilizer and improved seed adoption. This result supports the hypothesis that better infrastructure may help to cut transaction costs increasing the likelihood of adoption of market-provided inputs. We also find that smallholder farmers who are further away from daily market are less likely to adopt inorganic fertilizer perhaps due to increased transaction costs (Feder et al., 1985; Feder and Umali, 1993). Consistent with our expectations, the lower the area planted due to drought the lower the adoption of inorganic fertilizer.

Finally, as documented in Section 3.2, the likelihood of adoption is strongly associated with the AEZ in which the farmer operates. As we would expect by looking at Table 11, the likelihood of maize-legume intercropping adoption is lower in the Eastern Plateaux and Mountain Blocks (AEZ III) and higher in the Western Highlands (AEZ IX) than in the Central Plains (AEZ I), the base category in our model specification. We find that organic fertilizer is significantly more adopted in the High Plains and Plateaux, Ufipa Plateau and Volcanoes and Rift Depressions areas (AEZ IV, VII and VIII) while inorganic fertilizer is more adopted in the High Plains and Plateaux, Inland Sediments and Rukwa-Ruaha Rift Zone-Alluvial Flats zones (AEZ IV, V and VI) and significantly less adopted in the Eastern Plateaux and Mountain Blocks (AEZ III). As for SWC measures, the probability of adoption is significantly lower in the Coastal Plains, Eastern Plateaux and Mountain Blocks and Inland Sediments (AEZ II, III and V) and higher in the Volcanoes and Rift Depressions zone (AEZ VIII) than in Central Plains. Finally, improved seeds are significantly less adopted in the Eastern Plateaux and Mountain Blocks, Inland Sediments and Western Highlands (AEZ III, V and IX) and more adopted in the Volcanoes and Rift Depressions area.

5.2 Impact of adoption on maize productivity

In this section we investigate the determinants of maize productivity represented by the quantity of maize produced per hectare of land. Table 10 reports the estimates of the hybrid production function in equation (4.7). The first column is from pooled OLS, the second and third columns from random-effects (RE) and correlated random-effects (RE Mundlak), while the last column reports the Mundlak corrected IV estimates (2SLS Mundlak).

Before turning to the discussion of the results, we briefly discuss the endogeneity issue looking at the Mundlak corrected IV estimates. With the only exception of maize-legume intercropping, we find that the considered instruments are significantly correlated with the adoption variables (Table 10). The multivariate Angrist and Pischke (2009) F-statistic is almost equal or greater than 10, thus passing the weak instruments hurdle. The Hansen J statistic confirms the usefulness of the Lewbel (2012) approach, pointing towards the coherence of the considered instruments.[2] The Kleibergen-Paap LM statistic as well as the Anderson-Rubin test strongly reject under identification and weak instruments hypotheses, respectively. Nevertheless, looking at the C statistic test (reported in the last row of Table 10) we cannot reject the hypothesis of exogeneity. This result is coherent with Mundlak (2001) who pointed out that the issue of input endogeneity may be cured by fixed-effects estimation. It is worth noting that the Mundlak correction appears to be justified in our case as we find evidence of correlation between time-invariant unobservables and covariates (see Table 10, robust Hausman test). Given this evidence, we will mainly draw our conclusions based on correlated random-effects estimates (column "RE Mundlak" of Table 10).

Maize-legume intercropping, SWC and inorganic fertilizers all have positive and statistically significant effects on maize yields. The former two impacts estimated suggest synergies between sustainable land practices and food security. The average percentage yield gains from the adoption of maize-legume intercropping and SWC are, respectively, about 10% and 14%. The use of inorganic fertilizer increases average maize productivity by about 36%, the highest impact among the considered practices. This results is coherent with the evidence that chemical fertilizer are more productive in the short run, thus contrasting the adverse impact of climate change. On the other hand, it is worth noting the use of chemical fertilizer cannot be properly defined as “sustainable” given that they are the main cause of environmental problems such as eutrophication in water systems and/or land degradation. Unexpectedly, the effect of improved seeds adoption is not statistically different from zero. As discussed in Section 3.2, this result should be interpreted in the light of the fact that about 75% of the farmers have adopted improved varieties without using fertilizer, thus not exploiting the high-yield potential of the

[2]See for instance Parente and Santos Silva (2012) for the interpretation of overidentifying restrictions tests.

improved seeds. Interestingly, organic fertilizer does not significantly increase the maize yields. A possible explanation is that the farmers in our sample have adopted this agricultural practice only recently while the use of organic fertilizer appears to be more effective in the long run (Reganold et al., 1987).

As expected, seasonal weather conditions variables strongly affect maize productivity. In particular, we find that farmers located in EAs where the within-season rainfall's CoV is higher than its long run average (i.e. rainfall variability has been very high in the cropping season) have 15% lower maize yields. Similarly, farmers located in EAs where the cropping season maximum temperature has been very high (i.e. above 30 Celsius degrees) are characterized by maize yields that are approximately 25% lower than those in other EAs. Unexpectedly, we find a similar evidence in the case of seasonal total rainfall, but the coefficient becomes not statistically different from zero once we control for household level fixed effects. We also investigated whether the adoption of practices analyzed here is able to mitigate the negative impact of rainfall variability and extreme temperatures by using interaction terms between the adoption dummies and the considered weather indicators. We find that only organic fertilizer use mitigates the negative impacts of rainfall shocks, but the interaction terms are not significant for other practices. *The results with interaction terms are not presented here, but are available upon request.*

As for the other inputs, we find that labor has a positive and significant effect on maize yield. In particular, we find that the elasticity of maize yield to both the number of workers devoted to planting and harvesting is about 29% and 22%, respectively. As for other capital inputs, the positive and significant elasticities of maize yield to ox-based machinery and pesticides vanish after controlling for fixed-effects. Similarly, farmers with irrigated plots do not seem to gain in terms of maize productivity.

Among the household characteristics, we find that the effects of gender, education, dependency ratio and household size all vanish after controlling for time-invariant unobserved heterogeneity at household level indicating that cross sectional studies may attribute an erroneous productivity impact to these variables.

Our estimates also show the presence of an inverse relation between land size devoted to maize and productivity of maize which is consistent with many other findings in the literature. The coefficient of land size devoted to maize becomes negative and highly significant after controlling for fixed effects. The inverse land size-productivity relation has been mostly explained by market failures (Eswaran and Kotwal, 1985; Barrett, 1996), while recent explanations are related to errors in land measurements (Lamb, 2003). Contrary to earlier evidence, Carletto et al. (2013) find that the empirical validity of the inverse relation hypothesis is strengthened, not weakened, by the availability of better measures of land size collected using GPS devices in Uganda.

While we find no evidence of effect of access to credit (likely due to not enough heterogeneity in our sample with an average access rate of 2%), maize productivity significantly increases with both the wealth and the agricultural implement indices as expected. The distance of the land from home seems to have a small positive and significant effect while the distance to a daily market does not seem to significantly affect maize yields.

As expected, if the land is only partially cultivated due to drought, farmers obtain (on average) lower maize yields, while the presence of soils characterized by higher pH levels (than the average in the sample, about 5.7) is productivity enhancing. This result is expected since maize grows in a range of soil types but optimally in a well-drained, moist loam with a pH of 5.8 to 6.5. As for land characteristics, tenure status does not have a direct influence on maize productivity controlling for adoption (while it has an indirect effect through the adoption of long run technologies such as SWC measures, as discussed in the previous section).

As widely documented in Section 3.2, the maize yields show a large geographical variation, here captured by significant and heterogenous (in terms of sign and magnitude) coefficients of the AEZ dummies. As expected, we find that maize productivity is 20%, 40% and 49% higher in the areas located in the south-west and north-east of the country (AEZ IV, VI and VII) than in Central Plains. Finally, we find that, *ceteris paribus*, maize productivity has increased by about 10% between 2008/09 and 2010/11 cropping years.

Conclusion and policy implications

This paper contributes to the agricultural technology adoption literature by using a novel data set that combines information coming from two large-scale household surveys with geo-referenced historical rainfall and temperature data in order to understand the determinants of the adoption of sustainable and productivity improving practices and their impacts on maize productivity in Tanzania. It also contributes to the nascent literature bridging technology adoption literature with adaptation literature by using variables to capture exposure to climatic risk, sensitivity and household adaptive capacity. The specific practices analyzed are: maize-legume intercropping, soil and water conservation practices, organic fertilizer, inorganic fertilizer and high yielding maize varieties.

Exploiting the panel structure of our data through transition matrices, we find that the most stable technology adoption is for inorganic fertilizer: 83% of adopters in 2008 still uses it in 2010, though only less than 20% used it in both years. The highest dis-adoption rate is observed among SWC practices (72%). Moreover, we find that among improved seeds adopters (18% of the sample), about 75% have not used any fertilizer, suggesting that most farmers are not able to exploit the potential benefits of their joint usage. This finding is strongly supported by our productivity analysis, where we do not find a significant impact of improved seeds on yields.

Our analysis of adoption is based on the estimation of a two-period panel data model of farmers' adoption of five practices simultaneously through a multivariate probit specification, which is able to capture the complementarities and/or substitutabilities among different practices, controlling for household-specific time-invariant unobserved heterogeneity. Our analysis on the impact of adoption on maize productivity takes explicitly into account the potential endogeneity of adoption as well as time-invariant household heterogeneity. This paper is unique in simultaneously addressing these multiple challenges faced by empirical studies of adoption and productivity using a novel data set and a robust empirical methodology.

From the analysis of the determinants of adoption, we find evidence that different agricultural practices are affected by different factors and that they are not mutually independent as shown by the estimated correlation coefficients between the error terms of each adoption equation. In particular, we find that improved seeds are complementary to inorganic fertilizers and SWC measures, and that inorganic fertilizers are complementary with the use of organic fertilizers as well as with maize-legume intercropping. These findings have important implications since they suggest that the promotion of sustainable and productivity increasing agricultural practices may exploit these complementarities to enhance their effectiveness.

We find a very strong negative relationship between historical climatic variability and the adoption of some practices. The higher the historical variability of rainfall, the lower the probability of organic and inorganic fertilizer adoption. Moreover, we find that the likelihood of inorganic fertilizer's adoption is higher in wetter areas, as the coefficient of the long rung average rainfall shortfall is negative and statistically significant. On the other hand, the likelihood of adopting improved seeds is higher in areas where the historical rainfall variability is high, suggesting that farmers use improved seeds as a strategy to mitigate the effects of highly variable rainfall that is expected to increase based on climate projections.

Access to government extension services significantly increases the likelihood of adoption of all practices but intercropping. We also find that access to information on input prices increases the probability to adopt inorganic fertilizer, SWC and improved seeds. These results clearly highlight the key role of rural institutions in governing the adoption decision of farmers, suggesting that improvements in the extension services, both in terms of coverage and efficiency, is essential in helping farmers to overcome barriers to information and adapt to climate change.

Consistent with the technology adoption literature, we also find that farmers with access to credit are more likely to adopt practices that involve liquidity, such as inorganic fertilizer and improved seeds. The adoption of maize-legume intercropping, on the other hand, is less likely if farmers have access to credit, suggesting that intercropping may be perceived as a way to compensate for the lack of fertilizers. Overall, this evidence suggests that improving access to credit is likely to increase the adoption of modern inputs but decrease maize-legume intercropping, which has longer run benefits for soil health and adaptation. This finding underlines the importance of extension services in providing information on both short-run and long-run benefits of all practices to farmers to improve productivity and adaptive capacity at the same time.

Our analysis of the determinants of maize productivity shows that the adoption of maize-legume intercropping, SWC and inorganic fertilizers all have positive and statistically significant effects on maize yields, suggesting the existence of synergies between these practices and food security. Unexpectedly, the effect of improved seeds and organic fertilizer adoption is not statistically significant. The former result is likely due to the fact that about 75% of the farmers have adopted improved varieties without using inorganic fertilizers which are required to reap the benefits from improved seeds.

We also find that actual weather conditions strongly affect maize productivity as farmers located in EAs where the cropping season's rainfall has been highly variable show a 15% lower maize yield. Similarly, farmers located in EAs where the cropping season's maximum temperature has been very high (above 30 Celsius degrees on average) are characterized by a lower maize yield, approximately 25% lower. Both rainfall variability and hotter temperatures are expected to increase under climate change, underlining the importance of policies to buffer food security from the effects of climatic conditions.

Our estimates also show the presence of a negative relationship between land size and maize productivity, confirming the inverse farm-size productivity relationship in the literature. Interestingly, we find that the effects of gender, education, dependency ratio and household size vanish after controlling for household level fixed effects, providing support to our robust empirical methodology.

A couple of salient policy implications emerge from our analyses: Dis-adoption of agricultural practices analyzed here is widespread and polices that promote them can improve adoption (and its stability) if targeting is based on the determinants of adoption and its impacts as analyzed in this paper. Especially the climatic shock variables present a challenge to policy as they are usually not used in targeting. Two important climatic shocks that are expected to become more frequent under climate change, i.e. variable rainfall and too hot temperatures during the growing season, have significant negative impacts on maize yields. Integrating site-specific information on both the levels and the variability of rainfall and temperature in extension policies can foster adoption of appropriate practices to improve food security under climate change. Improved land tenure is associated with higher adoption of practices that take long time to deliver full benefits, e.g. organic fertilizer and SWC. This finding suggests that land tenure should be considered as part of promotion activities of such practices if stable adoption is to be achieved. Two practices that are thought to help farmers to maintain soil quality and confront changing climate better, i.e. maize-legume intercropping and SWC, have significant positive impacts on productivity. They are also complementary with each other in adoption decisions. Efforts to promote these practices can exploit the understanding of the determinants of and the complementarities between adoption decisions generated in this paper. Finally, most farmers are not benefiting from the synergies that exist between some of these agricultural practices as we documented. Agricultural and food security policies can become more effective by exploiting the synergies between different practices as well as integrating climate change considerations into agricultural policy making.

Bibliography

Abdulai, A. and Huffman, W. E. (2005). The diffusion of new agricultural technologies: The case of crossbred-cow technology in tanzania. *American Journal of Agricultural Economics*, 87(3):645–659.

Angrist, J. and Pischke, J. (2009). *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton University Press, Princeton.

Arndt, C., Farmer, W., Strzepek, K., and Thurlow, J. (2012). Climate change, agriculture and food security in tanzania. *Review of Development Economics*, 16(3):378–393.

Arslan, A., McCarthy, N., Lipper, L., Asfaw, S., and Cattaneo, A. (2014). Adoption and intensity of adoption of conservation farming practices in zambia. *Agriculture, Ecosystems & Environment*, 187(0):72 – 86. Evaluating conservation agriculture for small-scale farmers in Sub-Saharan Africa and South Asia.

Asfaw, S., McCarthy, N., Lipper, L., Arslan, A., Cattaneo, A., and Kachulu, M. (2014). Climate variability, adaptation strategiesand food security in malawi. ESA Wrking Paper 14-08, FAO.

Barrett, C. B. (1996). On price risk and the inverse farm size-productivity relationship. *Journal of Development Economics*, 51:193–215.

Barrios, S., Ouattara, B., and Strobl, E. (2008). The impact of climatic change on agricultural production: Is it different for africa? *Food Policy*, 33(4):287 – 298.

Baum, C. F., Schaffer, M. E., and Stillman, S. (2007). Enhanced routines for instrumental variables/generalized method of moments estimation and testing. *Stata Journal*, 7(4):465–506.

Benjamin, D. (1992). Household composition, labor markets, and labor demand: Testing for separation in agricultural household models. *Econometrica*, 60(2):287–322.

Besley, T. (1995). Property rights and investment incentives: Theory and evidence from ghana. *Journal of Political Economy*, 103(5):903–37.

Carletto, C., Savastano, S., and Zezza, A. (2013). Fact or artifact: The impact of measurement errors on the farm size-productivity relationship. *Journal of Development Economics*, 103:254 – 261.

De Groote, H. and Coulibaly, N. (1998). Gender and generation: an intra-household analysis on access to resources in southern mali. *African Crop Science Journal*, 6:79–96.

Delforce, J. C. (1994). Separability in farm-household economics: An experiment with linear programming. *Agricultural Economics*, 10(2):165–177.

Deressa, T. T. and Hassan, R. M. (2009). Economic impact of climate change on crop production in ethiopia: Evidence from cross-section measures. *Journal of African Economies*.

Di Falco, S., Veronesi, M., and Yesuf, M. (2011). Does adaptation to climate change provide food security? a micro-perspective from ethiopia. *American Journal of Agricultural Economics*, 93(3):825–842.

Dorfman, J. H. (1996). Modeling multiple adoption decisions in a joint framework. *American Journal of Agricultural Economics*, 78(3):547–557.

Doss, C. R. (2003). Understanding Farm Level Technology Adoption: Lessons Learned from CIMMYT's Micro Surveys in Eastern Africa. Economics Working Papers 03-07, CIMMYT.

Eswaran, M. and Kotwal, A. (1985). A theory of two-tier labor markets in agrarian economies. *American Economic Review*, 75(1):162–77.

Feder, G. (1982). Adoption of interrelated agricultural innovations: Complementarity and the impacts of risk, scale, and credit. *American Journal of Agricultural Economics*, 64(1):94–101.

Feder, G., Just, R., and Zilberman, D. (1985). Adoption of Agricultural Innovations in Developing Countries: A Survey. *Economic Development and Cultural Change*, 33(2):255–298.

Feder, G. and Umali, D. L. (1993). The adoption of agricultural innovations: A review. *Technological Forecasting and Social Change*, 43(3-4):215–239.

Fischer, D. (2003). Assessment of the agricultural sector in tanzania. Technical report, USAID and Tanzania Economic growth office.

Hausman, J. A. (1978). Specification tests in econometrics. *Econometrica*, 46(6):1251–71.

Just, R. and Zilberman, D. (1983). Stochastic Structure, Farm Size and Technology Adoption in Developing Agriculture. *Oxford Economic Papers, New Series*, 35(2):307–328.

Kassie, M. and Holden, S. (2007). Sharecropping efficiency in ethiopia: threats of eviction and kinship. *Agricultural Economics*, 37(2-3):179–188.

Kassie, M., Jaleta, M., Shiferaw, B., Mmbando, F., and Mekuria, M. (2013). Adoption of interrelated sustainable agricultural practices in smallholder systems: Evidence from rural tanzania. *Technological Forecasting and Social Change*, 80(3):525 – 540. ¡ce:title¿Future-Oriented Technology Analysis¡/ce:title¿.

Kassie, M., Zikhali, P., Pender, J., and Köhlin, G. (2010). The economics of sustainable land management practices in the ethiopian highlands. *Journal of Agricultural Economics*, 61(3):605–627.

Lamb, R. L. (2003). Inverse productivity: land quality, labor markets, and measurement error. *Journal of Development Economics*, 71(1):71 – 95.

Lapar, M. A. and Pandey, S. (1999). Adoption of soil conservation: the case of the philippine uplands. *Agricultural Economics*, 21(3):241 – 256.

Lau, L. J., Lin, W.-L., and Yotopoulos, P. A. (1978). The linear logarithmic expenditure system: An application to consumption-leisure choice. *Econometrica*, 46(4):843–68.

Lewbel, A. (2012). Using heteroskedasticity to identify and estimate mismeasured and endogenous regressor models. *Journal of Business and Economic Statistics*, 30(1):67–80.

LO-FTF (2013). Tanzania and zanzibar labour market profile. Technical report, LO-FTF Council, Denmark.

MAFAP (2013). Review of food and agricultural policies in the united republic of tanzania. Mafap country report series, FAO-UN, Rome, Italy.

Marenya, P. P. and Barrett, C. B. (2007). Household-level determinants of adoption of improved natural resources management practices among smallholder farmers in western kenya. *Food Policy*, 32(4):515–536.

McCarthy, N., L., L., and Branca, G. (2011). Climate-smart agriculture: smallholder adoption and implications for climate change adaptation and mitigation. *FAO Working Papers, Mitigation of Climate Change in Agriculture (MICCA) Series 4*.

Mduma, J. K. and Wobst, P. (2005). Determinants of rural labor market participation in tanzania. *African Studies Quarterly*, 8(2):32–47.

Minot, N. and Benson, T. (2009). Fertilizer subsidies in africa: Are vouchers the answer? IFPRI Issue Brief 60, International Food Policy Research Institute.

Morton, J. F. (2007). The impact of climate change on smallholder and subsistence agriculture. *Proceedings of the National Academy of Sciences*, 104(50):19680–19685.

Mundlak, Y. (1978). On the pooling of time series and cross section data. *Econometrica*, 46(1):69–85.

Mundlak, Y. (2001). Production and supply. In Gardner, B. L. and Rausser, G. C., editors, *Handbook of Agricultural Economics*, volume 1 of *Handbook of Agricultural Economics*, chapter 1, pages 3–85. Elsevier.

NAPA (2007). National adaptation programme of action (napa). Technical report, Vice President's Office, DIvision of Environment, Dar es Salaam, Tanzania.

Nelson, G. C., Rosegrant, M. W., Koo, J., Robertson, R., Sulser, T., Zhu, T., Ringler, C., Msangi, S., Palazzo, A., Batka, M., Magalhaes, M., and Va (2009). Climate change: Impact on agriculture and costs of adaptation. Food policy reports 21, International Food Policy Research Institute (IFPRI).

Parente, P. M. and Santos Silva, J. (2012). A cautionary note on tests of overidentifying restrictions. *Economics Letters*, 115(2):314–317.

Patt, A. G. and Winkler, J. (2007). Applying climate information in africa: An assessment of current knowledge. Technical report, Prepared for the U.S. National Oceanic and Atmospheric Administration.

Reganold, J., Elliott, L. F., and Unger, Y. L. (1987). Long-term effects of organic and conventional farming on soil erosion. *Nature*, 330:370–372.

REPOA (2007). Annual report. Technical report, Research on Poverty Alleviation.

Rosenzweig, M. R. (1980). Neoclassical theory and the optimizing peasant: An econometric analysis of market family labor supply in a developing country. *The Quarterly Journal of Economics*, 94(1):31–55.

Rosenzweig, M. R. and Wolpin, K. I. (1993). Credit Market Constraints, Consumption Smoothing, and the Accumulation of Durable Production Assets in Low-Income Countries: Investment in Bullocks in India. *Journal of Political Economy*, 101(2):223–44.

Rusinamhodzi, L., Corbeels, M., Nyamangara, J., and Giller, K. E. (2012). Maize-grain legume intercropping is an attractive option for ecological intensification that reduces climatic risk for smallholder farmers in central mozambique. *Field Crops Research*, 136(0):12 – 22.

Ruttan, V. W. (1977). The green revolution: Seven generalizations. *International Development Review*, 19:16–23.

Schmidt, O., Clements, R., and Donaldson, G. (2003). Why do cereal-legume intercrops support large earthworm populations? *Applied Soil Ecology*, 22(2):181 – 190.

Schultz, T. W. (1975). The value of the ability to deal with disequilibria. *Journal of Economic Literature*, 13(3):827–46.

Singh, I., Squire, L., and Strauss, J. (1985). *Agricultural Household Models: Extensions, Applications' and Policy.* Johns Hopkins Press for the World Bank.

Smit, B. and Wandel, J. (2006). Adaptation, adaptive capacity and vulnerability. *Global Environmental Change*, 16(3):282 – 292.

Staiger, D. and Stock, J. H. (1997). Instrumental variables regression with weak instruments. *Econometrica*, 65(3):557–586.

Strauss, J. (1982). Determinants of food consumption in rural sierra leone : Application of the quadratic expenditure system to the consumption-leisure component of a household-firm model. *Journal of Development Economics*, 11(3):327–353.

Tanzania National Bureau of Statistics (2012). National panel survey report. Wave 2 - 2010/11, Tanzania National Bureau of Statistics.

Tanzania National Bureau of Statistics (2013). 2012 population and housing census. Technical report, National Bureau of Statistics and Office of Chief Government Statistician.

TDRG (2008/2009). Tanzania governance review. Technical report, Tanzania Development Research Group.

Teklewold, H., Kassie, M., and Shiferaw, B. (2013). Adoption of multiple sustainable agricultural practices in rural ethiopia. *Journal of Agricultural Economics*, 64(3):597–623.

Tenge, A. J., De Graaff, J., and Hella, J. P. (2004). Social and economic factors affecting the adoption of soil and water conservation in west usambara highlands, tanzania. *Land Degradation & Development*, 15(2):99–114.

TZG (1997). Agricultural and livestock policy. Technical report, Ministry of Agriculture and co-operative development.

TZG (2008). Study on strategies for addressing negative effects of climate change in food insecure areas of tanzania. Technical report, Ministry of Agriculture, Food and Cooperatives, Dar es Salaam, Tanzania.

TZG (2009). Climate change and agriculture policy brief. Technical report, Dar es Salaam, Tanzania.

TZG (2010). Aide memoire, accelerated food security project (credit 4619-ta). Technical Report Mid-Term Review, United Republic of Tanzania.

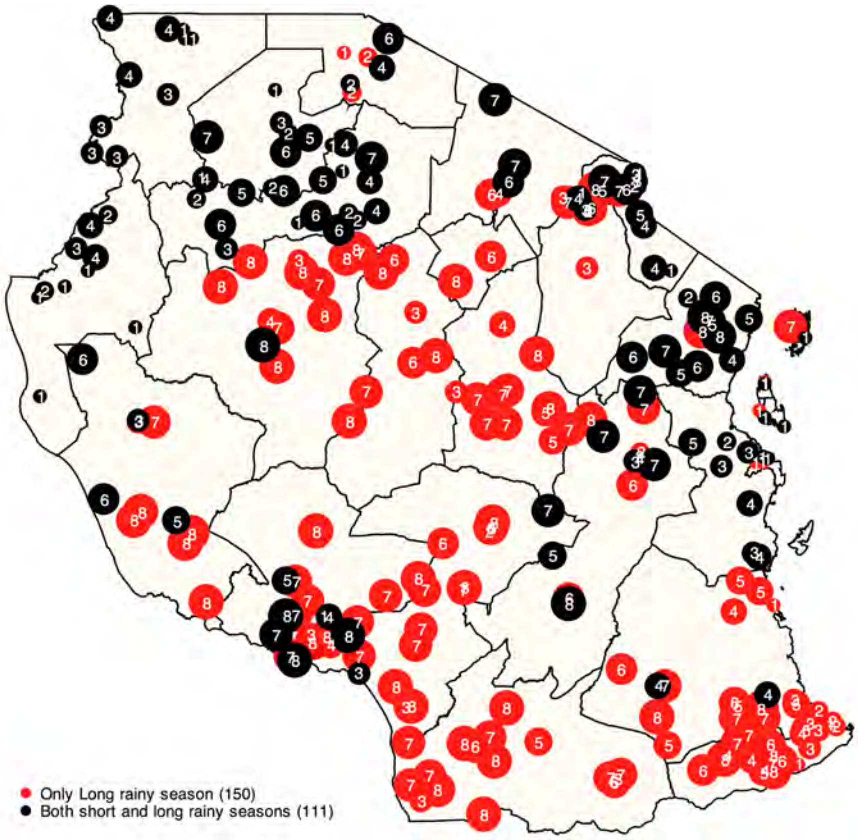
USAID (2010). Staple foods value chain analysis. country report tanzania. Technical report, United States Agency for International Development (USAID), Competetiveness and Trade Expansion Program (COMPETE)., Washington, DC.

World Bank (2010). Silent and lethal: How quiet corruption undermines africa's development efforts. Technical report, World Bank.

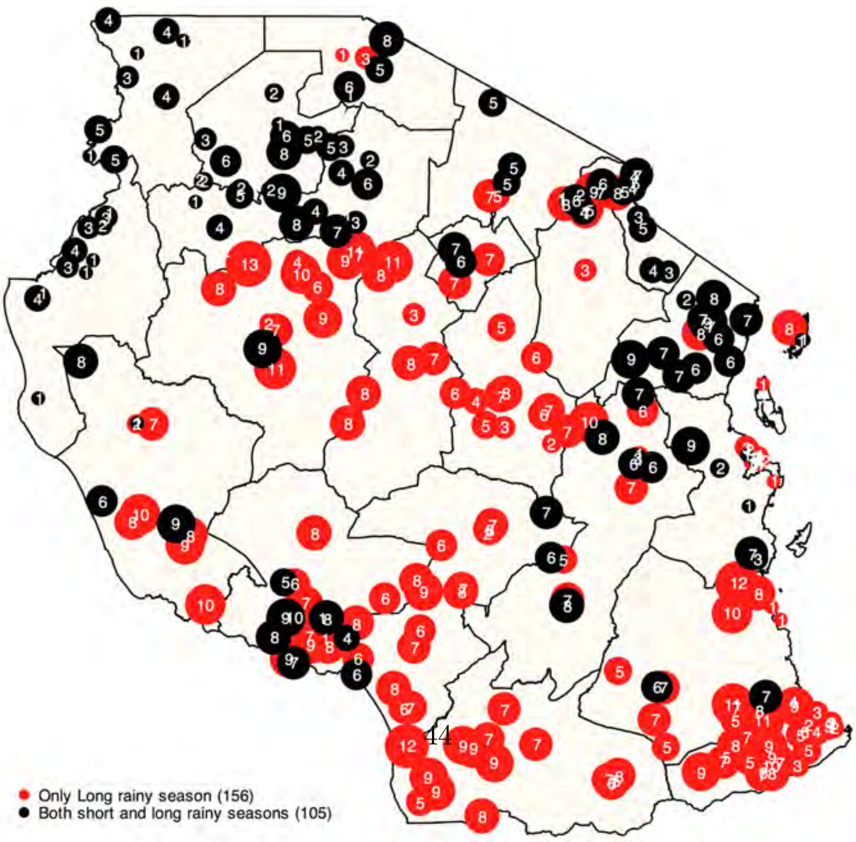
World Bank (2013). Tanzania economic update: Opening the gates. Technical report, World Bank.

Ziervogel, G., Cartwright, A., Tas, A., Adejuwon, J., Zermoglio, F., Shale, M., and Snith, B. (2008). Climate change and adaptation in african agriculture. Technical report, Prepared for Rockefeller Foundation by Stockholm Environment Institute.

Figure 1: Sample coverage at EAs level (unbalanced sample)

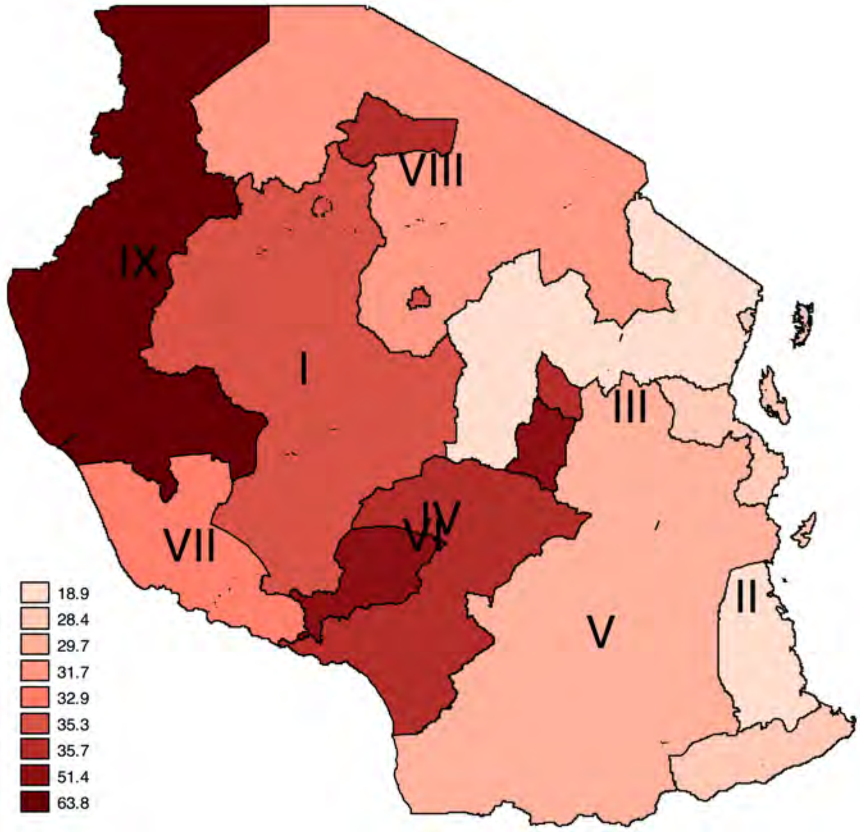


(a) Wave 1

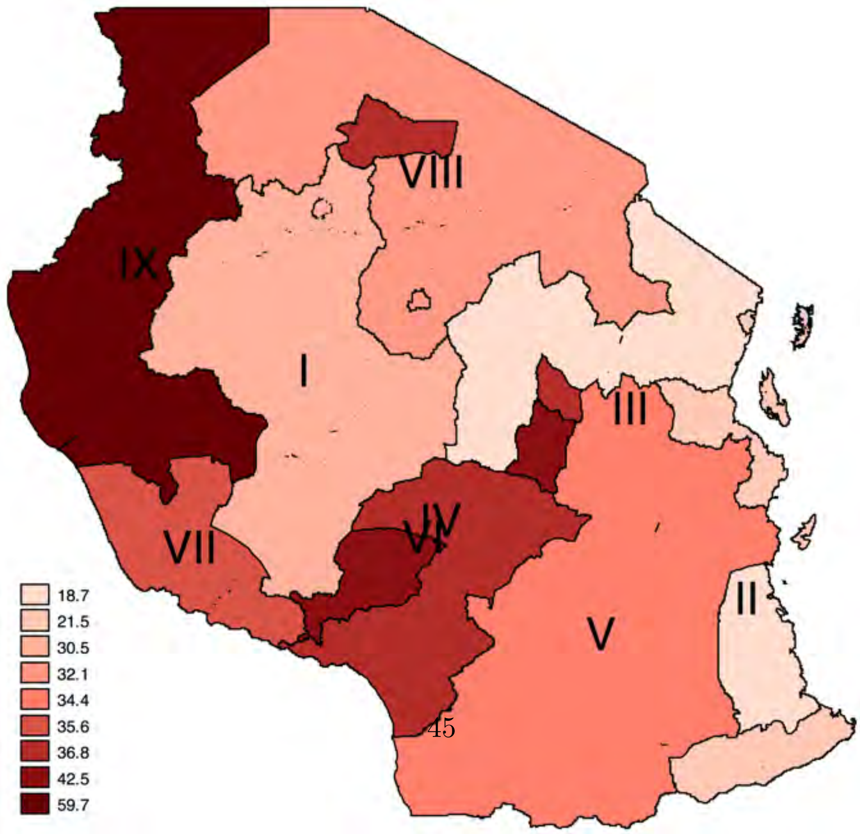


(b) Wave 2

Figure 2: Maize-Legume intercropping adoption by AEZ (%)

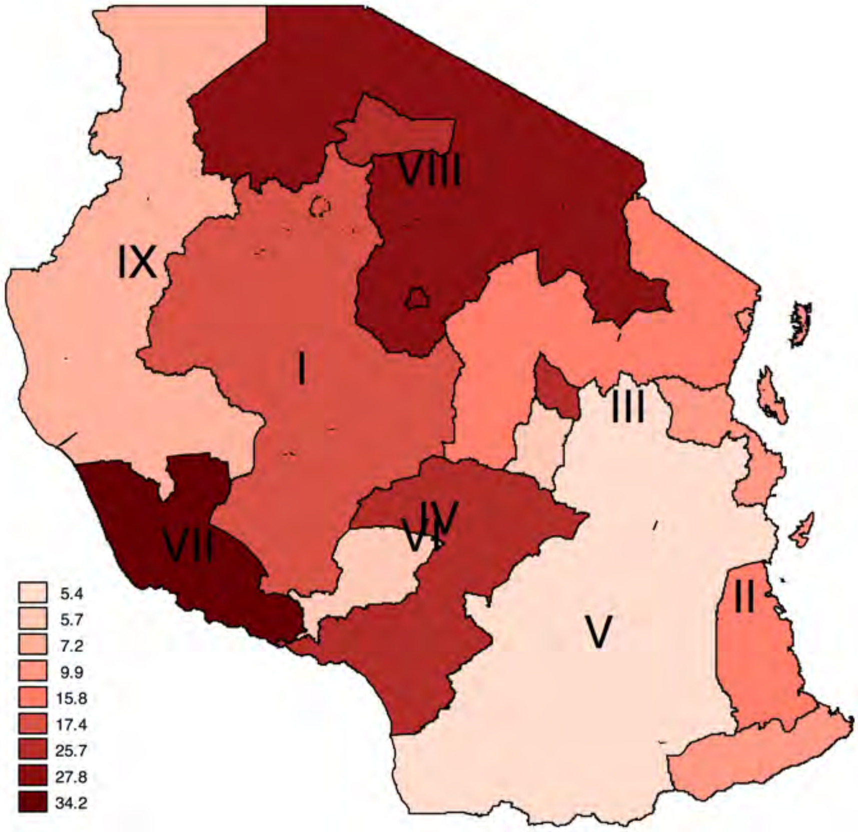


(a) Wave 1

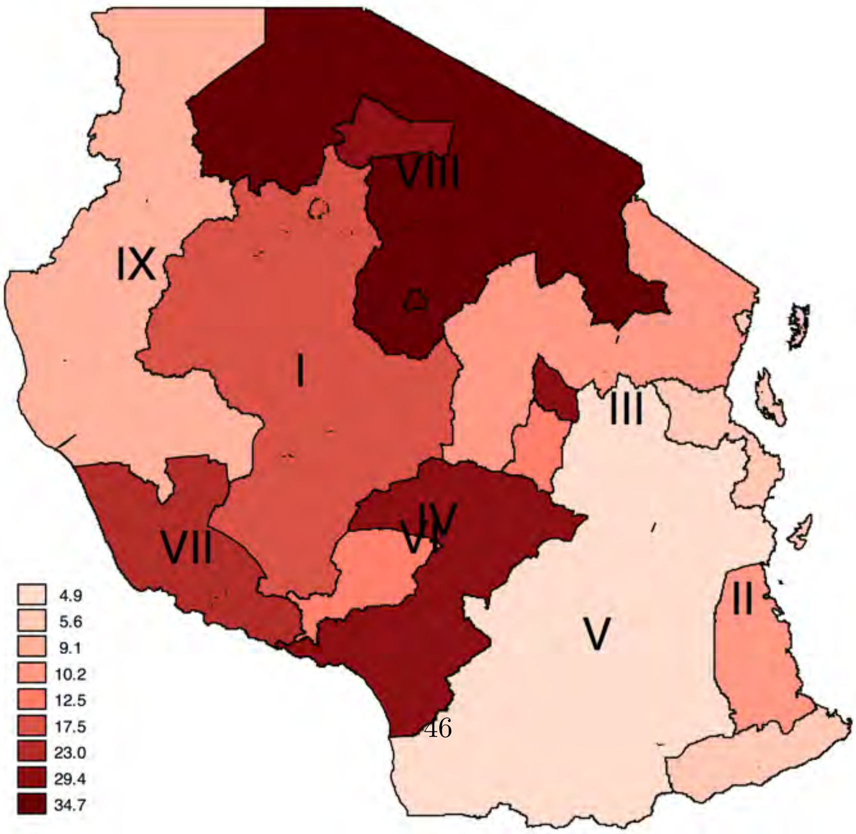


(b) Wave 2

Figure 3: Organic fertilizer adoption by AEZ (%)

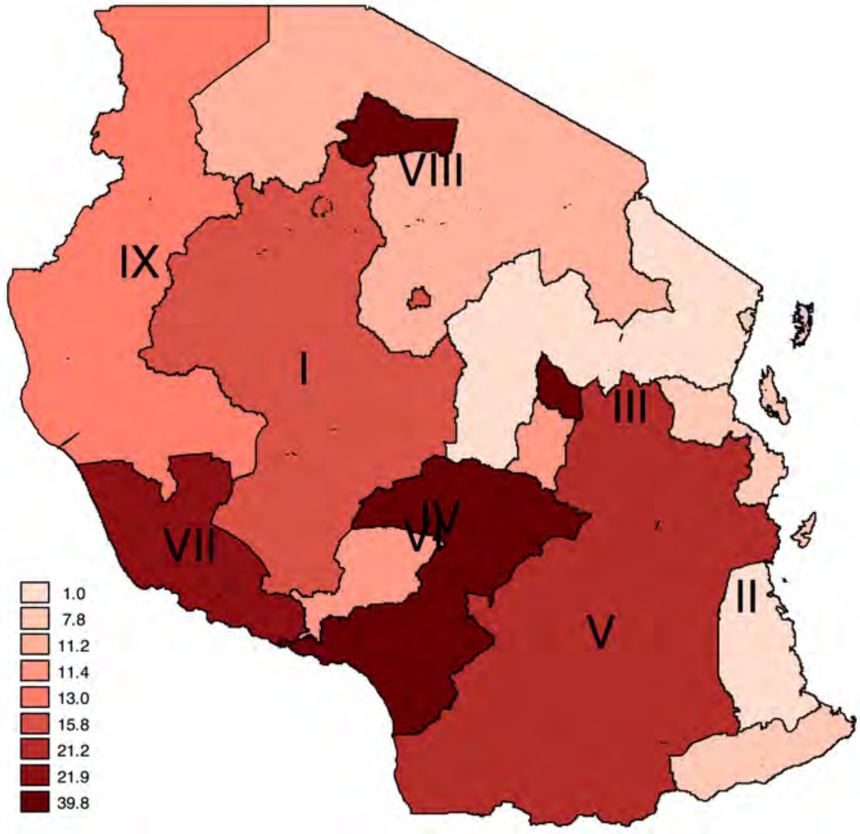


(a) Wave 1

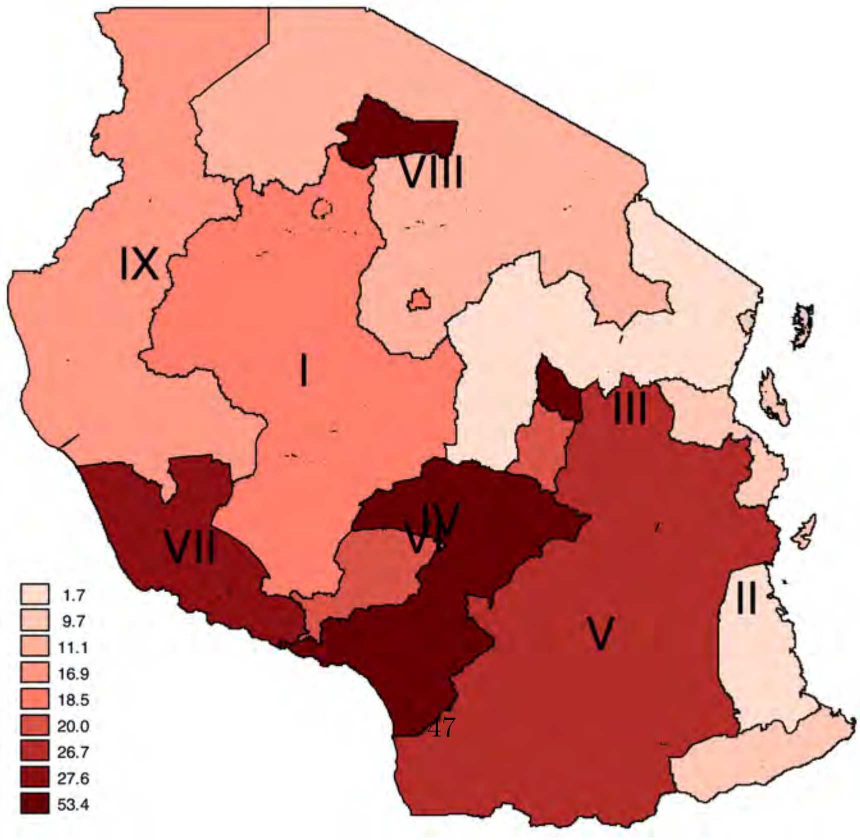


(b) Wave 2

Figure 4: Inorganic fertilizer adoption by AEZ (%)

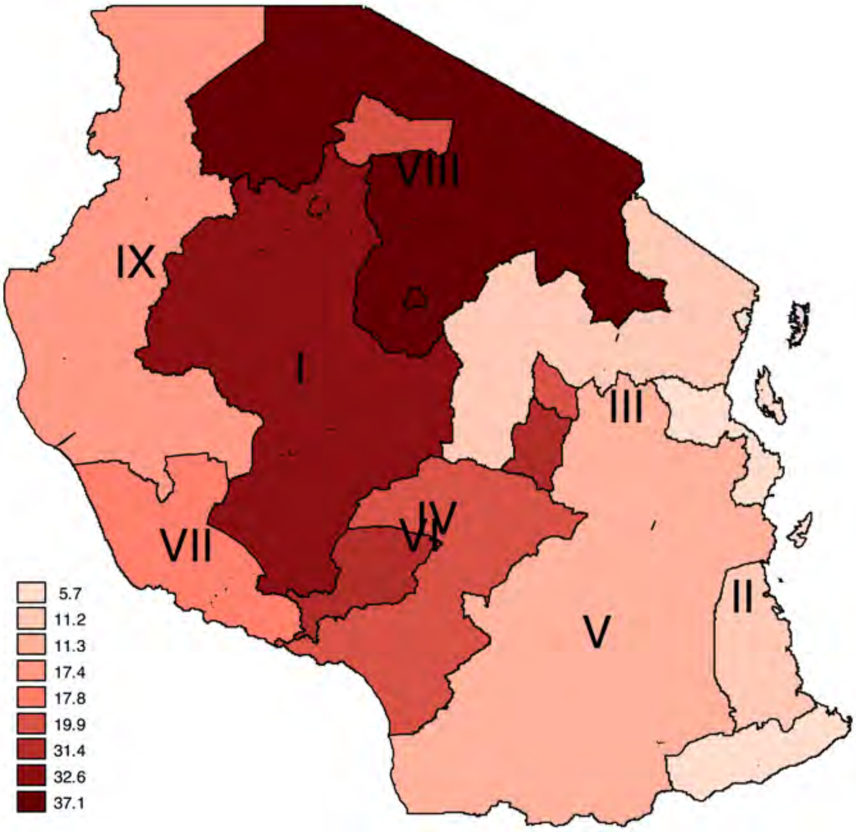


(a) Wave 1

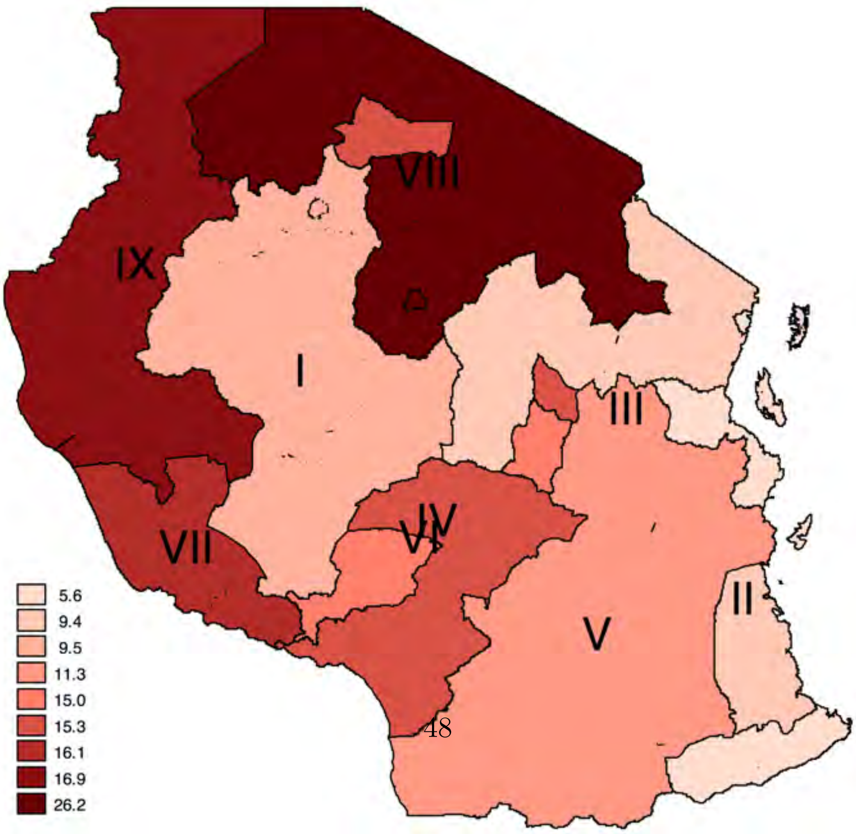


(b) Wave 2

Figure 5: Soil and Water structures adoption by AEZ (%)

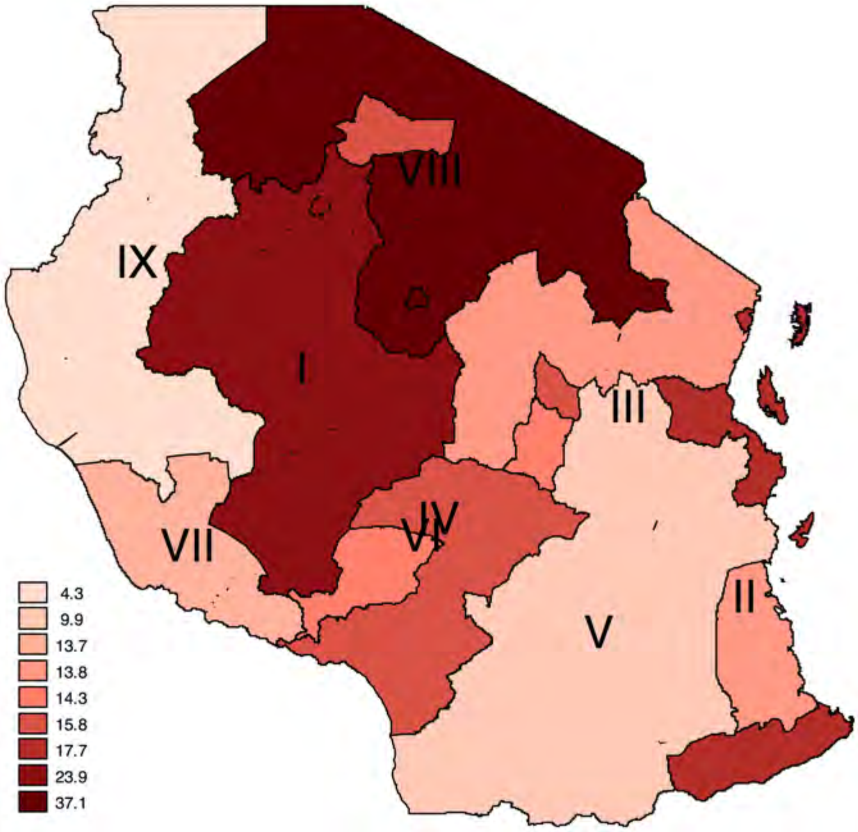


(a) Wave 1

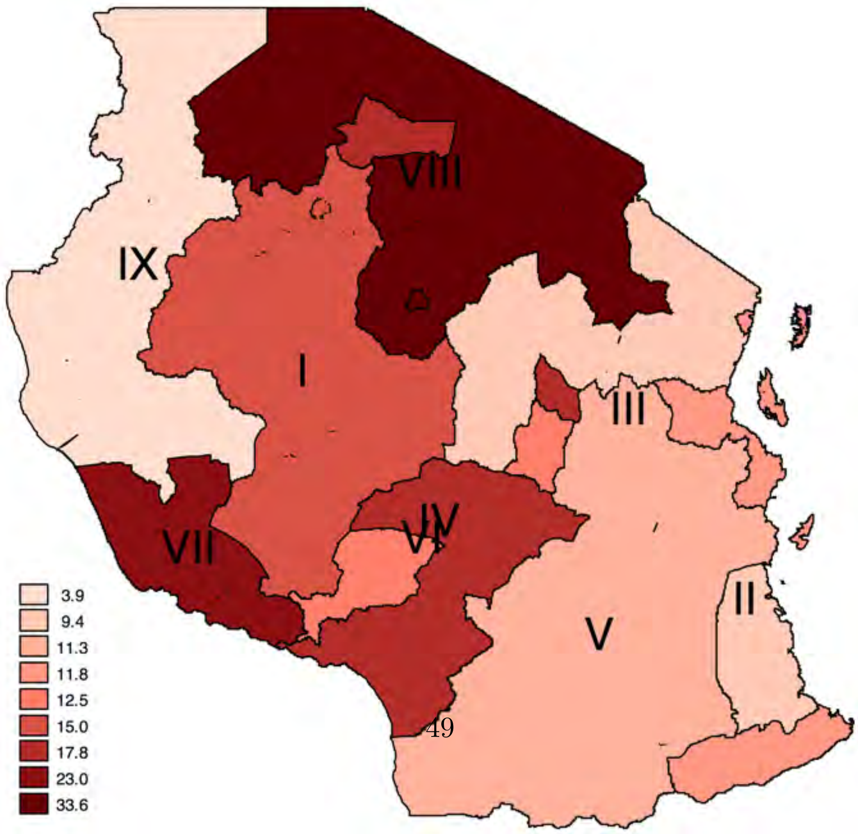


(b) Wave 2

Figure 6: Improved seeds adoption by AEZ (%)

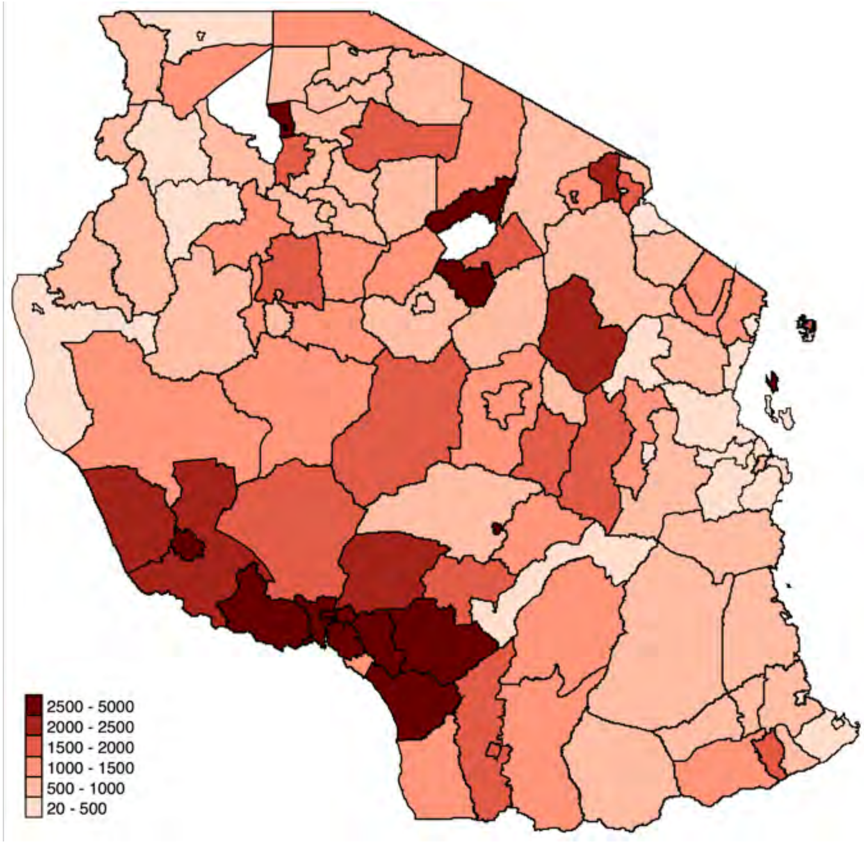


(a) Wave 1

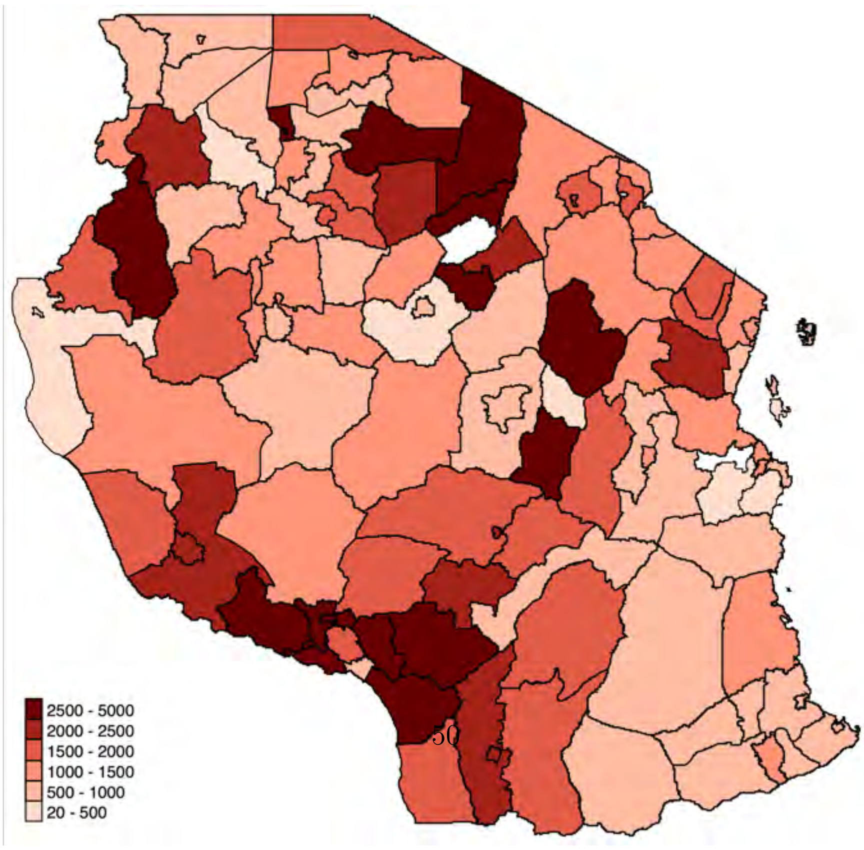


(b) Wave 2

Figure 7: Maize production by district and wave (Kg/ha)



(a) Wave 1



(b) Wave 2

Figure 8: Long run rainfall's coefficient of variation (1983-2012)

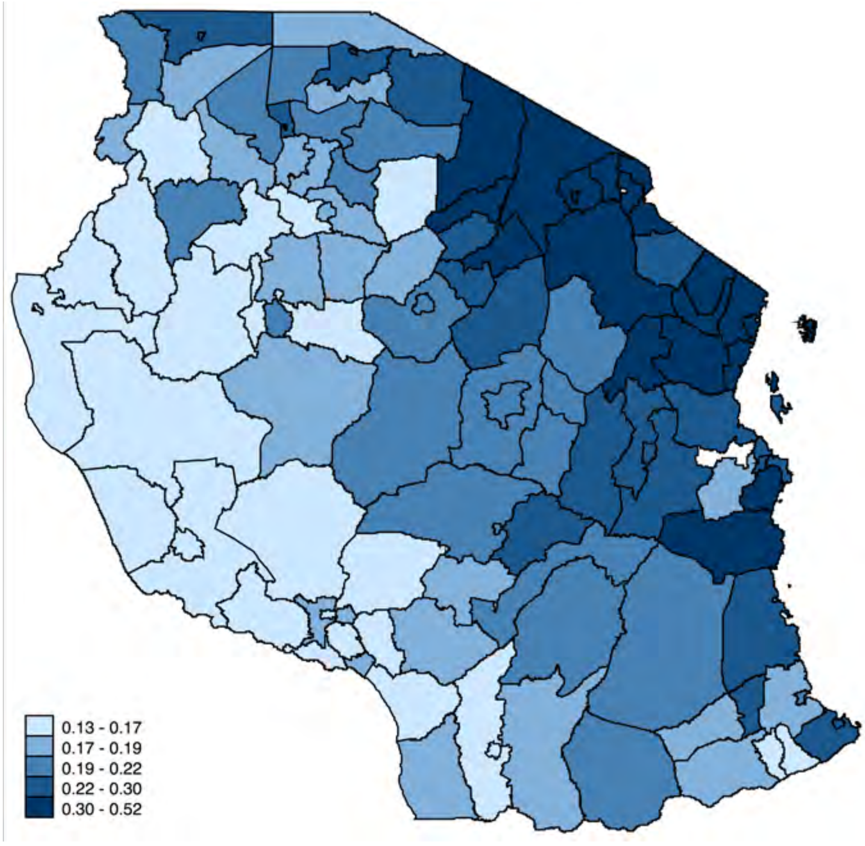


Figure 9: Long run average rainfall shortfall (1983-2012)

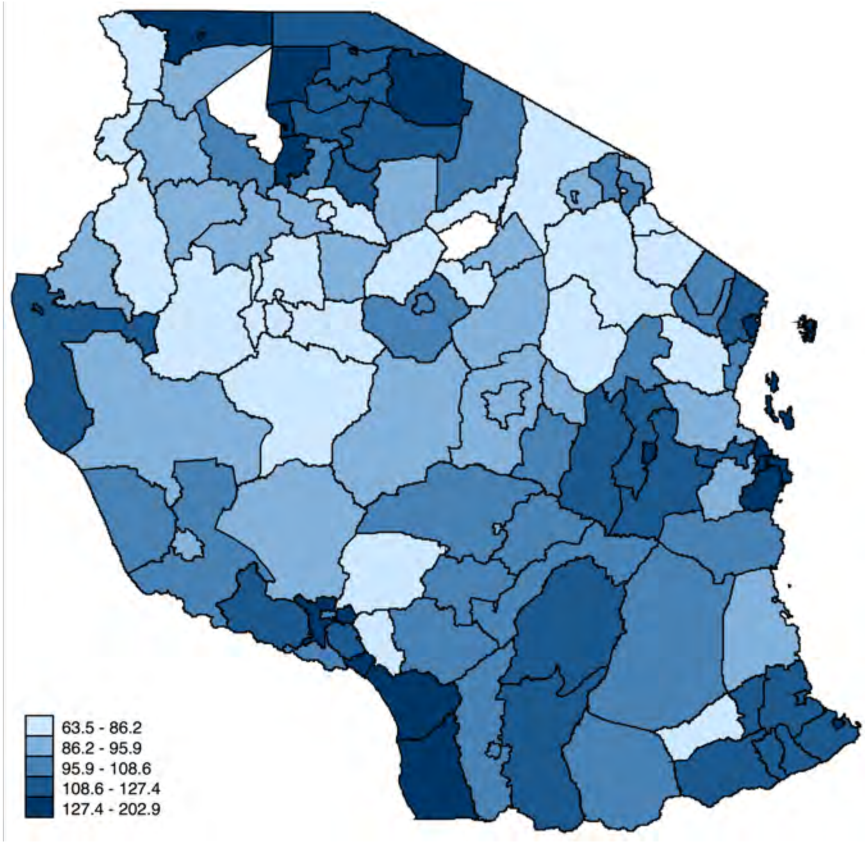
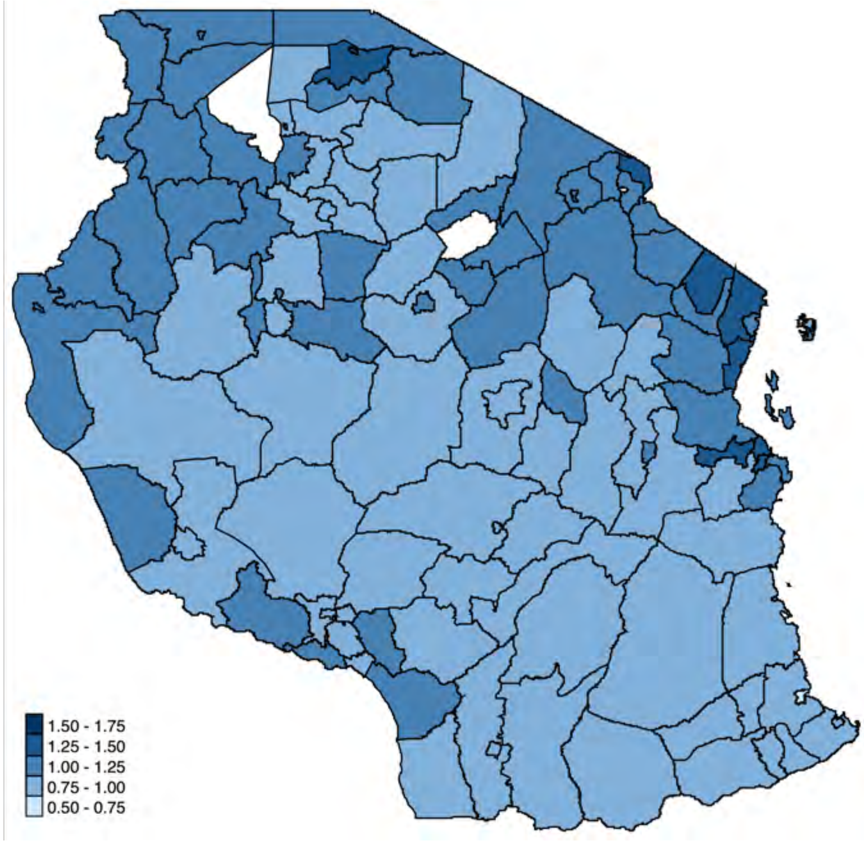
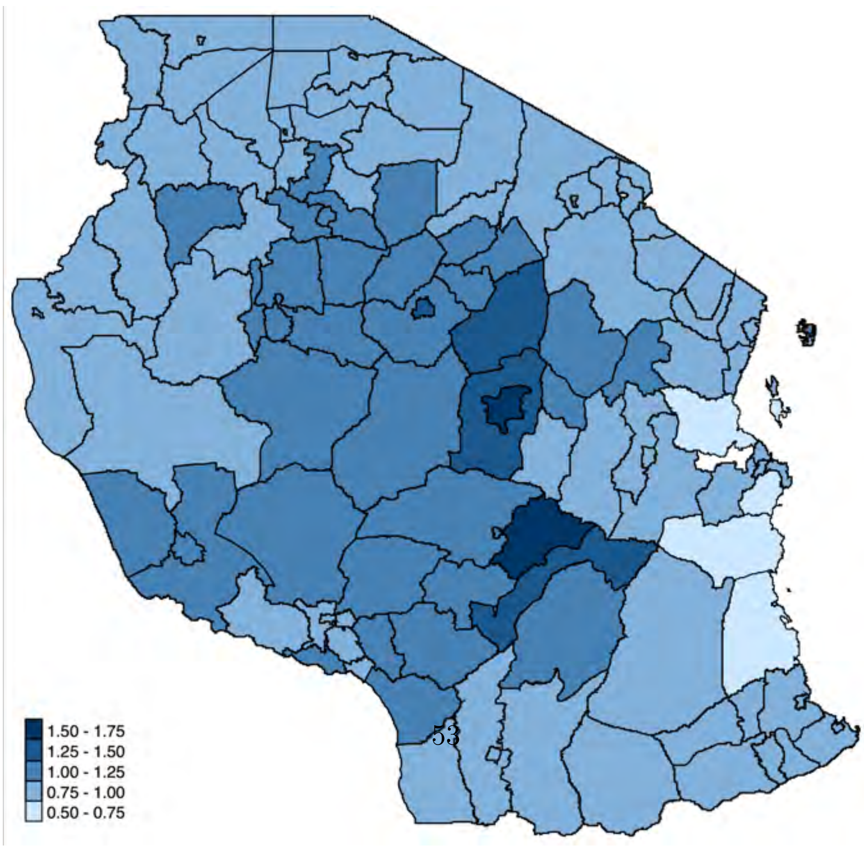


Figure 10: Within-season rainfall CoV over LR avg

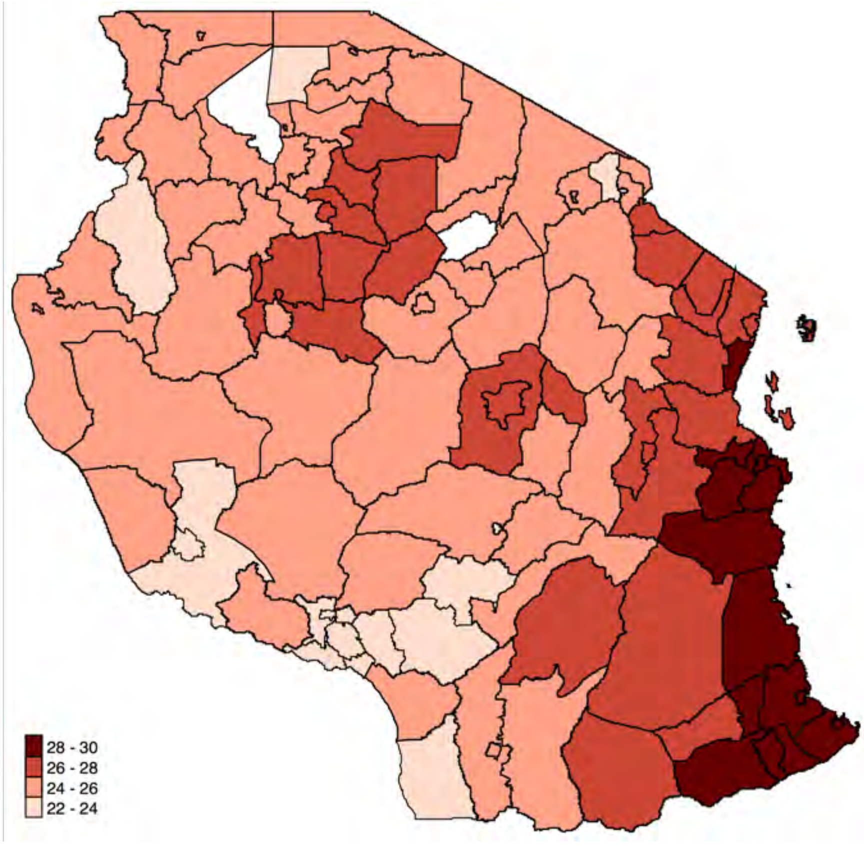


(a) Wave 1

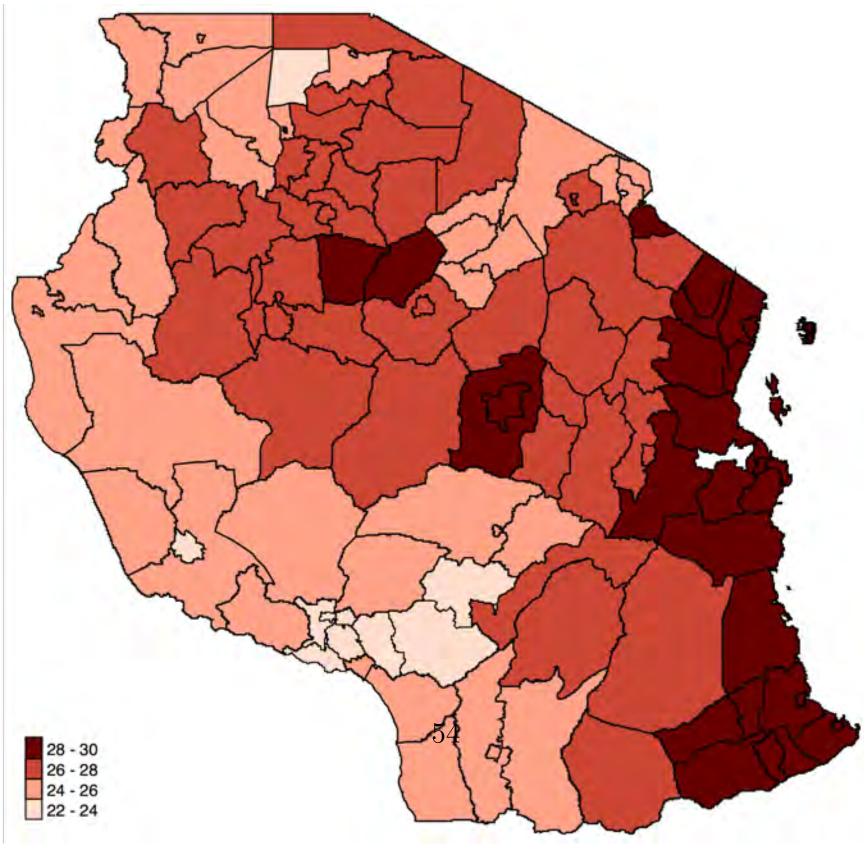


(b) Wave 2

Figure 11: Average maximum temperature



(a) Wave 1



(b) Wave 2

Figure 12: Soil pH (avg/15Km EA radius)

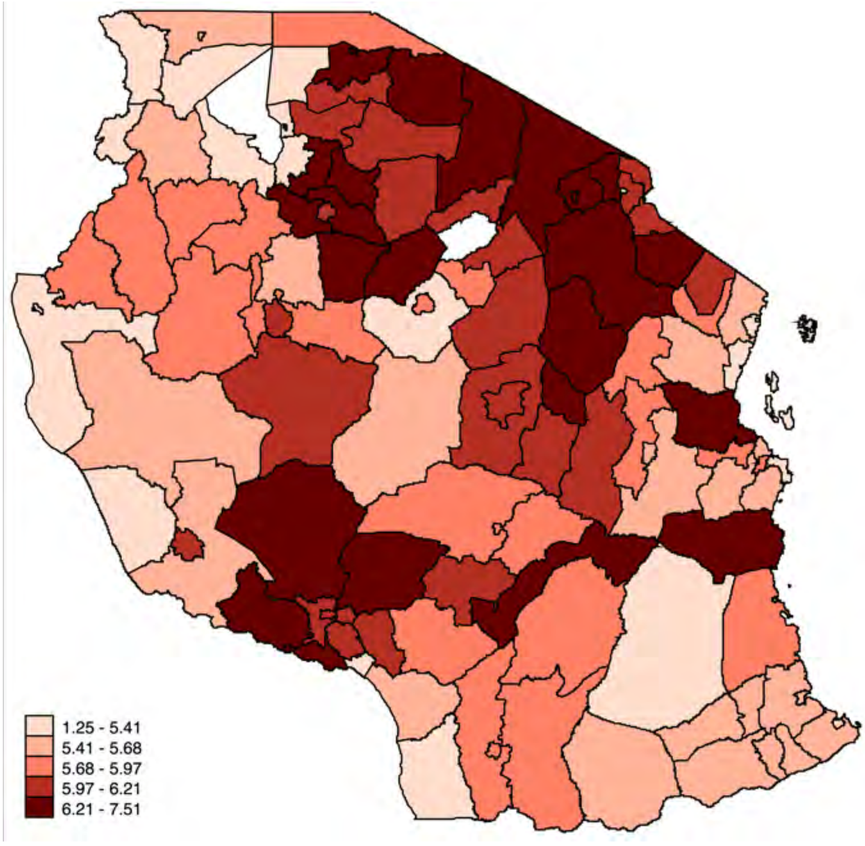


Figure 13: Road density (Km/15Km EA radius)

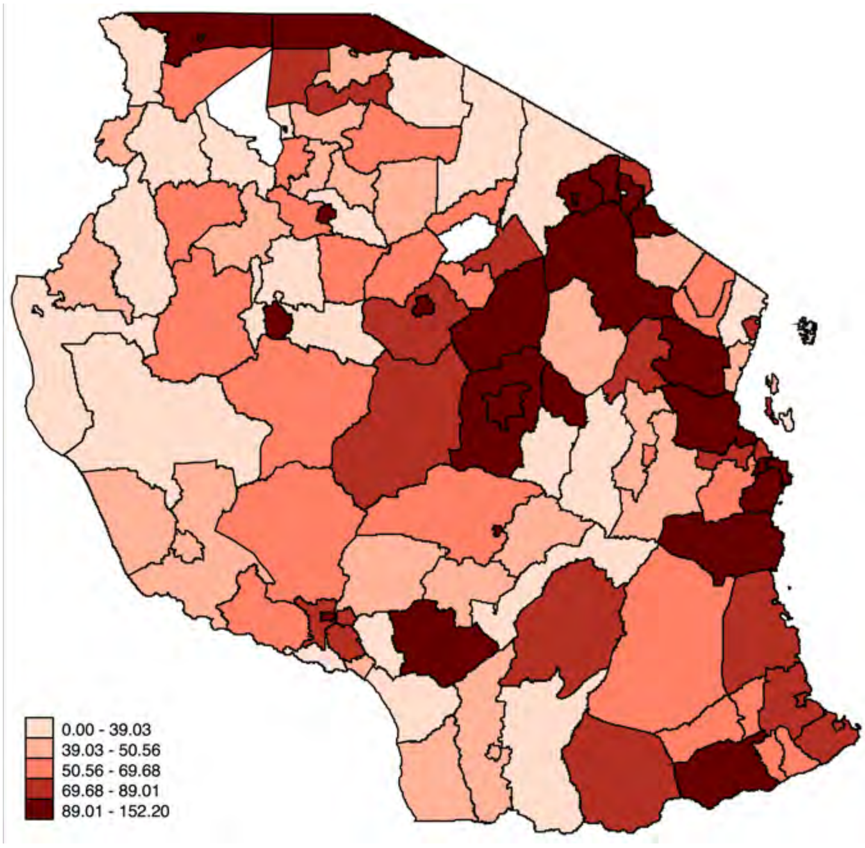


Table 1: Number of farmers by survey status and wave

(a) Original sample

	Wave1	Wave2
Original HH in the same location	2193	2193
Original HH in a new location	328	328
Splitted-off HH	647	1403
Attrition	97	0
Total	3265	3924

(b) Unbalanced sample

	Wave1	Wave2
Original HH in the same location	927	951
Original HH in a new location	75	89
Splitted-off HH	271	475
Attrition	23	0
Total	1296	1515

(c) Balanced sample

	Wave1	Wave2
Original HH in the same location	746	746
Original HH in a new location	55	55
Splitted-off HH	176	176
Total	977	977

Table 2: Maize yield and fertilizer application by seed type and wave

(a) 2008 season

			Organic fert		Inorganic fert	
	No. of hhs	Kg maize/ha	% of adopters	Kg/ha	% of adopters	Kg/ha
Traditional	1057	1382.6	15.2	351.0	13.3	30.0
Improved	239	1855.7	25.5	2027.4	28.4	433.8
Total	1296	1469.9	17.1	660.1	16.1	104.5

(b) 2010 season

			Organic fert		Inorganic fert	
	No. of hhs	Kg maize/ha	% of adopters	Kg/ha	% of adopters	Kg/ha
Traditional	1264	1416.5	14.4	356.6	16.4	306.7
Improved	251	2065.7	29.4	1206.4	31.9	68.3
Total	1515	1524.0	16.9	497.4	19.0	267.2

Table 3: Combined adoption of practices by wave

	Wave1 (n=1296)	Wave2 (n=1515)
Maize-Legume intercropping	0.324 (0.468)	0.312 (0.464)
Organic fertilizer	0.171 (0.377)	0.169 (0.375)
Inorganic fertilizer	0.161 (0.368)	0.190 (0.393)
SWC measures	0.201 (0.401)	0.138 (0.345)
Improved seeds	0.184 (0.388)	0.166 (0.372)
M-L intercropping only	0.134 (0.341)	0.155 (0.362)
Organic fertilizer only	0.050 (0.218)	0.047 (0.211)
Inorganic fertilizer only	0.038 (0.191)	0.046 (0.209)
SWC measures only	0.050 (0.218)	0.044 (0.206)
Improved seeds only	0.052 (0.222)	0.053 (0.224)
Intercropping and Organic	0.019 (0.138)	0.020 (0.142)
Intercropping and Inorganic	0.030 (0.171)	0.044 (0.204)
Intercropping and SWC	0.048 (0.214)	0.010 (0.099)
Intercropping and Iseeds	0.028 (0.164)	0.019 (0.137)
Organic and Inorganic	0.013 (0.114)	0.014 (0.117)
Organic and SWC	0.016 (0.126)	0.015 (0.122)
Organic and Iseeds	0.011 (0.103)	0.015 (0.122)
Inorganic and SWC	0.006 (0.078)	0.009 (0.092)
Inorganic and Iseeds	0.016 (0.126)	0.012 (0.108)
SWC and Iseeds	0.019 (0.135)	0.007 (0.085)
Intercropping, Organic and Inorganic	0.009 (0.096)	0.011 (0.102)
Intercropping, Organic and SWC	0.010 (0.100)	0.007 (0.085)
Intercropping, Organic and Iseeds	0.002 (0.039)	0.006 (0.077)
Intercropping, Inorganic and SWC	0.006 (0.078)	0.009 (0.096)
Intercropping, Inorganic and Iseeds	0.006 (0.078)	0.013 (0.114)
Intercropping, SWC and Iseeds	0.005 (0.068)	0.004 (0.063)
Organic, Inorganic and SWC	0.003 (0.055)	0.002 (0.044)
Organic, Inorganic and Iseeds	0.007 (0.083)	0.007 (0.085)
Organic, SWC and Iseeds	0.007 (0.083)	0.005 (0.068)
Inorganic, SWC and Iseeds	0.006 (0.078)	0.007 (0.085)
Intercropping, Organic, Inorganic and SWC	0.003 (0.055)	0.004 (0.063)
Intercropping, Organic, Inorganic and Iseeds	0.005 (0.068)	0.003 (0.051)
Intercropping, Organic, SWC and Iseeds	0.010 (0.100)	0.004 (0.063)
Intercropping, Inorganic, SWC and Iseeds	0.006 (0.078)	0.001 (0.036)
Organic, Inorganic, SWC and Iseeds	0.003 (0.055)	0.007 (0.085)
All five	0.003 (0.055)	0.002 (0.044)
None	0.379 (0.485)	0.398 (0.490)

* Standard deviation in parenthesis.

Table 4: Transition matrices of agricultural practice adoption

(a) Maize-Legume intercropping

	2010/2011	
2008/2009	No	Yes
No	508	151
	(0.771)	(0.229)
Yes	152	166
	(0.478)	(0.522)

(b) Organic fertilizer

	2010/2011	
2008/2009	No	Yes
No	744	67
	(0.917)	(0.083)
Yes	70	96
	(0.422)	(0.578)

(c) Inorganic fertilizer

	2010/2011	
2008/2009	No	Yes
No	720	73
	(0.908)	(0.092)
Yes	32	152
	(0.174)	(0.826)

(d) SWC measures

	2010/2011	
2008/2009	No	Yes
No	707	74
	(0.905)	(0.095)
Yes	141	55
	(0.719)	(0.281)

(e) Improved seeds

	2010/2011	
2008/2009	No	Yes
No	717	87
	(0.892)	(0.108)
Yes	122	51
	(0.705)	(0.295)

Table 5: Maize yield by adoption status (Kg/ha)

	Wave1	Wave2
Maize-legume intercrop		
No	1242.0***	1264.6***
	(52.4)	(45.6)
Yes	1945.1***	2095.7***
	(111.2)	(108.6)
T-test		
Difference	703.1***	831.1***
	(107.9)	(99.7)
Organic fertilizer		
No	1292.1***	1399.2***
	(46.7)	(47.5)
Yes	2329.9***	2138.0***
	(186.3)	(147.9)
T-test		
Difference	1037.7***	738.8***
	(133.1)	(124.6)
Inorganic fertilizer		
No	1287.1***	1264.3***
	(49.3)	(43.4)
Yes	2420.3***	2630.8***
	(174.6)	(149.2)
T-test		
Difference	1133.2***	1366.5***
	(136.0)	(115.1)
SWC measures		
No	1371.0***	1441.9***
	(53.1)	(48.1)
Yes	1862.1***	2037.2***
	(141.3)	(159.6)
T-test		
Difference	491.1***	595.3***
	(127.3)	(136.1)
Improved seeds		
No	1382.6***	1416.5***
	(49.5)	(46.4)
Yes	1855.7***	2065.7***
	(169.7)	(159.1)
T-test		
Difference	473.1***	649.2***
	(131.7)	(125.9)
nr. of households	1296	1515

*Standard errors in parenthesis

* p<.10, ** p<.05, *** p<.01

Table 6: Summary statistics of the selected variables by wave

	Mean	Std Dev	Mean	Std Dev
Household level variables	Wave1		Wave2	
Age of hh's head	47.380	15.561	48.592	15.865
Female hh's head	0.244	0.430	0.237	0.425
hh's head married (1=yes)	0.645	0.479	0.593	0.491
hh's head yrs of education	4.624	3.424	4.697	3.500
hh's size	5.353	2.986	5.615	3.083
Dependency ratio	1.192	0.962	1.135	0.942
Ag-wealth index	0.000	1.022	0.017	1.008
Wealth index	0.166	1.321	0.070	1.060
Land area devoted to maize (ha)	0.883	2.109	0.847	1.059
Land tenure (1=owned)	0.894	0.308	0.885	0.319
Plot has good quality (1=yes)	0.563	0.496	0.532	0.499
Plot has steep slope (1=yes)	0.047	0.212	0.049	0.216
Irrigation (1=yes)	0.026	0.160	0.021	0.144
Gov AG extension advices (1=yes)	0.143	0.350	0.076	0.265
Crops' price info-index	-0.014	0.928	0.067	1.016
Land-home distance (Km)	2.869	5.177	5.184	25.103
Land-mkt distance (Km)	7.751	8.781	12.130	16.228
Credit on inputs (1=yes)	0.019	0.138	0.018	0.135
Pesticides (1=yes)	0.123	0.328	0.108	0.310
Less area planted due to drought (1=yes)	0.190	0.392	0.268	0.443
Workers - plant (persons/ha)	17.371	27.292	17.180	23.606
Workers - weed (persons/ha)	16.679	25.125	16.815	22.844
Workers - harvest (persons/ha)	17.285	27.805	17.770	25.110
Ox based machinary (units/ha)	0.495	7.185	0.891	3.682
Central Plateaux (plains)	0.142	0.349	0.132	0.339
Coastal Plains	0.109	0.312	0.129	0.335
Eastern Plateaux and Mountain Blocks	0.151	0.358	0.155	0.362
High Plains and Plateaux	0.132	0.339	0.108	0.310
Inland Sediments	0.171	0.377	0.163	0.370
Rukwa-Ruaha Rift Zone-Alluvial Flats	0.027	0.162	0.026	0.160
Ufipa Plateau	0.056	0.231	0.057	0.233
Volcanoes and Rift Depressions	0.158	0.365	0.179	0.383
Western Highlands	0.053	0.225	0.051	0.220
EA level variables	Wave1		Wave2	
CoV rainfall (1983-2012)	0.220	0.069	0.221	0.069
Avg rain shortfall (1983-2012)	104.605	22.599	105.490	22.889
Season total rainfall	660.421	209.979	666.677	204.150
Season avg MAX temp	25.731	1.684	26.666	1.792
Season rainfall CoV / LR avg	0.970	0.120	0.982	0.163
Soil nutrient avail (Severe constrs)	0.093	0.290	0.091	0.288
Soil Ph (avg/15Km EA radius)	5.784	0.740	5.761	0.762
Road density (Km/15Km EA radius)	64.538	32.225	66.157	31.619
CCM party community leader (1=yes)	0.933	0.250	0.424	0.494

Table 7: Summary statistics of the selected variables by AEZ

AEZ	I	II	III	IV	V	VI	VII	VIII	IX
Household level variables									
Age of hh's head	46.297	50.693	49.436	51.305	46.294	46.040	43.425	48.735	44.219
Female hh's head	0.177	0.298	0.241	0.299	0.200	0.347	0.119	0.273	0.233
hh's head married (1=yes)	0.628	0.628	0.666	0.551	0.603	0.507	0.631	0.651	0.548
hh's head yrs of education	4.716	4.378	4.162	4.488	5.222	4.053	5.044	4.891	4.425
hh's size	6.857	4.955	4.995	4.937	4.921	4.547	5.737	6.202	5.651
Dependency ratio	1.204	1.093	1.197	1.158	1.021	1.130	1.306	1.237	1.179
Ag-wealth index	0.685	-0.329	-0.128	-0.087	-0.344	-0.128	0.170	0.300	-0.284
Wealth index	0.183	0.338	-0.127	0.245	-0.069	-0.187	-0.222	0.373	0.106
Land area devoted to maize (ha)	1.304	0.816	0.783	0.712	0.765	0.775	1.155	0.809	0.623
Land tenure (1=owned)	0.854	0.863	0.907	0.931	0.934	0.920	0.906	0.826	0.925
Plot has good quality (1=yes)	0.370	0.637	0.698	0.542	0.584	0.587	0.613	0.445	0.479
Plot has steep slope (1=yes)	0.010	0.018	0.060	0.093	0.079	0.093	0.044	0.021	0.048
Irrigation (1=yes)	0.003	0.006	0.014	0.030	0.004	0.000	0.013	0.084	0.021
Gov AG extension advices (1=yes)	0.109	0.098	0.102	0.138	0.096	0.053	0.106	0.122	0.075
Crops' price info-index	0.314	-0.152	-0.100	0.002	-0.065	0.258	0.161	-0.003	0.290
Land-home distance (Km)	3.157	5.499	3.125	2.833	4.226	2.879	2.773	6.054	4.763
Land-mkt distance (Km)	12.563	5.264	10.192	10.544	12.442	10.922	10.855	8.796	9.155
Credit on inputs (1=yes)	0.083	0.006	0.009	0.006	0.006	0.013	0.019	0.004	0.027
Pesticides (1=yes)	0.151	0.095	0.049	0.204	0.075	0.107	0.156	0.137	0.068
Less area planted due to drought (1=yes)	0.344	0.205	0.329	0.132	0.149	0.173	0.056	0.332	0.103
Workers - plant (persons/ha)	12.999	18.416	11.971	26.720	15.029	37.521	17.156	15.656	22.042
Workers - weed (persons/ha)	12.828	17.101	10.751	26.134	14.165	35.274	18.345	16.712	19.706
Workers - harvest (persons/ha)	12.441	18.436	11.568	29.030	14.944	35.461	20.232	16.585	19.649
Ox based machinary (units/ha)	1.459	0.000	0.254	0.701	0.000	3.814	1.677	1.118	0.000
EA level variables									
CoV rainfall (1983-2012)	0.181	0.227	0.276	0.185	0.218	0.180	0.166	0.267	0.167
Avg rain shortfall (1983-2012)	86.830	125.824	100.279	113.464	113.058	104.729	103.741	98.638	97.393
Season total rainfall	644.794	733.887	514.898	804.737	705.437	731.347	871.694	513.987	761.658
Season avg MAX temp	26.467	28.640	27.975	24.074	26.201	24.303	24.364	25.685	24.841
Season rainfall CoV / LR avg	1.034	0.896	0.985	1.020	0.936	0.951	1.018	0.979	0.984
Soil nutrient avail (Severe constrs)	0.000	0.086	0.137	0.000	0.239	0.000	0.113	0.000	0.274
Soil Ph (avg/15Km EA radius)	6.024	5.145	5.757	5.899	5.662	6.162	5.796	6.089	5.395
Road density (Km/15Km EA radius)	60.034	82.620	73.244	65.800	56.799	56.494	46.120	72.875	44.981
CCM party community leader (1=yes)	0.599	0.741	0.780	0.656	0.608	0.800	0.531	0.708	0.342

Table 8: Results from the multivariate pooled probit model estimation - Determinants of adoption (N=2810, n=1833)

Variables	**Intercrop**		**Ofert**		**INOfert.**		**SWC**		**Iseed**	
CoV rainfall (1983-2012)	-0.002		-0.014	*	-0.028	***	-0.002		0.029	***
Avg rainfall shortfall (1983-2012)	-0.001		-0.002		-0.004	*	0.000		-0.000	
Gov AG extension advices (1=yes)	-0.128		0.209	**	0.509	***	0.291	***	0.168	*
CCM party community leader (1=yes)	0.145	**	0.228	***	0.042		0.024		-0.134	*
hh's size	0.001		-0.013		-0.028	*	0.015		0.036	***
Age of hh's head	0.001		0.003		0.006	**	0.000		-0.001	
hh's head yrs of education	0.002		0.039	***	0.073	***	0.028	***	0.050	***
Dependency ratio	-0.038		-0.054		0.010		-0.008		-0.065	*
Female hh's head	0.012		-0.029		0.126		0.017		-0.138	
hh's head married (1=yes)	-0.175	***	0.026		0.142	*	0.072		-0.036	
ln(land size devoted to maize)	-0.023		-0.115	***	0.066	*	0.007		0.010	
Land tenure (1=owned)	0.091		0.533	***	0.034		0.317	***	0.028	
Land-home distance (Km)	-0.001		-0.002		-0.002		-0.002		0.001	
Land-mkt distance (Km)	-0.003		-0.004		-0.005	*	0.002		0.001	
Ag-wealth index	0.045		0.314	***	-0.161	***	-0.063	*	-0.027	
Wealth index	0.022		0.148	***	0.204	***	0.077	***	0.135	***
Irrigation (1=yes)	-0.615	***	-0.221		-0.011		-0.050		-0.108	
Less area planted due to drought (1=yes)	-0.078		-0.051		-0.335	***	0.031		0.044	
Good soil qual (self reported)	0.012		-0.003		-0.013		0.112	*	0.035	
Credit on inputs (1=yes)	-0.707	***	0.241		1.909	***	0.095		0.576	***
Crops' price info-index	0.015		0.005		0.059	*	0.113	***	0.108	***
Plot has steep slope (1=yes)	0.177		0.379	***	0.085		0.788	***	-0.188	
Soil nutrient avail (Severe constrs)	0.044		-0.457	***	-0.373	**	-0.307	*	-0.096	
Soil Ph (avg/15Km EA radius)	0.089	*	0.050		0.228	***	-0.037		0.030	
Road density (Km/15Km EA radius)	-0.001		0.002		0.004	**	0.001		0.003	**
Coastal Plains	-0.185		-0.257		-0.288		-0.836	***	-0.223	
Eastern Plateaux and Mountain Blocks	-0.427	***	0.222		-0.903	***	-0.489	***	-0.415	***
High Plains and Plateaux	0.067		0.582	***	1.099	***	-0.211		0.058	
Inland Sediments	-0.005		-0.205		0.715	***	-0.435	***	-0.257	*
Rukwa-Ruaha Rift Zone-Alluvial Flats	0.263		-0.145		0.155		0.027		0.031	
Ufipa Plateau	0.040		0.736	***	0.599	***	-0.115		0.240	
Volcanoes and Rift Depressions	-0.010		0.700	***	-0.052		0.369	***	0.353	***
Western Highlands	0.774	***	0.050		0.280		-0.104		-0.723	***
Wave2	0.049		0.152	**	0.317	***	-0.253	***	-0.176	**
Constant	-0.812	**	-2.151	***	-2.694	***	-1.279	***	-2.116	***

Note: *** 1%, ** 5%, * 10%. Clustered standard errors at household level.

Table 9: Correlation matrix of the multivariate pooled probit model - Determinants of adoption

	Intercrop	Ofert	INOfert		SWC		Iseeds	
Intercrop	1.000	0.029	0.274	***	0.110	**	0.057	
Ofert		1.000	0.195	***	0.200	***	0.087	
INOfert			1.000		0.087		0.253	***
SWC					1.000		0.088	*
Iseeds							1.000	

Table 10: Results from the hybrid production function estimation (N=2810, n=1833)

Variables	**Pooled OLS**		**RE**		**RE Mundlak**		**2SLS Mundlak**	
M-L intercrop (1=yes)	0.104	***	0.109	***	0.102	***	0.207	**
Organic fert (1=yes)	0.010		-0.001		0.008		-0.039	
Inorganic fert (1=yes)	0.399	***	0.362	***	0.368	***	0.365	***
SWC (1=yes)	0.122	***	0.141	***	0.142	***	0.146	**
Iseeds (1=yes)	0.017		0.018		0.026		0.118	
ln(planting workers)	0.196	***	0.207	***	0.288	***	0.281	***
ln(weeding workers)	0.013		0.023		0.042		0.044	
ln(harvest workers)	0.354	***	0.331	***	0.221	***	0.219	***
ln(Ox machinary)	0.078	**	0.071	**	0.059		0.060	
Pesticides (1=yes)	0.142	**	0.130	**	0.113		0.115	
hh's size	-0.031	***	-0.029	***	-0.035		-0.035	
Age of hh's head	-0.008	***	-0.008	***	0.010		0.011	
hh's head yrs of education	-0.006		-0.005		0.004		0.003	
Dependency ratio	0.045	**	0.042	**	0.031		0.034	
Female hh's head	-0.085	*	-0.091	*	0.174		0.193	
hh's head married (1=yes)	-0.010		-0.004		0.038		0.049	
ln(land size devoted to maize)	0.099	***	0.077	***	-0.087	*	-0.088	**
Land tenure (1=owned)	-0.008		-0.013		-0.074		-0.081	
Land-home distance (Km)	0.000		0.000		0.003	***	0.003	***
Land-mkt distance (Km)	-0.001		-0.001		-0.000		-0.000	
Ag-wealth index	0.130	***	0.128	***	0.073		0.076	
Wealth index	0.038	*	0.041	**	0.094	*	0.098	*
ln(total rainfall)	-0.088	*	-0.081	*	0.117		0.120	
Season CoV > CoV LR avg (1=yes)	-0.076	**	-0.106	***	-0.149	***	-0.148	***
Season TMAX avg > 30 (1=yes)	-0.140	**	-0.145	**	-0.243	**	-0.250	**
Irrigation (1=yes)	0.183		0.183		0.038		0.039	
Less area planted due to drought (1=yes)	-0.276	***	-0.266	***	-0.256	***	-0.257	***
Plot has good quality (1=yes)	0.159	***	0.131	***	0.041		0.045	
Credit on inputs (1=yes)	0.030		0.027		-0.048		-0.018	
Crops' price info-index	0.042	**	0.040	**	0.034		0.029	
Plot has steep slope (1=yes)	-0.024		-0.032		-0.010		0.008	
Soil nutrient avail (Severe constrs)	-0.101		-0.113	*	-0.071		-0.070	
Soil Ph (avg/15Km EA radius)	0.058	**	0.068	**	0.055	**	0.050	*
Road density (Km/15Km EA radius)	-0.002	***	-0.002	***	-0.002	***	-0.002	***
Coastal Plains	-0.146		-0.161		-0.145		-0.106	
Eastern Plateaux and Mountain Blocks	0.038		0.030		0.019		0.067	
High Plains and Plateaux	0.176	***	0.184	***	0.203	***	0.207	***
Inland Sediments	-0.034		-0.042		-0.011		0.004	
Rukwa-Ruaha Rift Zone-Alluvial Flats	0.364	***	0.342	***	0.400	***	0.407	***
Ufipa Plateau	0.499	***	0.530	***	0.490	***	0.474	***
Volcanoes and Rift Depressions	-0.085		-0.106		-0.067		-0.056	
Western Highlands	-0.414	***	-0.417	***	-0.385	***	-0.413	***
Wave2	0.113	***	0.118	***	0.092	**	0.098	**
Constant	6.235	***	6.138	***	6.392	***	6.267	***
adj R^2	0.417		0.425		0.437		0.420	
Robust Hausman test - $\chi^2(30)$					71.8	***	75.8	***
Hansen J - $\chi^2(350)$							383.1	*
Excl susp ortogh conds - $\chi^2(345)$							358.4	
Kleibergen-Paap rk LM statistic - $\chi^2(350)$							409.2	***
Anderson-Rubin Wald test - $\chi^2(350)$							1097.4	***
AP mult. F test - Intercrop							3.5	***
AP mult. F test - Ofert							15.0	***
AP mult. F test - INOfert							17.1	***
AP mult. F test - SWC							11.2	***
AP mult. F test - Iseeds							9.4	***
Endogeneity test (C statistic)							4.228	

Note: *** 1%, ** 5%, * 10%. Clustered standard errors at household level.

Appendix

Table 11: Agricultural practice adoption by AEZ (proportions)*

(a) Wave 1 (n=1296)

	AEZ									
	I	II	III	IV	V	VI	VII	VIII	IX	Total
Maize-Legume intercropping	0.353	0.284	0.189	0.357	0.297	0.514	0.329	0.317	0.638	0.324
	(0.0353)	(0.0381)	(0.0280)	(0.0367)	(0.0307)	(0.0857)	(0.0554)	(0.0326)	(0.0583)	(0.0130)
Organic fertilizer	0.174	0.0993	0.158	0.257	0.0541	0.0571	0.342	0.278	0.0725	0.171
	(0.0280)	(0.0253)	(0.0261)	(0.0335)	(0.0152)	(0.0398)	(0.0559)	(0.0314)	(0.0314)	(0.0105)
Inorganic fertilizer	0.158	0.0780	0.0102	0.398	0.212	0.114	0.219	0.112	0.130	0.161
	(0.0269)	(0.0227)	(0.00720)	(0.0375)	(0.0275)	(0.0546)	(0.0488)	(0.0221)	(0.0408)	(0.0102)
SWC measures	0.326	0.0567	0.112	0.199	0.113	0.314	0.178	0.371	0.174	0.201
	(0.0347)	(0.0196)	(0.0226)	(0.0306)	(0.0213)	(0.0796)	(0.0451)	(0.0338)	(0.0460)	(0.0111)
Improved seeds	0.239	0.177	0.138	0.158	0.0991	0.143	0.137	0.371	0.0435	0.184
	(0.0315)	(0.0323)	(0.0247)	(0.0280)	(0.0201)	(0.0600)	(0.0405)	(0.0338)	(0.0247)	(0.0108)

(b) Wave 2 (n=1515)

	AEZ									
	I	II	III	IV	V	VI	VII	VIII	IX	Total
Maize-Legume intercropping	0.305	0.215	0.187	0.368	0.344	0.425	0.356	0.321	0.597	0.312
	(0.0326)	(0.0295)	(0.0255)	(0.0379)	(0.0303)	(0.0792)	(0.0516)	(0.0284)	(0.0563)	(0.0119)
Organic fertilizer	0.175	0.0564	0.102	0.294	0.0486	0.125	0.230	0.347	0.0909	0.169
	(0.0269)	(0.0166)	(0.0198)	(0.0358)	(0.0137)	(0.0530)	(0.0454)	(0.0290)	(0.0330)	(0.00963)
Inorganic fertilizer	0.185	0.0974	0.0170	0.534	0.267	0.200	0.276	0.111	0.169	0.190
	(0.0275)	(0.0213)	(0.00846)	(0.0392)	(0.0282)	(0.0641)	(0.0482)	(0.0191)	(0.0430)	(0.0101)
SWC measures	0.0950	0.0564	0.0936	0.153	0.113	0.150	0.161	0.262	0.169	0.138
	(0.0208)	(0.0166)	(0.0190)	(0.0283)	(0.0202)	(0.0572)	(0.0396)	(0.0268)	(0.0430)	(0.00886)
Improved seeds	0.150	0.118	0.0936	0.178	0.113	0.125	0.230	0.336	0.0390	0.166
	(0.0253)	(0.0232)	(0.0190)	(0.0300)	(0.0202)	(0.0530)	(0.0454)	(0.0287)	(0.0222)	(0.00956)

* Standard deviations in parenthesis

Table 12: Results from the multivariate fixed-effects probit model estimation - Determinants of adoption (N=2810, n=1833)

Variables	**Intercrop**		**Ofert**		**INOfert.**		**SWC**		**Iseed**	
CoV rainfall (1983-2012)	-0.003		-0.015	**	-0.028	***	-0.002		0.029	***
Avg rainfall shortfall	-0.001		-0.002		-0.004	*	0.000		-0.000	
Gov AG extension advices (1=yes)	-0.021		0.057		0.298	***	0.276	*	0.104	
CCM party community leader (1=yes)	0.003		0.019		0.114		-0.071		-0.063	
hh's size	-0.008		-0.015		-0.035		0.036		0.011	
Age of hh's head	-0.024		-0.014		0.012		-0.000		-0.004	
hh's head yrs of education	0.026		0.005		0.025		0.067	**	-0.022	
Dependency ratio	-0.047		-0.003		0.008		-0.001		-0.103	
Female hh's head	-0.645	*	-0.177		0.412		0.708		-0.063	
hh's head married (1=yes)	-0.163		-0.066		0.053		0.052		-0.215	
ln(land size devoted to maize)	-0.099	*	0.013		0.161	***	-0.020		0.116	
Land tenure (1=owned)	0.037		0.188		0.027		0.347		0.355	
Land-home distance (Km)	0.003		-0.002		-0.001		-0.013		0.001	
Land-mkt distance (Km)	-0.000		-0.001		0.001		0.001		0.001	
Ag-wealth index	0.026		0.081		0.071		-0.117		-0.106	
Wealth index	-0.058		0.028		0.219	**	0.111		-0.028	
Irrigation (1=yes)	0.046		-0.532		-0.422		-0.350		-0.584	*
Less area planted due to drought (1=yes)	-0.036		-0.120		-0.105		-0.065		0.096	
Good soil qual (self reported)	-0.005		0.108		-0.137	*	0.266	**	-0.129	
Credit on inputs (1=yes)	-1.028	***	0.247		0.682	**	0.013		0.128	
Crops' price info-index	0.068		-0.003		0.082	**	0.092	*	0.124	**
Plot has steep slope (1=yes)	-0.199		0.599	**	-0.029		0.380	*	-0.072	
Soil nutrient avail (Severe constrs)	0.033		-0.482	***	-0.361	**	-0.309	*	-0.077	
Soil Ph (avg/15Km EA radius)	0.081	*	0.039		0.237	***	-0.044		0.037	
Road density (Km/15Km EA radius)	-0.001		0.002		0.004	***	0.001		0.003	**
Coastal Plains	-0.198		-0.267		-0.250		-0.815	***	-0.217	
Eastern Plateaux and Mountain Blocks	-0.435	***	0.242		-0.840	***	-0.479	***	-0.402	***
High Plains and Plateaux	0.059		0.592	***	1.151	***	-0.206		0.074	
Inland Sediments	0.001		-0.169		0.760	***	-0.416	***	-0.239	*
Rukwa-Ruaha Rift Zone-Alluvial Flats	0.251		-0.134		0.205		0.037		0.054	
Ufipa Plateau	0.045		0.791	***	0.633	***	-0.087		0.251	
Volcanoes and Rift Depressions	0.006		0.702	***	0.019		0.377	***	0.366	***
Western Highlands	0.809	***	0.101		0.306		-0.082		-0.731	***
Wave2	0.040		0.098		0.276	***	-0.264	***	-0.196	**
Constant	-0.708	*	-2.178	***	-2.824	***	-1.245	**	-2.211	***
Robust Hausman test χ^2	28.389		37.013	**	48.394	***	17.323		25.445	

Note: *** 1%, ** 5%, * 10%. Clustered standard errors at household level.

Table 13: Correlation matrix of the multivariate fixed-effects probit model - Determinants of adoption

	Intercrop	Ofert	INOfert		SWC		Iseeds	
Intercrop	1.000	0.034	0.281	***	0.112	**	0.060	
Ofert		1.000	0.199	***	0.195	***	0.084	
INOfert			1.000		0.092		0.244	***
SWC					1.000		0.096	*
Iseeds							1.000	

ESA Working Papers

WORKING PAPERS

The ESA Working Papers are produced by the Agricultural Development Economics Division (ESA) of the Economic and Social Development Department of the Food and Agriculture Organization of the United Nations (FAO). The series presents ESA's ongoing research. Working papers are circulated to stimulate discussion and comments. They are made available to the public through the Division's website. The analysis and c onclusions are those of the authors and do not indicate concurrence by FAO.

AGRICULTURAL DEVELOPMENT ECONOMICS

Agricultural Development Economics (ESA) is FAO's focal point for economic research and policy analysis on issues relating to world food security and sustainable development. ESA contributes to the generation of knowledge and evolution of scientific thought on hunger and poverty alleviation through its economic studies publications which include this working paper series as well as periodic and occasional publications.

Agricultural Development Economics (ESA)
The Food and Agriculture Organization of the United Nations
Viale delle Terme di Caracalla
00153 Rome, Italy

Contact:
Office of the Director
Telephone: +39 06 57054368
Facsimile: + 39 06 57055522
Website: http://www.fao.org/economic/esa/esa-home/en/
e-mail: ESA@fao.org

I5556E/1/04.16