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# Smallholder productivity and weather shocks: Adoption and impact of widely promoted agricultural practices in Tanzania

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**Abstract**

Food security in Tanzania is projected to deteriorate as a result of climate change. In spite of the efforts to promote agricultural practices to 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 food security. 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 a set of agricultural practices and their impacts on maize productivity under weather shocks in Tanzania. The specific practices analyzed are: maize-legume intercropping, soil and water conservation practices (SWC), the use of organic fertilizers, inorganic fertilizers and high yielding maize varieties. We find strong complementarities between these practices both in terms

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of adoption and yield impacts. Long-run variability in rainfall decreases the adoption of fertilizers (both organic and inorganic) and increases that of improved seeds. Access to information and extension increase the incentives to adopt modern inputs as well as SWC. Farmers in areas where the cropping season's rainfall has been highly variable and temperature has been unexpectedly high have significantly lower maize yields. SWC emerges as one of the most important practices in increasing yields with significant benefits by itself, in combination with other practices, under average weather conditions as well as under rainfall and temperature shocks. The shocks we analyze are expected to increase under climate change, underlining the importance of policies to buffer food security from the estimated effects of climate change. This paper contributes to evidence base to support policies to advance food security under climate change by underlining the importance of integrating site-specific analyses of climatic variables and their interactions with promoted practices in policy design and targeting.

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

# 1 Introduction

Sub-Saharan Africa (SSA) remains the world's most food-insecure region characterized by high levels of child mortality and poverty, low levels of human and physical capital, and poor infrastructure (FAO, 2009). The economies of countries in SSA heavily depend on a smallholder-based agricultural sector, which in turn makes them particularly vulnerable to climate change (Ziervogel et al., 2008; Barrios et al., 2008; TZG, 2009). An estimated 90 percent of the population depends on rain-fed crop production and pastoralism to meet its basic food needs (Patt and Winkler, 2007). 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 percent, 34 percent, and 10 percent, respectively (Nelson et al., 2009).

In Tanzania, smallholder farmers account for about 84 percent of cultivated land, of which 45 percent is devoted to maize supporting the livelihoods of 82 percent of smallholders (i.e. 4.5 million households) (USAID, 2010). Projections from General Circulation Models show that food security in Tanzania is likely to deteriorate as a

consequence of climate change in the next 30 years (Arndt et al., 2012). Tanzania-specific models predict an average decrease in maize yields of 33 percent, with a wide variation (10-84 percent) across the the country (NAPA, 2007). Productivity decreases at this scale will affect the most vulnerable households that directly depend on climate patterns for their livelihoods and have weak risk management capacities. Tanzania's National Adaptation Plan of Action (NAPA) 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).

We 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), the use of organic fertilizers, inorganic fertilizers and high yielding maize varieties, as well as their impacts on productivity in rural Tanzania. We use the first two waves of the Tanzania National Panel Survey, a nationally representative household survey with a strong focus on agriculture merged with geo-referenced historical rainfall and temperature data 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.[1]

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 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 climatic risk factors and household-specific time-invariant unobserved heterogeneity. Second, after testing for the potential endogeneity of adoption, we study the impact of these practices (and combinations of them) on maize productivity. Third, we analyze the impact of specific weather shocks on technology adoption and productivity in general, as well as investigate the specific ways they modify the impacts of adoption.

We find evidence for the existence of complementarities between different practices, that can help improve targeting of extension interventions. There is a negative

[1]This implies that our results are valid for about 80 percent of all agricultural households in the sample, i.e. maize farmers.

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 are 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 and price information significantly increase the likelihood of adoption of modern inputs as well as SWC, highlighting the key role of extension services in influencing the adoption decisions of farmers.

As for the determinants of maize productivity conditional on adoption, SWC and inorganic fertilizers are the only practices with a positive and statistically significant impact on maize yields when analyzed by themselves. When the combinations of practices are accounted for, the yield effect of SWC emerges as the most robust given its significance in most of the combinations. All our specifications point to a strong negative relationship between maize productivity and two prominent shock indicators during the growing season: higher than average within-season rainfall variation and too high maximum temperatures. This indicates a lack of adaptive capacity to these shocks that are expected to increase in frequency under climate change. Therefore, we also analyze the ways in which the effect of the practices analyzed here changes in presence/absence of these shocks. SWC in combination with various practices is found to provide yield benefits that are resilient to these shocks, suggesting synergies between short-term productivity ad resilience benefits. Our policy implications draw on these results to improve the design and targeting of policies for food security under climate change.

The rest of this paper is organized as follows. We provide a short overview of the relevant literature in Section 2, present our conceptual framework and empirical specification in Section 3, and introduce our data with descriptive statistics in Section 4. We discuss our results in Section 5 and conclude in Section 6 with a brief summary of results and policy implications.

# 2 Literature Review

The well-established economic literature on the adoption of agricultural technologies and productivity provide the main back-drop for the analyses in this paper. Based on the theoretical model of constrained decision-making, this literature highlights the importance of risk and uncertainty, credit constraints, tenure security, wealth, access to information, gender and safety-first behaviour (Feder et al. (1985); Feder and Umali (1993); Just and Zilberman (1983); Rosenzweig and Wolpin (1993); Besley (1995); Doss (2003); De Groote and Coulibaly (1998); Kassie and Holden

(2007); Smale et al. (1994) among others) in shaping adoption decisions. Given our context of adoption and productivity under increasing climatic variability, it is important to underline how the changes brought by climate change are affecting the standard economic model. Even though the averages of climatic variables take a long time to manifest themselves, the extremes of the distribution change much faster (Fankhauser et al., 1999). The increasing frequency and intensity of extreme weather events primarily affects the risk profiles of alternative technologies (livelihood strategies), thereby changing incentives. Although agriculture has always been subject to weather risks, these new challenges increase the importance of controlling for the effects of relevant weather related risks on adoption decisions as well as productivity.

The more recent empirical literature tries to address this need assisted by the improvements in the availability of weather data. Most of this literature uses annual average rainfall and temperature data (lagged values, current year values or averages over a couple of years) from weather stations to capture their impacts on adoption behaviour (Deressa and Hassan, 2009; Chomba, 2004; Bezabih et al., 2013; Gebrehiwot and Veen, 2013; Falco and Bulte, 2013; Pangapanga et al., 2012). Annual averages from sparse weather station data over short time periods, however, fail to capture the spatial as well as temporal heterogeneity in these variables. This problem is addressed by some studies using interpolation techniques to introduce spatial heterogeneity to average rainfall and temperature data (Di Falco et al., 2011; Basinger et al., 2012). Average values of these variables, regardless of their resolution, fail to capture the impacts of changing expectations due to changes in weather patterns on adoption decisions. Longer time periods to control for variation in these variables is therefore desirable. Bezu et al. (2014) use 5 year averages and standard deviations to control for longer term expectations. Arslan et al. (2014) and Asfaw et al. (2014) improve on earlier studies by using longer term (29 years) data on temperature and rainfall at high resolution from satellite based sources to capture both the short- and the long-term changes in relevant variables (both in levels and variations) and their impacts on adoption and productivity in Zambia and Malawi, respectively.

When it comes to the impacts of agricultural technologies on productivity (or other welfare outcomes) there are two strands of literature relevant for our study: agronomic and socio-economic. Agronomic studies (specifically focused on the practices analyzed in this paper) find that maize-legume intercropping system has the potential to alleviate binding soil quality constraints and improve productivity compared to mono-cropping (Schmidt et al., 2003; Rusinamhodzi et al., 2012). The use of organic fertilizer is found to be one of the most important sustainable agricultural practices, since it improves 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 of chemical fertilizers, which is shown to cause environmental problems such as eutrophication in water system and land degradation (Marenya and Barrett, 2007). As pointed out by Reganold et al. (1987), though the impact on productivity of chemical fertilizer is higher than that of organic fertilizer in the short run, in the long run organic fertilizers appear to be more effective in reducing soil erosion and maintaining soil productivity. The adoption of SWC measures (e.g. erosion control bunds, terraces, gabions/sandbags, vetiver grass, tree belts, water harvest bunds or drainage ditches) 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 external benefits to neighbors and downstream water users by mitigating flooding, enhancing biodiversity, and reducing sedimentation of waterways (McCarthy et al., 2011).

Given that the technology adoption literature was prompted by the Green Revolution, the impacts of improved seeds and fertilizers are widely studied in the socio-economic literature (see Feder et al., 1985; Feder and Umali, 1993, and references therein). Though these modern inputs are found to improve food security by increasing productivity, most of this evidence either does not control for climatic variables or is valid under average climatic conditions. There is no a clear-cut evidence on their superiority on farmers' fields under harsh climatic conditions expected to get worse under climate change. Arslan et al. (2015) find that the productivity increasing effects of improved seeds disappear under very hot growing season temperatures, and that of inorganic fertilizers decrease significantly under false rainfall onsets in smallholder maize systems of Zambia.

Published literature on determinants of technology adoption and productivity implications in Tanzania mostly rely on cross-sectional data from small-samples that do not control for the effects of long-term changes in rainfall and temperature patterns (Mbaga Semgalawe and Folmer, 2000; Amare et al., 2012; Kassie et al., 2013; Bullock et al., 2014; Kassie et al., 2015). The oft-mentioned potential adaptation benefits of improved agricultural practices are usually taken as given based on agronomic literature, regardless of the potentially significant differences between farmers' and experimental plots. This paper contributes to this literature by using nationally representative panel data set together with high resolution historical rainfall and temperature data in a rigorous analysis of determinants of adoption of a set of widely promoted agricultural technologies and their impacts on maize productivity. It also pays special attention to the interactions between weather shocks and agricultural practices to assess the adaptation potential of analyzed practices.

# 3 Conceptual framework and econometric specification

## 3.1 Conceptual framework

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. Rather than going into the details of the general agricultural household model and its extensions, we discuss the outline of a stylized model that underlies the subsequent empirical analysis as in Benjamin (1992).[2]

Each household maximizes a twice differentiable, quasi-concave utility function defined over consumption and leisure subject to a budget constraint, where household's own production enters in the consumption bundle. The household also faces a twice differentiable, convex production function that depends on family and hired labor, capital, weather (rainfall and temperature) and land. In adoption models, adoption indicators enter the production function as additional inputs. If output and labor markets are competitive, their prices are exogenously determined and production decisions are separable from household preferences (Singh et al., 1985). The separability property does not hold if any prices in the model are affected by production decisions, which is generally the case when markets do not exist (or are imperfect) and/or if risk and risk aversion are recognized to be significant factors Delforce (1994).

Although households in rural Tanzania are very likely to be price takers in both output and labor markets (see for instance LO-FTF, 2013; Mduma and Wobst, 2005), asymmetric information between lenders and borrowers and uncertain conditions in agriculture and financial markets lead to imperfections in the credit market (Abdulai and Huffman, 2005). Especially given our focus on weather shocks and their projected impacts on production risk under climate change, we rely on the theoretical and empirical literature on the impacts of production risk on input choice and output to conceptualize weather shocks within the basic model above (Rosenzweig and Wolpin, 1993; Jean-Paul Chavas, 1996; Fafchamps, 1999; Dercon and Christiaensen, 2011).

In the most basic model of production choices under expected utility framework, risk averse farmers would use less new inputs (i.e. do not adopt a technology at

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

the optimal level) and systematically produce less than they would if there was no risk (or a perfect insurance market). This model however did not stand the test of empirical evidence, and its extensions introduce credit constraints and downside risk aversion (i.e. fear of crop failure) to more accurately characterise smallholder technology choice behaviour (Fafchamps, 1999). A similar result can be derived by differentiating between risk-increasing and risk-decreasing inputs (under normal risk aversion), which would result in risk-averse farmers using less of the former and more of the latter (Pope and Kramer, 1979).

The expected increases in weather extremes under climate change (some of which are already observed) can be conceptualized as an increase in downside risk, which would lead to decreasing incentives to adopt risky new technologies. If some technologies are perceived as risk-decreasing, on the other hand, we can expect their adoption to increase. These concepts are directly testable using carefully constructed long-term weather variables that affect technology choices. The second stage of the problem, production itself, is indirectly affected by these long-term variables through adoption and input use, while it is directly affected by the within-season distribution of rainfall and temperature. Whether an input is risk increasing or decreasing can also be tested by introducing input/technology and shock interactions in the production stage, to answer critical questions on adaptation benefits of certain technologies. Other reasons why separability may break down can also be tested by including explanatory variables that determine consumption decisions (e.g., household size, head's education, wealth etc.) as in Benjamin (1992).

## 3.2 Econometric specification

Given this conceptual framework and that a farmer's adoption decision would take the complementarities and/or substitutabilities between different practices into account (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:

$$g^*_{it,j} \quad = \quad \psi_{i,j} + \boldsymbol{z}_{it,j}\boldsymbol{\gamma}_j + \varepsilon_{it,j} \tag{1}$$

where

$$g_{it,j} = f(g^*_{it,j}) = \begin{cases} 1 & \text{if} \quad g^*_{it,j} > 0 \\ 0 & \text{if} \quad g^*_{it,j} \leq 0 \end{cases} . \tag{2}$$

and

$$\boldsymbol{\varepsilon}|\psi_{i,j}, \boldsymbol{z}_{it} \quad \sim \quad \text{i.i.d.}\mathcal{N}(\mathbf{0}, \Sigma). \tag{3}$$

Equation (1) defines the latent variable $g^*_{it,j}$ that captures the expected benefits from the adoption of the $j$th practice (with $j = 1, \ldots, 5$) for farmer $i$ at time $t$, $i = 1, \ldots, 977$ and $t = 1, 2$; $\boldsymbol{z}_{it,j}$ represents a vector of exogenous variables which are hypothesized to affect the adoption decision (see section 4.2), $\psi_{i,j}$ 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 Gaussian distribution with unstructured covariance matrix. This assumption explicitly allows for complementarities and/or substitutabilities among different practices. We estimate this model using a correlated random-effects approach a la Mundlak (1978) through maximum simulated likelihood.[3] The correlated random-effects (CRE) approach relaxes the assumption of zero correlation between random-effects and covariates introducing the assumption that, for each of the $J$ equations, $\psi_i = \pi \bar{\boldsymbol{z}}_i + \nu_i$, where $\bar{\boldsymbol{z}}_i$, the time average of $\boldsymbol{z}_{it}$, picks up any correlation between $\boldsymbol{z}_{it}$ and $\psi_i$. In this way we are modelling the adoption decisions by controlling for both the interdependencies between different practices and time-invariant unobserved heterogeneity. As far as we know, this is a novel contribution to the empirical literature which addresses only one of these challenges, if any, due to data limitations.

In a separate regression analysis, we investigate the impact of adoption on productivity using the following linear unobserved-effects panel data model

$$y_{it} \quad = \quad \alpha_i + \boldsymbol{g}_{it}\boldsymbol{\delta} + \boldsymbol{x}_{it}\boldsymbol{\beta} + \varepsilon_{it}, \tag{4}$$

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 4.2, $\boldsymbol{g}_{it}$ is the aforementioned $J-$vector of observed binary variables indicating the adoption of practices, $\alpha_i$ and $\varepsilon_{it}$ are the household-specific unobserved time-invariant heterogeneity and the idiosyncratic error term, respectively.

As Mundlak (2001) points out, input variables are likely to be correlated with unobserved time-invariant farmer characteristics and this makes them endogenous.

[3] We used the Roodman (2011)'s `cmp` Stata command for practical implementation. As usual, the Mundlak approach has been implemented including in each equation of the system the time averages of the time-varying covariates as additional explanatory variables. The leading competitor to our approach is the fixed-effects one which treat the time invariant unobserved heterogeneity as parameters to be estimated. As is well known, existing estimators for the fixed-effects multivariate probit model are inconsistent due to the incidental parameters problem. On the other hand, fixed-effects logit modelling is feasible but not currently developed in a multivariate framework.

Fixed-effects estimation allows to overcome this issue ruling out the main cause of endogeneity and is our benchmark for model (4).[4] However, recent literature points out that fixed-effects estimation might still produce biased estimates for the adoption variables' coefficients (Ricker-Gilbert et al., 2011; Mathenge et al., 2014; Bezu et al., 2014; Manda et al., 2016). 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 this phase has run its course, 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 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 test for the potential endogeneity of the agricultural practices adoption, we use a fixed-effects instrumental variable approach by applying the fixed-effects two-stage least squares estimator.[5] Our instrumenting strategy exploits the key role played by "social learning" in the adoption of agricultural practices (see, among the others, Foster and Rosenzweig, 1995, on this point). To capture the "learning from others" notion, we use the average adoption rate of each practice at ward level.[6] Furthermore, following Ricker-Gilbert et al. (2011), we consider as a second instrument a measure of socio-political capital that could influence the probability of adoption, i.e. the number of years that the household's head has lived in the village. This second instrument increases the relevance of our instrumenting strategy, allowing at the same time to test for the required orthogonality conditions through the Hansen J test statistic.

We also specify two extensions to the productivity model in equation (4). We first estimate a model where we introduce all possible combinations of practices in $\boldsymbol{g}_{it}$ to understand the effect of bundles of practices with potential complementarities on

[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.

[5]We used the Baum et al. (2007)'s `ivreg2` Stata command for practical implementation. As pointed out by Angrist (2001), two-stage least squares is consistent even in presence of binary endogenous variables. Moreover, at the cost of less efficiency, it is free from any distributional assumption.

[6]We also tried using averages at EA and district level. Results remain unchanged and are available from the corresponding author upon request.

yields. A technology can be said to have adaptation benefits if it can be shown that it ameliorates the negative effects of shocks on production (e.g. legume-intercropping in Arslan et al., 2015). We investigate this using another extension to equation (4), where we introduce interaction terms of practices and their combinations with cropping season rainfall and temperature shock indicators. This specification is intended to provide evidence on potential impacts of these practices/packages in ameliorating the negative impacts of weather shocks. It also provides an opportunity to identify potential synergies and tradeoffs between short-term yield benefits and longer term resilience benefits from these practices.

# 4 Data sources and variables

## 4.1 Data

The Tanzania National Panel Survey (TZNPS), implemented by the Tanzania National Bureau of Statistics, is nationally representative and collects information on socio-economic characteristics, production activities in agricultural, livestock and fisheries sectors, non-farm income generating activities and consumption expenditures.[7] For our empirical analysis, we use the first two waves of this survey, the first conducted over twelve months from October 2008 to September 2009 and the second over the same period of 2010-11. In particular, since our econometric strategy is based on fixed-effects estimation (see Section 3.2 for details), we focus on the balanced panel of 977 households which have cultivated and harvested maize during the main cropping season. For more details on the TZNPS as well as for a comprehensive descriptive analysis, we refer the interested reader to (Arslan et al., 2016). This sample, which covers 221 EAs and 9 AEZ, has then been merged with historical rainfall and temperature data at 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. Temperature data are decadal surface temperature measurements for the period of 1989-2012 obtained from the European

[7]TZNPS is part of the World Bank's Living Standards Measurement Study-Integrated Surveys on Agriculture, that collect nationally representative household panel data on a wide range of topics with a strong focus on agriculture and rural development in eight partner countries in SSA. For more information visit `http://go.worldbank.org/BCLXW38HY0`.

Centre for Medium-Range Weather Forecasts (ECMWF).[8]

Using the extracted EA level data, we construct variables to define exposure to risk including indicators of climatological variability (characterized by spatial variation only) as well as short-run indicators of weather conditions (characterized by spatial and time variation). These variables are created for the main cropping season that goes from December to June, based on the rainfall patterns and the specific planting and harvesting calendar for the main crops in Tanzania.[9]

Long-term climatological variability is represented by the Coefficient of Variation (CoV) between years of season total rainfall and the long-term average total rainfall shortfall defined as the between-years average of the difference between total seasonal rainfall and its long run average, both computed for the 1983-2012 period at EA level. Both of these variables use data for the longest time period available, as the climatic variability can be better measured over the long run. Being proxies of the climate uncertainty that shapes household expectations, we expect these indicators to be key determinants of adoption decisions. As for short-run weather conditions, we consider the total seasonal rainfall, an indicator variable if the within-season rainfall CoV exceeded its long run average (the average computed on the previous 25 years) and an indicator variable for cases where the seasonal maximum temperature exceeded 28 degrees Celsius, which is shown to affect maize productivity negatively. We expect these indicators to be key determinants of maize productivity, but not adoption, given that adoption decisions are taken prior to the seasonal weather observations.

Finally, we use the information available in the FAO crop calendar to construct an indicator of the main Agro-Ecological Zones (AEZ).[10]

## 4.2 Variables and descriptive analysis

The dependent variables for the adoption models in this study are defined as indicator variables if the households have treated at least one plot with the practices analyzed here, i.e. maize-legume intercropping, SWC practices, the use of organic fertilizers, inorganic fertilizers or high yielding maize varieties (irrespective of the area covered). Summary statistics in Table 1 indicate that maize-legume intercropping is the most prevalent practice in our sample practiced by about 33 percent of

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

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

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

households in both waves. Intercropping adoption is lowest around the coastal regions and increases towards the Western Highlands, where more than 60 percent of households have used this practice in both years. About 17 percent of farmers used organic fertilizer, with an average quantity of about 660 and 497 kg/ha in wave 1 and 2, respectively. The Ufipa Plateau has the highest rates of adoption in the first wave (35.3 percent) and in the Volcanoes and Rift depressions region in the second wave (34 percent). Organic fertilizer adoption is lowest in the southern Inland Sediments zone. SWC structures were adopted by about 20 percent and 13 percent of households in wave 1 and 2, respectively.[11] This figure is highest in the Volcanoes and Rift depressions region in both waves (35.5 percent in wave 1 and 23.4 percent in wave 2) and lowest in the Coastal Plains and Eastern Plateaus and Mountains. Inorganic fertilizer adoption was around 18-23 percent, which is relatively low given the farm input subsidy program implementation during the study period. Looking across the different AEZ, adoption is highest in High Plains and Plateaus in the south-west (56.6 percent in wave 2) followed by the Ufipa Plateau, and lowest in Coastal Plains and Eastern Plateaus and Mountains. The share of adopters of improved maize varieties is above 30 percent in the Volcanoes and Rift depressions region and almost null in the Western Highlands.

Table 2 shows descriptive statistics on the use of multiple practices at the same time.[12] Overall, the extent of multiple adoption is relatively small. Of the 977 households who have cultivated at least one maize plot in 2009 (2011), about 62 percent (60 percent) have benefited from one or more practices, while all considered practices were jointly adopted in only 0.3 percent in both years. Maize-legume intercropping is the most commonly used practice by the households in our sample. It is applied on at least one plot as a single technology by the 12.5 percent (16 percent) of the farmers, in combination with SWC measures by 5.3 percent (1.1 percent) of the households and in combination with inorganic fertilizer on 3.4 percent (5.5 percent) of the cases in 2009 (2011). Improved seed alone is adopted by 4.7 percent (4.3 percent) of the farmers, in combination with SWC measures by 1.5 percent (0.4 percent) in 2009 (2011). Around 5 percent used only organic fertilizer in both waves, while inorganic fertilizer alone is adopted only in 4.4 percent (5.9 percent) of the cases in 2009 (2011).

Summary statistics of the maize yield per hectare and the selected explanatory variables by survey wave are presented in Table 3. As for the average maize yield per hectare, it increases by about 6.5 percent between the two waves showing at the same

[11] 63 percent of the SWC adopters have used terraces or erosion control bunds.

[12] 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.

time an almost constant and very high heterogeneity among the considered households. In terms of explanatory variables, 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. These variables control for the effects of access to human capital as well as labor availability on adoption and production decisions. 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 to control for the expected effects of wealth on easing the credit constraints or on risk preferences (Fafchamps, 1999).[13] 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.

Access to extension information is one of the important determinants of technology adoption, and we observe that the proportion of farmers who have benefitted from extension advice has decreased from 15 percent to about 8 percent between the two cropping seasons. Access to price information is controlled for by an index summarizing the number and type of source (Government, radio, publication, etc.) from which the household received information about agricultural input prices. Access to markets is captured by the distance from the plot to markets, which was around 10km on average.

As for the main production inputs, we consider the total number of workers used by the farmer for weeding, planting and harvesting, the number of ox-based machinery as well as a dummy variable for the use of pesticides. 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 94 percent to 43 percent between two survey years.

The primary focus of this study is on the climatic variables reported in the EA level variables panel of Table 3 and include: CoV and average rainfall shortfall for the period 1983-2012, total rainfall of the cropping season in question, and the within-season rainfall and temperature shock variables defined above.

Figure 1 shows the geographic distribution of the long run rainfall CoV and average rainfall shortfall at district level. The long run rainfall CoV increases as one moves from south-west to north-east across Tanzania, while we observe that areas that are more likely subjected to drought (i.e., subjected to a higher shortfall)

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

are concentrated in the north-east of Tanzania. This spatial characterization of the Tanzania climatic variability is confirmed by the short-run weather indicators reported in Figure 2. In fact, the total rainfall of the considered cropping seasons (2009 and 2011) is markedly lower for north-east districts and the same is true for the ratio between the within-season rainfall CoV and its long run (1983-2012) average. Finally, it is worth noting that the centre-east (and partially some northern district) of Tanzania shows the highest seasonal average maximum temperature.

# 5 Empirical results

## 5.1 Determinants of agricultural practices adoption

Results from the estimation of the multivariate CRE model are presented in Table 4 and the associated cross-equation correlation matrix is in Table 5, which clearly shows complementarities between the decisions to adopt certain practices.[14] 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 fertilizers. 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 SWC is also significantly complementary with organic fertilizers as well as intercropping. 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.

In terms of the effects of climatic variability on adoption incentives, we find that uncertainty in the rainfall, as represented by the long run CoV of rainfall, is strongly associated with the adoption of organic and inorganic fertilizers as well as improved seeds, although the effect is heterogeneous. The higher the long run variability of rainfall, the lower the probability of organic and inorganic fertilizer adoption. This

[14] We also tested for the presence of correlated effects using the approach in Arellano (1993). The time averages of the time-varying covariates are jointly significant suggesting the presence of time-invariant unobserved heterogeneity that is correlated with the explanatory variables. Therefore, the CRE estimator has been preferred to the RE and pooled ones. Robust Hausman test results for each equation of the system are available from the corresponding author upon request. We refer the interested reader to Arslan et al. (2016).

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. On the other hand, the likelihood of adopting improved seeds is higher in areas where the historical rainfall variability is high, suggesting that farmers perceive the use of improved seeds as a strategy to mitigate the effects of unpredictable climatic conditions and water stress.[15] 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 for the effect of weather shocks, being contemporaneous to the TZNPS data collection, they do not affect ex-ante decision on adoption as expected.

Household head's education is significantly correlated with the adoption of SWC only, which is coherent with those obtained by Lapar and Pandey (1999) in the Philippine highlands and by Tenge et al. (2004) in Tanzanian west Usambara highlands. Our wealth related variables (land size and wealth indices) are significantly positively correlated with the adoption of improved technologies (inorganic fertilizers and improved seeds) as in Teklewold et al. (2013) and Kassie et al. (2013). When interpreted as proxies for risk preferences (and under the assumption of decreasing risk aversion), these findings suggest that households perceive these technologies as risk-increasing. We also find that farmers with access to credit are more likely to adopt inorganic fertilizers, consistent with the technology adoption literature (Feder et al., 1985; Feder and Umali, 1993).

Farmers that perceive their soils quality as good are less likely use inorganic fertilizers and more likely to use SWC as expected. We also find that farmers who have cultivated very steep plots are more likely to implement SWC measures and use organic fertilizer as in Teklewold et al. (2013) and Kassie et al. (2013), suggesting that farmers are using SWC to prevent soil erosion.

Access to information on prices as well as new technologies is critical in shaping farmers' technology adoption decisions (Feder et al., 1985). We find that better access to price information and government extension services significantly increase the likelihood of adoption of fertilizers (organic and inorganic) and SWC. These results highlight the importance of rural institutions in helping farmers to overcome barriers to information regarding both new technologies and prices. Finally, we find a significant increase in the probability of adoption of inorganic fertilizers between

[15] Although the TZNPS data does not identify the specific varietal 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 two waves, whereas this probability has decreased for SWC and improved seeds.

## 5.2 Impact of adoption on maize productivity

We analyze the impact of adoption on productivity in three separate models: first by using the practice indicators by themselves, then by accounting for the complementarities between practices found in the adoption analysis above, and finally by introducing interaction variables between practices and relevant weather shocks to understand whether and how yield effects change under these conditions.

Table 6 reports the estimates of the production function in equation (4) using two different estimation strategies; a fixed-effects (FE) model and a fixed-effects model with instrumental variables (IV-FE) using the instrumenting strategy described in Section 3.2. We report the IV-FE for robustness check only to rule out any remaining endogeneity concerns. The Angrist and Pischke (2009) first-stage multivariate F-statistics are by far greater than 10 and the Hansen J statistic does not allow to reject the null hypothesis of correct model specification and the orthogonality conditions. We cannot reject the exogeneity of our adoption variables and note that, indeed, the two model results are statistically equivalent. Moreover, the robust Hausman test reported in the bottom panel of Table 6 confirms the presence of time-invariant unobserved heterogeneity that is correlated with the explanatory variables (see pag. 273 of Cameron and Trivedi, 2005, for details on the test implementation). We, therefore, interpret the FE model results in what follows.

Inorganic fertilizers and SWC are the only two practices with positive and statistically significant effects on maize yields when analyzed without accounting for between-practice interactions. The average percentage yield gains from the adoption of inorganic fertilizers and SWC are, respectively, about 15 and 23 percent. The effect of improved seeds on yields is not statistically different from zero, which should be interpreted in the light of the fact that about 75 percent of the farmers have adopted improved varieties without using fertilizer as discussed in Section 4.2, thus cannot exploit the high-yield potential of the improved seeds.

In the simplest production function specification without any interactions, total seasonal rainfall is not significant, while two variables characterising seasonal weather shocks 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 higher in the cropping season compared to farmer expectations) have 16 percent lower maize yields. Similarly, farmers located in EAs where the cropping season maximum temperature has been very high (i.e. above 28 Celsius degrees) are characterized by maize yields that are approximately 29 percent

lower than those in other EAs. Both of these variables are related with the types of shocks that are expected to get worse with climate change, and their significant negative impact underlines the need to address their impact on livelihoods that depend on maize production through targeted interventions.

Given the significant complementarities between different practices we report above, we also run the production function with all possible interactions between the practices. Table 7 reports the results of this analysis. Panel A of Table 7 reports only statistically significant coefficients from the full set of agricultural practice interactions. The full set is reported in Table 3. SWC emerges as the practice that is significant in almost all combinations with other practices, and the yield effect increases as more practices (e.g. intercropping, inorganic fertilizers and improved seeds) are added to the combination. Whereas intercropping by itself did not have a significant yield impact, it becomes significant when combined with other practices. In spite of the decreasing number of observations as more practices are combined, these results provide robust evidence that promotion efforts to increase productivity are much more likely to be successful when interdependencies are taken into account.

The negative effects of weather shock variables (higher than long-run average within-season rainfall variation and too high maximum temperatures) found in the basic model remain significant even after controlling for the practice interactions. In order to understand whether and how the effect of these practices (and their combinations) on productivity changes under weather shocks, we close our empirical analysis by analyzing the heterogenous yield impact of all practice interactions. This is done by introducing interaction variables between practice indicators and weather shock variables as in Arslan et al. (2015). Given the large number of interactions that result from this exercise, Table 8 reports only the significant coefficients with and without shocks.

The positive and significant yield impact of SWC under average weather shock conditions, becomes even more significant if the season maximum temperature exceeds 28 degrees, indicating that this practice has the potential to improve the stability of maize yields under temperature shocks providing synergies between productivity and resilience. The positive average effect of SWC combined with intercropping found above persists only under conditions when neither of the two seasonal shocks are experienced. When organic fertilizer is also added to this combination, the yield effect becomes significantly positive under high temperature shocks. While the positive yield effect of intercropping is not resilient to temperature shocks when combined with organic fertilizers, it becomes resilient when combined with inorganic fertilizers. The only combination that provides a yield effect that is resilient to our rainfall shock includes SWC, intercropping, inorganic fertilizers and improved seeds (note

that this combination had the highest coefficient under average weather conditions as reported in Table 7). The use of fertilizers without any other practice analyzed here has significant positive yield benefits only under average weather conditions as found above, and this effect is still observed in Table 8, though it disappears under a temperature shock.

While the results in Table 8 are informative, the excluded insignificant results also illustrate pertinent results. It is important to note that the use of inorganic fertilizers without any other practice analyzed here does not have a positive yield effect in any of the specifications. The lack of a significant effect of improved seeds by themselves also stands out, though as noted above this may be attributed to the fact that 75 percent of improved seed adopters do not use fertilizers (see the descriptive analysis in Arslan et al., 2016, on this point). Looking at the combination of these two modern practices, however, also does not provide significant yield effect unless they are combined with SWC and intercropping or organic fertilizers. Similar results have been reported on the decreasing/disappearing yield benefits of fertilizers and improved seeds under various shocks in Zambia (Arslan et al., 2015).

This analysis provides many insights into the types of interventions that can be used to improve productivity and make it more resilient to shocks. Especially given the robust specifications and significant yield differences under different shock conditions, they highlight an important point for effective policy design. A thorough understanding of the types of site-specific shocks that matter and how they alter the effects of agricultural practices is essential in designing more effective policies if agricultural productivity and its resilience are to be improved in spite of climate projections.

# 6 Conclusion and policy implications

This paper contributes to the agricultural technology adoption literature by using a novel data set that combines a large-scale household panel data with geo-referenced historical rainfall and temperature data in order to understand the determinants of the adoption of a set of agricultural 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 (both short-term and long-term risk) as well as analyzing heterogenous productivity effects under various shocks. The specific practices analyzed are: maize-legume intercropping, soil and water conservation practices, organic fertilizer, inorganic fertilizer and high yielding maize varieties.

Our analysis of adoption is based on the estimation of a fixed-effects model of

farmers' adoption of five practices simultaneously through a multivariate probit specification to capture the complementarities and/or substitutabilities among different practices. Our analysis on the impact of adoption on maize productivity explicitly accounts for complementarities between different practices as well as heterogeneity of yield impacts under two prominent seasonal weather shocks. This paper is unique in simultaneously addressing multiple empirical and conceptual challenges faced by 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 of complementarities between the adoption decisions for different practices. In particular, we find that improved seeds are complementary to inorganic fertilizers, inorganic fertilizers are complementary with the use of organic fertilizers, and SWC is complementary with maize-legume intercropping and organic fertilizers. The latter combination is also found to provide significant yield benefits that are robust to temperature shocks in our yield analysis. These findings have important implications since they suggest that the promotion of agricultural practices may exploit these complementarities to enhance their effectiveness.

We find that the higher the historical variability of rainfall, the lower the household's probability of adopting organic and inorganic fertilizer. 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 and price information significantly increases the likelihood of adoption of inorganic fertilizer, SWC and improved seeds, highlighting the key role of rural institutions in helping farmers to overcome barriers to information and adapt to climate change.

Our analysis of the determinants of maize productivity shows that SWC is the only practice with significant effects on maize yields under most specifications. These positive effects are observed when SWC is used by itself, in combination with other practices, as well as under various weather shocks indicating that it has both food security and adaptation benefits. Inorganic fertilizers have positive yield effects, though these are mostly observed when they are combined with other practices. The effect of improved seeds is not statistically significant, which is likely due to the fact that the majority of farmers that use them do not use inorganic fertilizers required to reap the benefits from improved seeds.

Seasonal deviations of rainfall and temperature strongly affect maize productivity in all specifications. Maize yields of farmers located in EAs where the cropping season's rainfall has been highly variable are 16 percent lower. Similarly, farmers

located in EAs where the cropping season's maximum temperature has been unexpectedly high have about 29 percent lower maize 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 effects of climatic conditions.

In order to provide more insights into the last point, we also analyze maize yield impacts under these shocks to assess the potential of the practices analyzed here in buffering the effects of shocks. SWC emerges as the main component of any combination of practices that provide yield benefits that are resilient to the rainfall and temperature shocks we analyze. Consistent with the nascent literature on this type of analysis, we find that the benefits of modern inputs are better reaped in combination with other more sustainable practices, and tend to be not resilient to shocks.

A couple of salient policy implications emerge from our analyses: Two important climatic shocks that are expected to become more frequent under climate change, i.e. variable rainfall and increased temperatures during the growing season, have significant negative impacts on maize yields and they alter the impacts of practices in significant ways. 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. Finally, most farmers are not benefiting from the synergies that exist between some of these agricultural practices documented here. 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.

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Figure 1: Long run rainfall variability

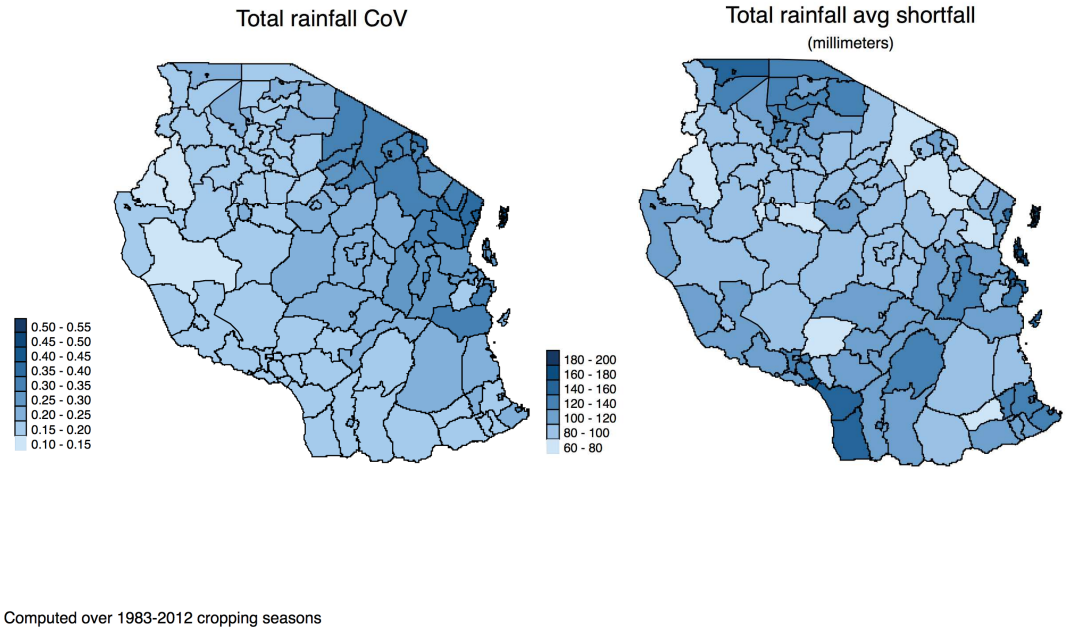


Figure 2: Seasonal weather variables

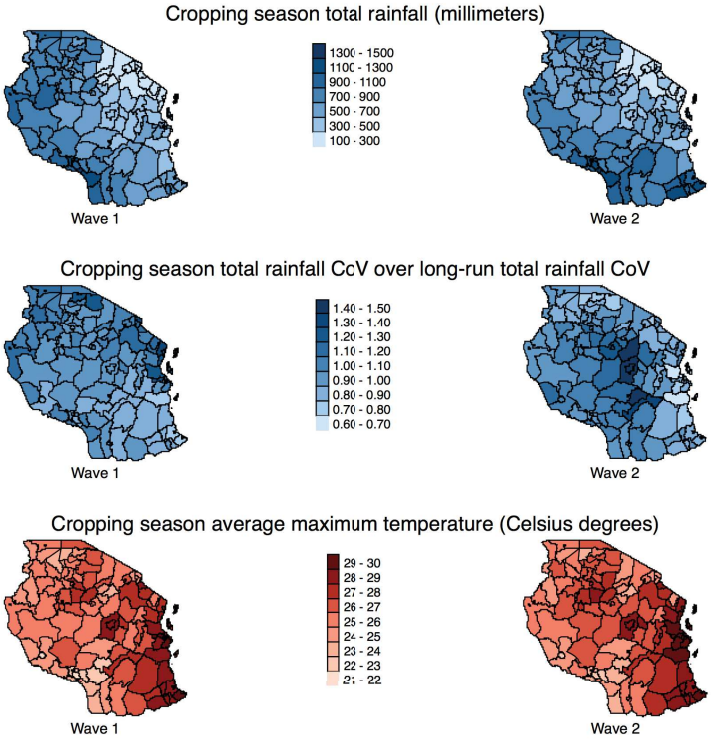


Table 1: Agricultural practices adoption by AEZ (proportions)*

(a) Wave 1 (n=977)

| | I | II | III | IV | V | VI | VII | VIII | IX | All sample |
|---|---|---|---|---|---|---|---|---|---|---|
| M-L intercrop (1=yes) | 0.389 | 0.263 | 0.175 | 0.368 | 0.326 | 0.586 | 0.309 | 0.305 | 0.688 | 0.325 |
| | (0.489) | (0.442) | (0.381) | (0.484) | (0.470) | (0.501) | (0.465) | (0.462) | (0.471) | (0.469) |
| Organic fert (1=yes) | 0.153 | 0.101 | 0.136 | 0.250 | 0.059 | 0.069 | 0.353 | 0.305 | 0.031 | 0.170 |
| | (0.361) | (0.303) | (0.344) | (0.435) | (0.236) | (0.258) | (0.481) | (0.462) | (0.177) | (0.376) |
| Inorganic fert (1=yes) | 0.198 | 0.111 | 0.006 | 0.419 | 0.230 | 0.103 | 0.235 | 0.142 | 0.219 | 0.188 |
| | (0.400) | (0.316) | (0.081) | (0.495) | (0.422) | (0.310) | (0.427) | (0.350) | (0.420) | (0.391) |
| SWC (1=yes) | 0.336 | 0.051 | 0.104 | 0.235 | 0.123 | 0.310 | 0.162 | 0.355 | 0.188 | 0.201 |
| | (0.474) | (0.220) | (0.306) | (0.426) | (0.329) | (0.471) | (0.371) | (0.480) | (0.397) | (0.401) |
| Iseeds (1=yes) | 0.252 | 0.162 | 0.117 | 0.154 | 0.091 | 0.172 | 0.147 | 0.369 | 0.031 | 0.177 |
| | (0.436) | (0.370) | (0.322) | (0.363) | (0.288) | (0.384) | (0.357) | (0.484) | (0.177) | (0.382) |

(b) Wave 2 (n=977)

| | I | II | III | IV | V | VI | VII | VIII | IX | All sample |
|---|---|---|---|---|---|---|---|---|---|---|
| M-L intercrop (1=yes) | 0.275 | 0.222 | 0.175 | 0.390 | 0.374 | 0.483 | 0.426 | 0.291 | 0.781 | 0.324 |
| | (0.448) | (0.418) | (0.381) | (0.489) | (0.485) | (0.509) | (0.498) | (0.456) | (0.420) | (0.468) |
| Organic fert (1=yes) | 0.153 | 0.071 | 0.110 | 0.294 | 0.053 | 0.103 | 0.250 | 0.340 | 0.031 | 0.167 |
| | (0.361) | (0.258) | (0.314) | (0.457) | (0.226) | (0.310) | (0.436) | (0.476) | (0.177) | (0.373) |
| Inorganic fert (1=yes) | 0.244 | 0.111 | 0.019 | 0.566 | 0.278 | 0.138 | 0.294 | 0.121 | 0.281 | 0.230 |
| | (0.431) | (0.316) | (0.139) | (0.497) | (0.449) | (0.351) | (0.459) | (0.327) | (0.457) | (0.421) |
| SWC (1=yes) | 0.107 | 0.061 | 0.104 | 0.154 | 0.107 | 0.138 | 0.147 | 0.234 | 0.156 | 0.132 |
| | (0.310) | (0.240) | (0.306) | (0.363) | (0.310) | (0.351) | (0.357) | (0.425) | (0.369) | (0.339) |
| Iseeds (1=yes) | 0.145 | 0.081 | 0.071 | 0.154 | 0.091 | 0.103 | 0.235 | 0.305 | 0.000 | 0.141 |
| | (0.353) | (0.274) | (0.258) | (0.363) | (0.288) | (0.310) | (0.427) | (0.462) | (0.000) | (0.348) |

* Standard deviations in parenthesis

Table 2: Combined adoption of practices by wave

| | Wave1 (n=977) | Wave2 (n=977) |
|---|---|---|
| Maize-Legume intercropping | 0.325 (0.469) | 0.324 (0.468) |
| Organic fertilizer | 0.170 (0.376) | 0.167 (0.373) |
| Inorganic fertilizer | 0.188 (0.391) | 0.230 (0.421) |
| SWC measures | 0.201 (0.401) | 0.132 (0.339) |
| Improved seeds | 0.177 (0.382) | 0.141 (0.348) |
| M-L intercropping only | 0.125 (0.331) | 0.160 (0.366) |
| Organic fertilizer only | 0.047 (0.212) | 0.049 (0.216) |
| Inorganic fertilizer only | 0.044 (0.205) | 0.059 (0.236) |
| SWC measures only | 0.045 (0.207) | 0.040 (0.196) |
| Improved seeds only | 0.047 (0.212) | 0.043 (0.203) |
| Intercropping and Organic | 0.017 (0.131) | 0.015 (0.123) |
| Intercropping and Inorganic | 0.039 (0.193) | 0.055 (0.229) |
| Intercropping and SWC | 0.053 (0.225) | 0.011 (0.106) |
| Intercropping and Iseeds | 0.023 (0.148) | 0.015 (0.123) |
| Organic and Inorganic | 0.015 (0.123) | 0.019 (0.138) |
| Organic and SWC | 0.017 (0.131) | 0.016 (0.127) |
| Organic and Iseeds | 0.011 (0.106) | 0.014 (0.119) |
| Inorganic and SWC | 0.007 (0.084) | 0.011 (0.106) |
| Inorganic and Iseeds | 0.018 (0.135) | 0.011 (0.106) |
| SWC and Iseeds | 0.015 (0.123) | 0.004 (0.064) |
| Intercropping, Organic and Inorganic | 0.009 (0.096) | 0.013 (0.115) |
| Intercropping, Organic and SWC | 0.009 (0.096) | 0.005 (0.071) |
| Intercropping, Organic and Iseeds | 0.002 (0.045) | 0.002 (0.045) |
| Intercropping, Inorganic and SWC | 0.007 (0.084) | 0.012 (0.110) |
| Intercropping, Inorganic and Iseeds | 0.008 (0.090) | 0.015 (0.123) |
| Intercropping, SWC and Iseeds | 0.005 (0.071) | 0.003 (0.055) |
| Organic, Inorganic and SWC | 0.004 (0.064) | 0.001 (0.032) |
| Organic, Inorganic and Iseeds | 0.007 (0.084) | 0.006 (0.078) |
| Organic, SWC and Iseeds | 0.006 (0.078) | 0.004 (0.064) |
| Inorganic, SWC and Iseeds | 0.006 (0.078) | 0.005 (0.071) |
| Intercropping, Organic, Inorganic and SWC | 0.003 (0.055) | 0.005 (0.071) |
| Intercropping, Organic, Inorganic and Iseeds | 0.006 (0.078) | 0.004 (0.064) |
| Intercropping, Organic, SWC and Iseeds | 0.008 (0.090) | 0.002 (0.045) |
| Intercropping, Inorganic, SWC and Iseeds | 0.007 (0.084) | 0.002 (0.045) |
| Organic, Inorganic, SWC and Iseeds | 0.003 (0.055) | 0.006 (0.078) |
| All five | 0.003 (0.055) | 0.003 (0.055) |
| None | 0.380 (0.486) | 0.385 (0.487) |

* Standard deviation in parenthesis.

Table 3: Summary statistics of the selected variables by wave (n=977)

| | Mean | Std Dev | Mean | Std Dev |
|---|---|---|---|---|
| **Household level variables** | Wave1 | | Wave2 | |
| Maize kg/per/Ha | 1593.07 | 1961.72 | 1705.28 | 1977.61 |
| Nr. of Workers | 52.37 | 77.50 | 54.77 | 70.35 |
| Ox based machinary (per/ha) | 0.59 | 8.26 | 0.98 | 3.83 |
| Pesticides (1=yes) | 0.12 | 0.33 | 0.12 | 0.33 |
| hh's size | 5.28 | 2.72 | 5.61 | 2.99 |
| Age of hh's head | 47.16 | 15.28 | 49.26 | 15.25 |
| hh's head yrs of education | 4.72 | 3.37 | 4.70 | 3.37 |
| Dependency ratio | 1.20 | 1.00 | 1.15 | 0.92 |
| Female hh's head | 0.23 | 0.42 | 0.24 | 0.43 |
| hh's head married (1=yes) | 0.66 | 0.47 | 0.59 | 0.49 |
| Ha of land devoted to maize | 0.91 | 2.17 | 0.90 | 1.03 |
| Land tenure (1=owned) | 0.90 | 0.30 | 0.92 | 0.28 |
| Land-home distance (Km) | 2.79 | 4.52 | 3.81 | 17.45 |
| Land-mkt distance (Km) | 7.99 | 8.90 | 12.73 | 16.93 |
| Ag-wealth index | 0.01 | 1.03 | 0.02 | 0.95 |
| Wealth index | 0.10 | 1.18 | 0.00 | 0.92 |
| Credit on inputs (1=yes) | 0.02 | 0.15 | 0.02 | 0.15 |
| Crops' price info-index | -0.06 | 0.89 | 0.07 | 1.07 |
| Plot has steep slope (1=yes) | 0.05 | 0.22 | 0.05 | 0.23 |
| Irrigation use (1=yes) | 0.02 | 0.14 | 0.02 | 0.14 |
| Less area planted due to drought (1=yes) | 0.18 | 0.39 | 0.28 | 0.45 |
| Plot has good quality (1=yes) | 0.57 | 0.50 | 0.53 | 0.50 |
| Gov AG extension advices (1=yes) | 0.15 | 0.35 | 0.08 | 0.27 |
| **EA level variables** | Wave1 | | Wave2 | |
| Season total rainfall | 631.98 | 279.05 | 719.63 | 296.51 |
| Season CoV > LR Season CoV avg (1=yes) | 0.34 | 0.47 | 0.44 | 0.50 |
| Season TMAX > 28 (1=yes) | 0.18 | 0.38 | 0.28 | 0.45 |
| Total rainfall CoV (1983-2012) | 0.22 | 0.07 | 0.22 | 0.07 |
| Avg. rainfall shortfall (1983-2012) | 104.25 | 21.74 | 104.25 | 21.74 |
| CCM party community leader (1=yes) | 0.94 | 0.24 | 0.43 | 0.50 |
| Central Plateaux (plains) | 0.13 | 0.34 | 0.13 | 0.34 |
| Coastal Plains | 0.10 | 0.30 | 0.10 | 0.30 |
| Eastern Plateaux and Mountain Blocks | 0.16 | 0.36 | 0.16 | 0.36 |
| High Plains and Plateaux | 0.14 | 0.35 | 0.14 | 0.35 |
| Inland Sediments | 0.19 | 0.39 | 0.19 | 0.39 |
| Rukwa-Ruaha Rift Zone-Alluvial Flats | 0.03 | 0.17 | 0.03 | 0.17 |
| Ufipa Plateau | 0.07 | 0.25 | 0.07 | 0.25 |
| Volcanoes and Rift Depressions | 0.14 | 0.35 | 0.14 | 0.35 |
| Western Highlands | 0.03 | 0.18 | 0.03 | 0.18 |

Table 4: Results from the multivariate correlated random-effects probit model - Determinants of sustainable agricultural practices' adoption (N=1954)

| **Variables** | **Intercrop** | **Ofert** | **INOfert.** | **SWC** | **Iseed** |
|---|---|---|---|---|---|
| Total rainfall CoV (1983-2012) | -0.013 | -0.033 ** | -0.039 * | -0.004 | 0.034 *** |
| Avg. rainfall shortfall (1983-2012) | 0.001 | -0.002 | -0.001 | 0.001 | -0.001 |
| hh's size | -0.008 | -0.002 | -0.039 | 0.042 | 0.030 |
| Age of hh's head | -0.023 | -0.002 | 0.015 | 0.011 | 0.017 |
| hh's head yrs of education | 0.026 | 0.004 | 0.027 | 0.067 * | -0.019 |
| Dependency ratio | -0.050 | -0.010 | 0.003 | -0.020 | -0.129 |
| Female hh's head | -0.660 * | -0.072 | 0.431 | 0.882 | 0.122 |
| hh's head married (1=yes) | -0.178 | -0.102 | 0.039 | 0.053 | -0.237 |
| ln(land size devoted to maize) | -0.101 * | 0.024 | 0.151 *** | -0.022 | 0.125 |
| Land tenure (1=owned) | 0.036 | 0.226 | 0.034 | 0.344 | 0.401 * |
| Land-home distance (Km) | 0.007 | -0.002 | -0.001 | -0.013 | 0.001 |
| Land-mkt distance (Km) | -0.000 | 0.001 | 0.001 | 0.002 | 0.002 |
| Ag-wealth index | 0.042 | 0.086 | 0.068 | -0.119 | -0.116 |
| Wealth index | -0.055 | 0.018 | 0.227 *** | 0.125 | -0.052 |
| Irrigation use (1=yes) | 0.058 | -0.537 | -0.395 | -0.361 | -0.641 |
| Less area planted due to drought (1=yes) | -0.026 | -0.088 | -0.123 | -0.078 | 0.119 |
| Plot has good quality (1=yes) | -0.008 | 0.095 | -0.121 | 0.289 ** | -0.144 |
| Credit on inputs (1=yes) | -1.065 *** | 0.287 | 0.692 ** | -0.020 | 0.073 |
| Crops' price info-index | 0.069 | -0.008 | 0.080 ** | 0.095 * | 0.132 *** |
| Plot has steep slope (1=yes) | -0.213 | 0.617 *** | -0.029 | 0.379 * | -0.079 |
| Gov AG extension advices (1=yes) | -0.031 | 0.033 | 0.293 *** | 0.281 * | 0.088 |
| CCM party community leader (1=yes) | -0.036 | -0.097 | 0.109 | -0.149 | -0.182 |
| Season CoV > LR Season CoV avg (1=yes) | -0.110 | -0.067 | 0.054 | -0.028 | 0.069 |
| Season TMAX > 28 (1=yes) | -0.039 | -0.409 | 0.278 | 0.573 | 0.205 |
| Coastal Plains | 0.338 | 0.354 | 1.213 * | -0.191 | -0.468 |
| Eastern Plateaux and Mountain Blocks | -0.113 | 0.756 *** | -0.136 | -0.232 | -0.670 ** |
| High Plains and Plateaux | -0.041 | 0.699 *** | 1.027 *** | -0.298 | 0.175 |
| Inland Sediments | -0.039 | 0.010 | 0.608 * | -0.535 ** | -0.249 |
| Rukwa-Ruaha Rift Zone-Alluvial Flats | 0.241 | -0.203 | -0.333 | -0.132 | 0.098 |
| Ufipa Plateau | -0.012 | 0.905 *** | 0.452 | -0.337 | 0.368 |
| Volcanoes and Rift Depressions | -0.115 | 0.864 *** | 0.017 | 0.234 | 0.330 |
| Western Highlands | 1.097 *** | -0.214 | 0.328 | -0.091 | -1.408 *** |
| Wave2 | 0.024 | -0.024 | 0.249 ** | -0.414 *** | -0.442 *** |
| Constant | -1.092 | -2.724 *** | -2.784 ** | -2.106 *** | -2.298 *** |

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

Table 5: Correlation matrix

| | Intercrop | Ofert | INOfert | SWC | Iseeds |
|---|---|---|---|---|---|
| Intercrop | 1 | -0.027 | 0.309 *** | 0.152 *** | 0.094 |
| Ofert | | 1 | 0.205 ** | 0.225 *** | 0.065 |
| INOfert | | | 1 | 0.052 | 0.257 *** |
| SWC | | | | 1 | 0.090 |
| Iseeds | | | | | 1 |

Table 6: Maize yield (per hectare) and sustainable agricultural practices (N=1954)

| **Variables** | **FE** | **IV-FE** |
|---|---|---|
| *Agricultural practices:* | | |
| M-L intercrop (1=yes) | 0.074 | 0.091 |
| Organic fert (1=yes) | -0.002 | 0.114 |
| Inorganic fert (1=yes) | 0.148* | 0.320 |
| SWC (1=yes) | 0.227*** | 0.414*** |
| Iseeds (1=yes) | 0.001 | 0.021 |
| *Weather shocks:* | | |
| ln(Season total rainfall) | 0.114 | 0.108 |
| Season CoV > LR Season CoV avg (1=yes) | -0.157*** | -0.159*** |
| SeasonTMAX > 28 (1=yes) | -0.286* | -0.298** |
| *Other controls:* | | |
| log(Nr. of Workers) | 0.501*** | 0.493*** |
| log(Ox based machinary) | 0.075 | 0.096 |
| log(Nr. of Workers)$^2$ | 0.000 | 0.001 |
| log(Ox mach.)$^2$ | 0.013 | 0.004 |
| log(Nr. of Workers)×(Ox mach.) | -0.011 | -0.009 |
| Pesticides (1=yes) | 0.117 | 0.106 |
| hh's size | -0.037 | -0.037 |
| Age of hh's head | 0.010 | 0.009 |
| hh's head yrs of education | 0.003 | -0.001 |
| Dependency ratio | 0.031 | 0.032 |
| Female hh's head | 0.189 | 0.143 |
| hh's head married (1=yes) | 0.046 | 0.044 |
| ln(land size devoted to maize) | -0.070 | -0.077* |
| Land tenure (1=owned) | -0.094 | -0.109 |
| Land-home distance (Km) | 0.004*** | 0.004*** |
| Land-mkt distance (Km) | 0.000 | 0.000 |
| Ag-wealth index | 0.082** | 0.080* |
| Wealth index | 0.102* | 0.089 |
| Credit on inputs (1=yes) | -0.017 | -0.052 |
| Crops' price info-index | 0.036 | 0.027 |
| Plot has steep slope (1=yes) | -0.023 | -0.056 |
| Gov AG extension advices (1=yes) | -0.026 | -0.051 |
| CCM party community leader (1=yes) | -0.010 | -0.003 |
| Wave2 (1=yes) | 0.073 | 0.087 |
| *Diagnostics:* | | |
| Hansen J ($\chi^2_1$) | | 0.493 |
| Hansen J (p-value) | | 0.483 |
| Endogeneity test ($\chi^2_5$) | | 3.022 |
| Endogeneity test (p-value) | | 0.697 |
| Robust Hausman test ($\chi^2_{32}$) | 200.487 | |
| Robust Hausman test (p-value) | 0.000 | |
| $R^2$ (within) | 0.315 | 0.306 |
| Fraction of variance due to fixed-effects | 0.569 | 0.560 |

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

Table 7: Maize yield (per hectare) and sustainable agricultural practices complementarities (N=1954)

| **Variables** | **FE** |
|---|---|
| *Panel A* | |
| SWC | 0.254* |
| Intercropping, Organic | 0.295* |
| Intercropping, SWC | 0.328** |
| Organic, Inorganic | 0.377** |
| Intercropping, Inorganic, SWC | 0.410** |
| Intercropping, Inorganic, SWC, Iseeds | 0.858*** |
| Intercropping, Organic, Inorganic, SWC, Iseeds | 0.637*** |
| *Panel B* | |
| log(Nr. of Workers) | 0.497*** |
| log(Ox based machinary) | 0.062 |
| log(Nr. of Workers)$^2$ | 0.001 |
| log(Ox mach.)$^2$ | 0.018 |
| log(Nr. of Workers)×(Ox mach.) | -0.012 |
| Pesticides (1=yes) | 0.127 |
| hh's size | -0.038 |
| Age of hh's head | 0.009 |
| hh's head yrs of education | 0.003 |
| Dependency ratio | 0.029 |
| Female hh's head | 0.196 |
| hh's head married (1=yes) | 0.041 |
| ln(land size devoted to maize) | -0.070 |
| Land tenure (1=owned) | -0.090 |
| Land-home distance (Km) | 0.003*** |
| Land-mkt distance (Km) | 0.001 |
| Ag-wealth index | 0.077* |
| Wealth index | 0.105* |
| ln(Season total rainfall) | 0.124 |
| Season CoV > LR Season CoV avg (1=yes) | -0.160*** |
| Season TMAX > 28 (1=yes) | -0.292* |
| Credit on inputs (1=yes) | 0.075 |
| Crops' price info-index | 0.036 |
| Plot has steep slope (1=yes) | -0.030 |
| Gov AG extension advices (1=yes) | -0.037 |
| CCM party community leader (1=yes) | -0.005 |
| Wave2 | 0.074 |

*Note*: *** 1%, ** 5%, * 10%. Clustered standard errors at EA level.
Panel A reports only statistically significant coefficients from the full set of agricultural practice interactions. The full set is reported in Table 3.

Table 8: Heterogeneity of agricultural practices impact on per hectare maize yield by weather shocks (N=1954)

| **Variables** | **TMAX > 28** | **SCoV>LRCoV** |
|---|---|---|
| SWC | | |
| Without shock | 0.067 | 0.164 |
| With shock | 0.590** | 0.154 |
| Intercropping, Organic | | |
| Without shock | 0.299* | 0.199 |
| With shock | -0.153 | 0.176 |
| Intercropping, Inorganic | | |
| Without shock | -0.133 | -0.062 |
| With shock | 0.627* | -0.055 |
| Intercropping, SWC | | |
| Without shock | 0.266* | 0.249* |
| With shock | 0.083 | 0.240 |
| Organic, Inorganic | | |
| Without shock | 0.308* | 0.170 |
| With shock | -0.240 | 0.218 |
| Intercropping, Organic, SWC | | |
| Without shock | -0.100 | -0.064 |
| With shock | 0.894*** | -0.052 |
| Organic, Inorganic, SWC | | |
| Without shock | 0.296 | 0.326* |
| With shock | 0.000 | 0.183 |
| Intercropping, Inorganic, SWC, Iseeds | | |
| Without shock | 0.570*** | 0.548*** |
| With shock | 0.000 | 0.489*** |
| Organic, Inorganic, SWC, Iseeds | | |
| Without shock | 0.281 | 0.443 |
| With shock | 1.294*** | 0.442 |

*Note*: *** 1%, ** 5%, * 10%. Clustered standard errors at EA level.
This table reports only statistically significant coefficients from the full set of interactions between agricultural practice and weather shocks. Full tabulations are available from the corresponding author upon request.

# A Appendix

Table 1: Results from the multivariate correlated random-effects probit model - Determinants of sustainable agricultural practices' adoption (N=2810, unbalanced panel)

| **Variables** | **Intercrop** | | **Ofert** | | **INOfert.** | | **SWC** | | **Iseed** | |
|---|---|---|---|---|---|---|---|---|---|---|
| Total rainfall CoV (1983-2012) | -0.005 | | -0.018 | | -0.028 | | -0.005 | | 0.031 | *** |
| Avg. rainfall shortfall (1983-2012) | -0.001 | | -0.001 | | -0.004 | | 0.001 | | -0.001 | |
| hh's size | -0.011 | | -0.013 | | -0.039 | | 0.031 | | 0.012 | |
| Age of hh's head | -0.026 | | -0.017 | | 0.012 | | -0.003 | | -0.001 | |
| hh's head yrs of education | 0.026 | | 0.003 | | 0.026 | | 0.068 | * | -0.020 | |
| Dependency ratio | -0.043 | | 0.003 | | 0.008 | | -0.002 | | -0.106 | |
| Female hh's head | -0.685 | * | -0.219 | | 0.396 | | 0.714 | | -0.052 | |
| hh's head married (1=yes) | -0.176 | | -0.086 | | 0.055 | | 0.058 | | -0.205 | |
| ln(land size devoted to maize) | -0.098 | * | 0.020 | | 0.163 | *** | -0.026 | | 0.114 | |
| Land tenure (1=owned) | 0.033 | | 0.161 | | 0.031 | | 0.351 | | 0.356 | * |
| Land-home distance (Km) | 0.003 | | -0.002 | | -0.001 | | -0.012 | | 0.001 | |
| Land-mkt distance (Km) | -0.000 | | -0.000 | | 0.001 | | 0.001 | | 0.001 | |
| Ag-wealth index | 0.037 | | 0.085 | | 0.064 | | -0.115 | | -0.119 | |
| Wealth index | -0.054 | | 0.027 | | 0.225 | *** | 0.120 | | -0.032 | |
| Irrigation use (1=yes) | 0.048 | | -0.549 | | -0.398 | | -0.357 | | -0.578 | |
| Less area planted due to drought (1=yes) | -0.025 | | -0.100 | | -0.111 | | -0.084 | | 0.083 | |
| Plot has good quality (1=yes) | -0.008 | | 0.097 | | -0.132 | | 0.279 | ** | -0.125 | |
| Credit on inputs (1=yes) | -1.029 | *** | 0.280 | | 0.683 | ** | -0.003 | | 0.117 | |
| Crops' price info-index | 0.069 | | -0.003 | | 0.081 | ** | 0.092 | | 0.125 | *** |
| Plot has steep slope (1=yes) | -0.205 | | 0.573 | *** | -0.028 | | 0.399 | * | -0.061 | |
| Gov AG extension advices (1=yes) | -0.026 | | 0.049 | | 0.300 | *** | 0.278 | * | 0.114 | |
| CCM party community leader (1=yes) | -0.018 | | 0.012 | | 0.130 | | -0.056 | | -0.046 | |
| Season CoV > LR Season CoV avg (1=yes) | -0.107 | | -0.068 | | 0.048 | | -0.027 | | 0.076 | |
| Season TMAX > 28 (1=yes) | -0.056 | | -0.423 | | 0.121 | | 0.519 | | 0.125 | |
| Coastal Plains | 0.336 | | 0.177 | | 0.567 | | -0.432 | * | -0.511 | ** |
| Eastern Plateaux and Mountain Blocks | -0.076 | | 0.520 | ** | -0.401 | | -0.216 | | -0.602 | *** |
| High Plains and Plateaux | 0.000 | | 0.536 | *** | 1.148 | *** | -0.250 | | 0.113 | |
| Inland Sediments | -0.007 | | -0.164 | | 0.759 | ** | -0.390 | ** | -0.261 | * |
| Rukwa-Ruaha Rift Zone-Alluvial Flats | 0.191 | | -0.145 | | 0.068 | | 0.043 | | 0.077 | |
| Ufipa Plateau | -0.013 | | 0.734 | *** | 0.635 | * | -0.137 | | 0.294 | |
| Volcanoes and Rift Depressions | -0.006 | | 0.707 | *** | -0.016 | | 0.394 | ** | 0.371 | *** |
| Western Highlands | 0.756 | *** | 0.052 | | 0.269 | | -0.117 | | -0.699 | *** |
| Wave2 | 0.053 | | 0.138 | | 0.280 | *** | -0.271 | *** | -0.215 | ** |
| Constant | -0.726 | | -2.289 | *** | -2.619 | *** | -1.331 | ** | -2.161 | *** |

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

Table 2: Correlation matrix

| | Intercrop | Ofert | INOfert | | SWC | | Iseeds | |
|---|---|---|---|---|---|---|---|---|
| Intercrop | 1 | 0.026 | 0.270 | *** | 0.104 | ** | 0.071 | |
| Ofert | | 1 | 0.195 | ** | 0.195 | *** | 0.088 | * |
| INOfert | | | 1 | | 0.093 | | 0.254 | *** |
| SWC | | | | | 1 | | 0.102 | * |
| Iseeds | | | | | | | 1 | |

Table 3: Maize yield and sustainable agricultural practices complementarities (N=1954) - full estimation set

| **Variables** | **FE** |
|---|---|
| Intercropping | 0.071 |
| Organic | -0.013 |
| Inorganic | 0.172 |
| SWC | 0.254* |
| Iseeds | 0.036 |
| Intercropping, Organic | 0.295* |
| Intercropping, Inorganic | 0.139 |
| Intercropping, SWC | 0.328** |
| Intercropping, Iseeds | 0.040 |
| Organic, Inorganic | 0.377** |
| Organic, SWC | 0.061 |
| Organic, Iseeds | 0.070 |
| Inorganic, SWC | 0.242 |
| Inorganic, Iseeds | -0.103 |
| SWC, Iseeds | 0.252 |
| Intercropping, Organic, Inorganic | 0.124 |
| Intercropping, Organic, SWC | 0.120 |
| Intercropping, Organic, Iseeds | -0.611 |
| Intercropping, Inorganic, SWC | 0.410** |
| Intercropping, Inorganic, Iseeds | 0.398 |
| Intercropping, SWC, Iseeds | 0.324 |
| Organic, Inorganic, SWC | 0.429 |
| Organic, Inorganic, Iseeds | -0.249 |
| Organic, SWC, Iseeds | 0.219 |
| Inorganic, SWC, Iseeds | 0.099 |
| Intercropping, Organic, Inorganic, SWC | 0.329 |
| Intercropping, Organic, Inorganic, Iseeds | -0.009 |
| Intercropping, Organic, SWC, Iseeds | 0.559 |
| Intercropping, Inorganic, SWC, Iseeds | 0.858*** |
| Organic, Inorganic, SWC, Iseeds | 0.669 |
| Intercropping, Organic, Inorganic, SWC, Iseeds | 0.637*** |

*Note*: *** 1%, ** 5%, * 10%. Clustered standard errors at EA level.
This table reports the full set of interaction estimates not reported in Table 7.

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