IMPACT OF LAND CONSERVATION TECHNOLOGIES ON AGRICULTURAL PRODUCTIVITY IN TANZANIA

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Abstract

Land management and conservation have been considered the most important aspects of sustainable productivity in economically developing countries where land degradation is a major challenge. In Tanzania, both the government and international organizations have been promoting adoption of land management and conservation technologies (LMCTs) for a long time. This paper establishes the impact of three LMCTs – soil water conservation technologies and erosion control (SWCEC), organic and inorganic fertilizers – on maize crop yields in different rainfall zones, using national panel survey data. The study employs static panel models to analyse the two-period data sets for 2008-2009 and 2010-2011. The results indicate that adoption of LMCTs do contribute significantly to maize yield. The greatest effects of organic and SWCEC methods on crop yield were realized in low rainfall zones, while that of inorganic fertilizers was observed in high rainfall zones. These findings support previous cross-sectional data analyses, suggesting for policy makers that a blanket land management and conservation programme applied uniformly to all agro-ecological zones is not strategically beneficial. The advisability of a technology employed in a given zone should be supported by local knowledge and research findings culled from that particular area.

Key words: land management, conservation technologies, maize yield, panel data, static panel analysis

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1. Introduction

Increasing agricultural productivity[2] has been emphasised by economists and other development agents as one of the key components in successful reduction of poverty and development strategy in economically developing countries. In Tanzania, agriculture sector contributes significantly to the national economy. The Government of Tanzania recognizes that higher levels of sustained agricultural productivity and growth is a top priority for meeting national targets of poverty reduction, as indicated in national and global development policies past and present, such as the Second National Strategy for Growth and Reduction of Poverty, the First National Five Year Development Plan (2010-2016), the UN Millennium Development Goals of halving poverty and food insecurity by 2015, the post-2015 UN Sustainable Development Goals, and the recently launched Second Five Year Development Plan (2016-2021). This is because the agriculture sector contributes 75 per cent of rural household incomes and it employs 67 per cent of the country's labour force, while accounting for about 25 per cent of Tanzania's GDP (Ministry of Agriculture Food Security and Cooperatives URT 2013, National Bureau of Statistics URT 2015, Ministry of Finance and Planning URT 2016)[3]. Hence, significant reduction in overall poverty levels, particularly rural poverty, will require raising agricultural productivity.

However, agricultural productivity is undermined by land degradation, particularly through the depletion of soil organic matter, soil mining which leads to inadequate plant nutrient supply, and soil erosion (Nyangena 2008, Pender et al. 2006, Todd et al. 2013). Many empirical studies show a close association between declining crop yield and land degradation in sub-Saharan Africa (Tenge et al. 2004, Pender and Gebremedh in 2007, Kassie et al. 2010, Selejio 2016). Based on simulation studies, the yield loss by 2020 due to land degradation in the form of soil erosion is anticipated to be approximately 14.5 per cent in sub Saharan Africa and 16.5 per cent for

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[2] Here 'productivity' technically connotes the ratio of output to input in the production process (Coelli et al. 2005). Specifically, 'agricultural productivity' in this essay refers to output per unit land. If output (yield) increases while input remains constant then productivity increases.

[3]URT stands for United Republic of Tanzania

the African continent overall (Lal 1995, Sherr and Yadav 1996).In Tanzania, the reduction in crop yield of maize grain on moderately and severely eroded soils, compared with non-eroded soils, was estimated to be approximately 14 per cent and 39 per cent, respectively (Lal and Singh 1998, cited by Tenge et al. 2004). Furthermore, different surveys conducted in rural areas of the semi-arid region of mid-western Tanzania indicated that low soil fertility was the most important constraint to improved production among smallholder farmers (Kangalawe et al. 2005, Ministry of Agriculture, Food Security and Cooperatives URT 2007, Hepelwa et al. forthcoming).

In order to increase agricultural productivity and food security in Tanzania, thereby reducing poverty, a number of national and international initiatives have been promoting sustainable environmental and land management conservation technologies since before Independence in 1961 (Tenge et al. 2004, Kassie et al. 2013,Lugandu 2013). These projects aim to increase farm productivity and production, thereby raising smallholders' incomes while reducing land degradation. Despite the benefits of sustainable environmental and land management and conservation technologies (LMCTs), their rate of adoption is still low among smallholder farmers in Tanzania, as in other agrarian economies (Tenge et al. 2004, Marenya and Barret 2007, Kassie et al. 2010, Lugandu 2013). Several empirical studies have been conducted in Tanzania and other economically developing countries to find the factors responsible for the low adoption rate of LMCTs (Tenge et al. 2004,Marenya and Barret 2007, Spielman et al. 2010, Shiferaw and Okello 2011,Kassie et al. 2013).

However, there is no rigorous study in Tanzania that has gone further than this to analyse the link between the adoption of different technologies and productivity in non-experimental settings. The few existing studies in other countries have relied mostly upon cross-sectional data, for which control of the endogeneity problem, resulting in estimation bias, is impossible (Nyangena 2008, Kassie et al. 2008, Kabamba and Muimba-Kankolongo 2009, Kassie et al. 2010). The low returns and high risks of investments in land management technologies are a disincentive to poor farmers. Studies in other countries show that there is prompt depreciation of technology uptake by many rural smallholder farmers with the termination of programmes providing support subsidies for improved inputs (Shiferaw and Holden 2001, Kerr et al. 1996, Nyangena 2008, Besley and Case 1993, cited by Marenya and Barret 2007). Although most previous cross-sectional studies have shown an increase of return from adoption of LMCTs, it is important to capture this gain with greater quantitative clarity. This paper establishes the impact of adoption of LMCTs on agricultural productivity (particularly of maize yield) in different rainfall zones in Tanzania, by using national panel survey data and panel models that address the weakness of previous studies.

Maize crop is chosen for this study because of its importance to food security and because it is the major, most preferred crop currently in Tanzania (see Isinika et al. 2003, Amani 2004, and National Bureau of Statistics URT 2012). Maize occupies 70 per cent of total land under cereals. It contributes more than 31 per cent to total national food production, accounting for 71.6 per cent and 75 per cent of the country's total cereal production and consumption, respectively.[4]

The rest of the paper is organized as follows: section two presents the relevant literature review of LMCTs and their impact on productivity; section three describes the analytical framework and model specification; section four presents empirical results; and the concluding section five suggests some policy implications.

2. Evidence of the impact of land conservation on productivity

A good number of empirical studies in developing countries have examined the impact of sustainable land conservation technologies on yield using cross-sectional data. However, some of these studies have presented mixed results, or failed to draw any empirical conclusion about the relationship between land conservation investment and productivity. For example, the study of Byiringiro and Reardon (1996) on the effects of farm size, erosion, and soil conservation investments on farm productivity in Rwanda concluded that farms with greater investments in soil conservation have much higher land productivity than other farms without

[4] Maize constitutes about 30 per cent and 10 per cent of the value of crop production and total value added in the agriculture sector, respectively. Maize dominated other crops in the national panel survey data used in this study, as described in the methodology section.

such initiatives. But the results from a study done in Ghana, Kenya and Rwanda (Place and Hazell 1993) showed, in contrast, that investment in land conservation technologies did not significantly influence crop yields. Both of these studies used cross-sectional data, and the Rwanda research (1996) did not specify the type of conservation under scrutiny. Thus the differences between the conclusions drawn by these researchers might have arisen from the cross-sectional data used and variations in the type of technologies under consideration in the two studies.

Based on a survey of 434 farming households from the highlands of Ethiopia in the Amhara region, Benin (2006) found a 42 per cent increase in average crop yields in farms conserved with stone terraces in reduced form regressions for lower rainfall parts of the region. In contrast the study reported insignificant impacts of stone terraces in areas of high rainfall in the same region. These findings are in agreement with the results of a 500 household survey conducted by Pender and Gebremedh in (2007), who found average crop yield increased by 23 per cent in plots with stone terraces in the semi-arid highlands in the Tigray region of Ethiopia. This implies that the conservation technologies work differently in different agro-ecological zones.

Using cross-sectional data from more than 900 households with multiple plots, Kassie et al. (2008) investigated the impact of stone bunds on the value of crop production in low and high rainfall areas of the Ethiopian highlands. They found that plots with stone bunds are more productive than those without the structures, in areas with low rainfall rather than in areas with high rainfall. The results were consistent using three different methods: (i) modified random effects models, (ii) stochastic dominance analysis, and (iii) matching methods. However, other studies based on farm-level trials in Ethiopian highlands got different results. For example, using a cost-benefit analysis in Amhara, Ethiopia, Shiferaw and Holden (2001) found that structural technologies (graded bund and *fanya juu* terraces) have very low return on investment, providing insufficient economic incentives for poor smallholder farming households to make the necessary investments. The difference in the findings between these two studies may have resulted from the different methodologies they used, and from the endogeneity problem which leads to estimation bias of cross-sectional data. These ambiguities are addressed in this paper.

Kassie et al. (2010) examines the contribution of sustainable land management technologies to net value of crop yield in areas with low and high agricultural potential in the highlands of Ethiopia[5]. Using a combination of parametric and non-parametric estimation techniques to check the results robustness, they find that in the low agricultural potential areas both techniques consistently indicate that minimum tillage is superior to the commercial fertilizers as well as farmers' traditional practices without commercial fertilizers, in enhancing crop yield per unit area. In contrast, the use of commercial fertilizers is superior to both minimum tillage and farmers' traditional practices without commercial fertilizers, in the high agricultural potential areas. These results concur to that of Nicou and Charreau (1985) who found that tillage increases maize and rice yield by 50% and 103% respectively in West African semi-arid tropics. Similarly, Kabamba and Muimba-Kankolongo (2009), from Kapiri-Mposhi district of Zambia, found that the adoption of conservation farming increases maize yield three times more than the yield from conventional farming. Hepelwa (2013) and Hepelwa et al. (forthcoming) found the use of inorganic fertilizers also increased significantly crop yield in Tanzania. However, unlike the present study, the findings from the studies of Nicou and Charreau (1985), Kabamba and Muimba-Kankolongo (2009), Hepelwa (2013) and Hepelwa et al. (forthcoming) we reall based on cross-sectional data and some of them used descriptive statistics; further, they did not specify the geographical characteristics or the agricultural potential of the areas under study.

It is worth noting that weather-sustainable land conservation technologies increase yield; but this is influenced by many other factors like agro-ecological zone, technology itself, and the time taken by a specific technology to realise its impact on productivity. For example, Nicou and Charreau (1985) argue that the impact of tillage systems on crop yield is not the same across all crops species since various soils react differently to

[5]The study used survey cross-sectional data collected at household and plot level from Amhara and Tigray regions of highland Ethiopia. The sample size consists of 1,365 (396) and 1,113 (357) plots (households) in the Amhara and Tigray regions, respectively.

the same tillage practice. Many other studies similarly conclude that soil water conservation practices (e.g. terraces, *fanya juu*, soil bunds) have a greater measurably positive impact on yield in moisture-stressed and soil-degraded areas than they do in high rainfall and good soils (Sutcliffe 1993, Tenge et al. 2004, Nyangena 2008, Pender and Gebremedh in 2007, Kassie et al. 2008).[6] This is because in semi-arid and dry areas, moisture is important for crop growth and increasing yield. Kabubo-Mariara and Linderh of (2011) and Kassie et al. (2013) argue that most of the conservation technologies are long-term investments and have long-term effects, so that it takes time to realize their impact. Studies that use cross-sectional data and descriptive analysis for conservation systems with long-term effects, such as organic manures and soil water conservation technologies, may lead to biased and inconclusive results.

3. Methodology and analytical framework

Estimation of impact of adoption of LMCTs on productivity for cross sectional data can be done by using the Propensity Score Matching (PSM) approach. Many existing studies that analyse impact of adoption of land conservation technologies on crop yield or value have used cross-sectional data and PSM (see Nyangena 2008, Kassie et al. 2008, Kassie et al. 2010, Hepelwa 2013, Hepelwa et al. forthcoming). However, PSM estimation assumes that there is no effect of unobservable characteristics on participation in the programme. In case of the presence of unobserved characteristics, the error term contains variables that are correlated with treatment or programme intervention (in this case, LMCT adoption). Failure to measure or account for unobservable characteristics leads to unobserved selection bias (Green 2002, Wooldridge 2012, World Bank 2010). Therefore, this study extends analytical framework to panel data analysis that uses methods which take into account unobservable factors.

Difference-in-difference (DID) with matching and instrumental variables (IV) are proposed as appropriate methods for measuring impact of intervention (adoption of technology) in the absence of randomized

[6]Pender and Gebremedh in (2006) and Kassie et al. (2008) used cross-sectional data and rigorous econometrics analysis, while Tenge et al. *(*2004) used cross-sectional data and descriptive analysis.

experimentation for panel data. Both DID and IV methods relax the assumption of no effect by unobservable characteristics on treatment or programme intervention, as is assumed in the PSM approach. However, the observable characteristics are assumed to be time-invariant in DID methods, while the IV methods allow for selection bias on unobserved characteristics to vary with time when used for panel data (Wooldridge 2012, World Bank 2010).

Although some studies, for example Nyangena and Juma (2014), have used DID methods in assessing the impact of adopting agricultural technology in the absence of baseline information, both DID and IV methods work more properly in the presence of baseline information for non-participants and (subsequent) participants (Cameroon and Trivedi 2010, World Bank 2010). The baseline information or data is important in order to establish counterfactuals when estimating the use of DID (Ravallion 2008, World Bank 2010). Similarly, baseline information depicts how the target population was selected for treatment or programme intervention, which in most cases also counts as the rationale for assigning relevant and valid instruments (World Bank 2010, Cameron and Trivedi 2010). Therefore the use of DID and IV for this study would be inappropriate, given that there was no baseline information available, and the adoption of technology was not controlled or determined by any intervention in order to select the right instruments for IV methods. In this light, the use of static panel models was chosen as appropriate to establish the impact of the treatment (adoption of LMCTs) for two-period panel data where there is no baseline information (Wooldridge 2012, Cameron and Trivedi 2010).

The main concern is to use the panel model which reflects the effect that adopting LMCTs has on crop yield from 2008-2009 to 2010-2011. Household crop yield is assumed to be affected by household characteristics (socio-economic and demographic), by plot characteristics (e.g. soil properties, topography) and by environmental characteristics (e.g. weather conditions, including rainfall). Therefore, the general panel model to include both the socioeconomic and biophysical characteristics as control variables is appropriate for analysing the effect of land management and conservation technologies on crop (maize) production for two periods for merged samples selected from national panel survey (NPS) data.

Consider a method for data analysis in which the dependent variable linearly depends on a set of predictor variables. We have a set of households/plots (i=1, 2, …, n). Each of these is measured at T points in time (t = 1,2,…,T). Let Y_{it} be the dependent variable. We have a set of predictor/explanatory variables that vary over time, represented by the vector Y_{it}, and another set of predictor variables $z_i$that are invariant over time. Therefore our basic model for is represented as:

$$Y_{it} = \mu_{it} + \beta X_{it} + \gamma z_i + \alpha_i + \varepsilon_{it} \quad (1)$$

whereμ_{it} is an intercept that may be different for each point in time, and β and γ are vectors of coefficients. The two "error" terms, α_i and ε_{it} behave somewhat differently. For each individual at each point in time, there is a different ε_{it} while α_i only varies across individuals but not over time. Thus, α_i represents the combined effects on Y of all unobserved variables that are constant over time, while ε_{it} represents purely random variations at each point in time.

Since we have a two-period panel, estimation of the model (1) is done when the variables are observed at only two points in time (t =2). Thus, we form the two equations as:

$$Y_{i1} = \mu_1 + \beta X_{i1} + \gamma z_i + \alpha_i + \varepsilon_{i1} \quad (2a)$$

$$Y_{i2} = \mu_2 + \beta X_{i2} + \gamma z_i + \alpha_i + \varepsilon_{i2} \quad (2b)$$

We form the first difference equation by subtracting 2a and 2b as shown in equation 3:

$$Y_{i2} - Q_{i1} = (\mu_2 - \mu_1) + \beta(X_{i2} - X_{i1}) + (\varepsilon_{i2} - \varepsilon_{i1}) \quad (3)$$

And finally we write an estimated model 4 as:

$$Y_i^* = \mu^* + \beta X_i^* + \varepsilon_i^* \quad (4)$$

We obtain consistent estimates of β by regressing Y_i^*on X_i^*.

In order to effectively and correctly gauge the impact of adoption of the LMCTs on crop yield among smallholder farmers using two-year panel data, the study employed the panel data analysis technique.

One way to take into account for the individuality of each household (plot) is to let the intercept vary for each household (plot). The assumed variables to influence crop yield in equation 1 exhibit different properties when a time aspect is included in the analysis. Some variables are time variant and others are time invariant. Thus, in this analysis, we run both fixed and random effects and then use the Hausman test to determine the suitable model.

The study employed the Least Square Dummy Variable (LSDV) approach for running the fixed effect model (FEM). We specify the LSDV by including the maize yield as the dependent variable; the independent variables are household characteristics and plot characteristics, as follows:

$$\mathrm{Y_{it}} = \mathrm{a_i} + \mathrm{a_1 Age_{it}} + \mathrm{a_2 hhsize_{it}} + \mathrm{a_3 offinc_{it}} + \mathrm{a_4 tfsize_{it}} + \mathrm{a_5 pltdistrd_{it}} + \mathrm{a_6 pltdistmk_{it}} + \mathrm{a_7 soileros_{it}} + \mathrm{a_8 plotgood_{it}} + \mathrm{a_9 plotaverg_{it}} + \mathrm{a_{10} pltirrgt_{it}} + \mathrm{a_{11} fallowplt_{it}} + \mathrm{a_{12} arain_{it}} + \mathrm{e_{it}} \ldots\ldots\ldots (5)$$

Where $\mathrm{Y_{it}}$ = maize yield (kg/acre), $\mathrm{Age_{it}}$= Age of the head of the household head (years);$\mathrm{hhsize_{it}}$ = household size (number);$\mathrm{offinc_{it}}$= household off-farm income (1= yes, 0= No); $\mathrm{tfsize_{it}}$ = farm size (acre);$\mathrm{pltdistrd_{it}}$ = plot distance to road (km);$\mathrm{pltdistmk_{it}}$ = plot distance to market (km);$\mathrm{soileros_{it}}$ = presence of soil erosion on a plot (1 if yes, 0 otherwise); $\mathrm{plotgood_{it}}$ = if soil quality of a plot is good (1 = yes , 0 = otherwise); $\mathrm{plotaverg_{it}}$ = if soil quality of a plot is average (1 = yes, 0 = otherwise); $\mathrm{pltirrgt_{it}}$ = if plot irrigated (1 = yes, 0 = otherwise); $\mathrm{fallowplt_{it}}$ = if plot was fallowed; and $\mathrm{arain_{it}}$ = amount of annual rainfall in millimetres (mm).

We include the dummy variables to represent those households that adopted (plots that received) one of the LMCTs – i.e., organic fertilizers, inorganic, and soil water conservation and erosion control in our modelling work. These dummy variables represent the effect of the adoption of the

LMCTs on crop yield at the household (plot) level for sampled maize smallholder farmers.

$$Y_{it} = u_1 + u_2 D_{it} + a_1 Age_{it} + a_2 hhsize_{it} + a_3 offinc_{it} + a_4 tfsize_{it} + a_5 pltdistrd_{it} + a_6 pltdistmk_{it} + a_7 soileros_{it} + a_8 plotgood_{it} + a_9 plotaverg_{it} + a_{10} pltirrgt_{it} + a_{11} fallowplt_{it} + a_{12} arain_{it} + e_{it} \text{ .... } (6)$$

Where,D_{it},i = 1 if the observation belongs to the household adopted (plot with LMCTs)organic fertilizers, inorganic fertilizers and SWCEC); and $i = 0$ if otherwise. In this model, a_i in equation 5is now represented by $u_1 + u_2 D_{1i}$, where u_1 represents the intercept of household adopted/plot with LMCT, and u_2 represents the differential intercept coefficient which indicates by how much the intercept of household adopted (plot with LMCT) differs from the intercept of those without LMCT. This implies that the household (plot without LMCT) becomes the reference category.

Further, we introduce the dummy variable to capture the effect of the time period on the dependent variable. We allow for time effect because of factors such as technological changes, changes in government regulations, changes in environment, and external effects such as variable weather. As we use a dummy variable to account for the effect of adopting LMCTs, time effects are accounted for by introducing time dummies. In this case we introduce one dummy that captures the second year, since we have two years of data, as follows:

$$Y_{it} = v_1 + v_2 D_{y2} + a_1 Age_{it} + a_2 hhsize_{it} + a_3 offinc_{it} + a_4 tfsize_{it} + a_5 pltdistrd_{it} + a_6 pltdistmk_{it} + a_7 soileros_{it} + a_8 plotgood_{it} + a_9 plotaverg_{it} + a_{10} pltirrgt_{it} + a_{11} fallowplt_{it} + a_{12} arain_{it} + e_{it} \text{........ } (7)$$

where D_{y2} takes a value of 1 for observation in year 2010, and 0 otherwise. We consider the year 2008 as the base year, whose intercept value is given by v_1.

Combining model (6) and (7) with individual characteristics and time effects respectively, we get one full fixed effect model in the LSDV approach represented as:

$$Y_{it} = w_1 + u_2 D_{it} + v_2 D_{y2} + a_1 Age_{it} + a_2 hhsize_{it} + a_3 offinc_{it} + a_4 tfsize_{it} + a_5 pltdistrd_{it} + a_6 pltdistmk_{it} + a_7 soileros_{it} + a_8 plotgood_{it} + a_9\, plotaverg_{it} + a_{10}\, pltirrgt_{it} + a_{11}\, fallowplt_{it} + a_{12} arain_{it} + e_{it} \quad \text{(8)}$$

The fixed effect model is now analysed by the least square dummy variable approach since we have introduced the dummy variable. The fixed-effect model controls for all time-invariant differences between the individuals; so the estimated coefficients of the fixed-effect models cannot be biased because of omitted time-invariant characteristics like gender and location of household/plot. However, we note that one side effect of the features of fixed-effects models is that they cannot be used to investigate time-invariant causes of the dependent variables. Technically, the time-invariant characteristics of the individuals are perfectly collinear with the person or entity dummies. The fixed-effect models are substantively designed to study the causes of changes within a person or entity. Such a change cannot be caused by a time-invariant characteristic, because it is constant to each person. We therefore specify a random model which can take into account the time-invariant characteristics.

As noted earlier, the random effect model (REM) has the advantage of taking into account the time invariant variables. The specification of the REM for this study is done by assuming a_i in equation 5 is a random variable with meanα_1 instead of being fixed. Similarly, instead of using a dummy variable to capture the adoption of LMCTs, we use the error termε_i. Therefore, the final REM is specified to include time-invariant explanatory variables such as gender, education level, and location of plot, as shown in equation.

$$Y_{it} = \alpha_1 + u_2 D_{it} + v_2 D_{y2} a_1 + Age_{it} + a_2 hhsize_{it} + a_3 offinc_{it} + a_4 tfsize_{it} + a_5 pltdistrd_{it} + a_6 pltdistmk_{it} + a_7 soileros_{it} + a_8 plotgood_{it} + a_9 plotaverg_{it} + a_{10} pltirrgt_{it} + a_{11} fallowplt_{it} + a_{12} arain_{it} + a_{13} gender_i + a_{14} educ_i + a_{15} fltbot_i + a_{16} topflt_i + a_{17} slgslop_i + \omega_{it} \quad \text{(9)}$$

Where $educ_i$=education of household head; $fltbot_i$= if flat bottom plot (1 = yes, 0 = otherwise);$topflt_i$= flat top plot (1 = yes, 0 = otherwise); and

$slgslop_i$ = if slightly sloped plot (1 = yes, 0 = otherwise). The rest of the variables are as defined in the previous equation.

Equation 10 is estimated to analyse the impact of the overall conservation and impact of individual main LMCTs (use of organic manures, inorganic fertilizers, and SWCEC) for panel data in the pooled sample (all areas), low and high rainfall zones. The choice of LMCTs and the control variables that are included in the above estimated model are based on existing literature and common factors in Tanzania (Nyangena 2008, Tenge et al. 2004, Kassie et al. 2010, National Bureau of Statistics URT 2012, Kassie et al. 2013).

We use the Hausman test to decide between the fixed effect model and the random effect model for the appropriate instrument. The null hypothesis underlying the Hausman test is that the FEM and REF estimators do not differ substantially, i.e. coefficients estimated by the efficient random effects estimator are the same as those estimated by the consistent fixed-effects estimator. The test statistic developed by Hausman has an asymptotic $\chi 2$ distribution. If the null hypothesis is accepted as implied by an insignificant p-value, the conclusion is that REM is more appropriate. Conversely, when the null hypothesis is rejected, i.e. the p-value is significant, the FEM should be used (Green 2002, Cameroon and Trivedi 2010).

3.1 Data and sources

The study is based on two waves of Nation Panel Survey data collected in 2008-2009 and 2010-2011 by Tanzania's National Bureau of Statistics in selected districts throughout the country. Only two waves are considered, since they match and merge well in order to give relatively large sample size for analysis.[7] However, the data used in this paper is based on a sample drawn from an agriculture data set for plots (households) that meet the sampling criteria (adopters and non-adopters of LMCTs) and who grow maize. Maize crop was sampled among other crops because it was a main crop grown widely on the majority of plots (38.4 per cent and 42.0 per cent

[7]As we increase the number of waves in non-experimental settings, the sample size declines significantly since merging involves a lot of parameters (household, plot, crop and technology).

of plots in 2008 and 2010, respectively) implying that the crop is grown by many households. Maize is also an important crop in terms of food security and income. Therefore, maize was regarded as a representative crop for studying the impact of SLMCTs on productivity and crop yield.[8] Finally, the sampled plots were matched with respective households.

4. Empirical results and discussion

4.1 Descriptive statistics

The summary of descriptive statistics for all the main variables used in this analysis is computed and presented in Table 1. The statistics are based on 1,287 and 1,566 maize plots from 2008 and 2010 data sets, respectively. The results indicate that the average crop yield is 405.0 kg/acre (1,012.5kg/ha) and 367.6 kg/acre (919kg/ha) for 2008 and 2010, respectively. The average yield estimate by this study is slightly below that obtained from the Food and Agriculture Organization Corporate Statistical Database (2013), 1,123kg/ha and 1,320kg/ha for the same years. Nevertheless, this maize yield is very low when compared to the world top maize yield (21,000kg/ha) implying that Tanzania needs to increase twenty one-fold to reach the top yield of countries worldwide (Msambichaka et al. 2016).

Regarding the household socio-economic characteristics of the sampled maize farming households in all years (2008 and 2010), the male headed households dominate. The statistics show that the male headed households were about 76.0 per cent of all households in each year. The mean age of household heads was about 47.2 and 48.6 in 2008 and 2010 respectively, implying that most of them are young or middle aged, energetic enough to be actively engaged in agricultural innovations and adoption of land management and conservation practices. The average of all the household heads' education is primary education (6.3 and 6.5 years of school).The majority of household heads of all ages had attained primary school education (60 per cent), implying that they have basic education, allowing them to acquire and adopt new farm skills from extension officers.

[8] Other studies which covered specific small areas have used the value of crops instead of crop yield and included a variety of crops (See Kassie et al. 2007, Kassie et al. 2010). But approach is not reliable where spatial price differences exist across districts and regions.

In addition to the household variables, several plot characteristics are included for analysis. In all the years surveyed, the majority of households had plots which were good (43 per cent in 2008, and 42 per cent in 2010), loam soils (58 per cent in 2008 and 57 per cent in 2010), and the plots were top flat (38 per cent in all years). Based on these farmers' perceptions, the qualities of sampled plots were good and therefore had productive soils. The mean rainfall was almost the same for all of the two periods: 1040.0mm. per annum with a range span between 462 mm. and 307 0mm. in 2008; and 1039.2 mm. per annum with the range between 290 mm. and 2377.0 mm. in 2010. We note that in 2010, the rainfall was low in terms of minimum and maximum realized, compared to 2008. This may explain the low average or mean crop yields in 2010**.**

Table 1 further presents descriptive statistics for seven different LMCTs which were identified from each wave of data for 2008 and 2010. These LMCTs include terraces, soil bunds, tree belts, drainage ditches, organic manure fertilizer, inorganic fertilizers, and land fallowing. Out of the seven identified LMCTs, three of them were found to be selected and adopted by the majority of households for each of the years. The leading LMCTs were adopted by more than 10.0 per cent of households in all years. These LMCTs include use of organic manure (15.7 per cent in 2008 and 15.8 per cent in 2010), use of inorganic fertilizers (15.4 per cent in 2008 and 18.2 per cent in 2010), and practice of soil water conservation technologies and soil erosion control (SWCEC)[9] (18.0 per cent in 2008, and 12.9 per cent in 2010). Tenge et al. (2004) and National Bureau of Statistics URT (2012) also found the same leading LMCTs as in the current study found adopted by many rural farming households. Therefore the study sampled commonly adopted LMCTs by smallholder farmers in Tanzania for ease of the analysis and comparison of the effect of the technologies.

[9] Water conservation and soil erosion technologies include use of terraces, soil bunds, tree belts, and drainage ditches. The initial aim of this paper was to analyse each practice separately. But the adoption rate of each technology was found to be below 10 per cent, and so the technologies were combined for the study to form one variable since they all share a common defining function in land management and conservation.

Table 1: Descriptive Statistics

		NPS I (2008/09)					NPS I (2010/11)				
Variable	Description	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
yield	Quantity of yield (Kg/acre)	1233	404.99	456.24	20	4000	1484	367.59	350.77	25	4320
Age	Age of household head (years)	1283	47.23	15.42	19	90	1564	48.55	15.74	18	90
gender	Gender of household head (0 = female; 1 = Male)	1287	0.76	0.43	0	1	1566	0.76	0.43	0	1
educ	Education level of household head (years of school)	937	6.31	2.39	0	19	1125	6.52	2.36	0	19
hhsize	Household size (number)	1287	5.35	3.00	1	46	1566	5.60	3.08	1	35
offinco	Off-farm income (1 = yes; 0 = no)	937	0.10	0.30	0		1505	0.16	0.37	0	1
tfsize	Total farm size owned (acres)	1275	6.19	11.25	0.25	300	1559	6.44	12.21	0.25	326
tenure	Plot owned by household (1 = yes; 0 = otherwise)	1068	0.87	0.33	0	1	1343	0.87	0.33	0	1
pltdistrd	Plot distance to road (km)	1068	1.83	2.84	0	25	1342	2.09	4.35	0	70
soileros	Presence of soil erosion on plot (1 = yes; 0 = otherwise)	1068	0.14	0.25	0	1	1343	0.14	0.25	0	1
eroscontr	Presence of soil water conservation and soil erosion control facility (1 = yes; 0 = otherwise)	1068	0.18	0.19	0	1	1343	0.13	0.34	0	1

		NPS I (2008/09)					NPS I (2010/11)				
Variable	Description	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
ercterrace	If terraces on plot (1 = yes; 0 = otherwise)	1068	0.09	0.09	0	1	1343	0.07	0.06	0	1
ercsoibund	If soil bunds on plots (1 = yes; 0 = otherwise)	1068	0.05	0.02	0	1	1343	0.12	0.03	0	1
ercdraigdt	If drainage ditches on plot (1 = yes; 0 = otherwise)	1068	0.02	0.03	0	1	1343	0.03	0.07	0	1
typsoil_l	Loam soil on plot (1 = yes; 0 = otherwise)	1287	0.58	0.49	0	1	1566	0.57	0.50	0	1
plotgood	Farmers' perception on soil fertility as Good (1 = yes; 0 = no)	1287	0.43	0.49	0	1	1566	0.42	0.49	0	1
topfltplt	Top flat plot (1 = yes; 0 = no)	1068	0.38	0.28	0	1	1566	0.36	0.24	0	1
slgsloptt	Slightly sloped plot (1 = yes; 0 = no)	1068	0.02	0.05	0	1	1566	0.28	0.25	0	1
orgferuse	Organic fertilizer use (1 = yes; 0 = no)	1067	0.16	0.36	0	1	1342	0.16	0.37	0	1
inoferuse	Inorganic Fertilizer use (1 = yes; 0 = no)	1067	0.16	0.17	0	1	1342	0.18	0.19	0	1
fallowplt	Plot was fallowed recent years (1 = yes; 0 = otherwise	1068	0.11	0.31	0	1	1341	0.07	0.25	0	1
areaharv	Area harvested (acres)	1264	1.48	1.65	0.05	20	1508	1.55	1.37	0.05	40

4.2 Adoption of LMCTs in different agro-ecological zones

Analysis was done to investigate the type land management and conservation practices adopted across agro-ecological zones in terms of amount of rainfall. The results of this analysis are presented in Table 2. The results show that there is a close association between the choice of land management for conservation and amount of rainfall in a given area.

Table 2: Types of land management practices in different rainfall zones

Amount of rainfall	**Organic manure**			**Inorganic fertilizer**			**Soil water conservation and erosion control**		
	No (%)	Yes (%)	Total	No (%)	Yes (%)	Total	No (%)	Yes (%)	Total
< 600 mm	70.65	29.35	92	98.91	1.09	14	84.78	15.22	14
600 to 1000 mm	84.12	15.88	1,159	89.82	10.18	420	84.04	15.96	420
1000 to 1500 mm	85.15	14.85	936	72.33	27.67	1,145	85.49	14.51	1,146
1500 to 2500	85.8	14.2	176	78.98	21.02	172	85.31	14.69	173
Total	84.13	15.87	2,363	82.44	17.56	1,767	84.74	15.26	1,769
Df = 3	**χ^2 =13.6, Pr = 0.003**			**χ^2 =128.4, Pr = 0.000**			**χ^2 = 0.9, Pr = 0828**		

From Table 2, the results reveal that the number of adopters of soil erosion control measures and use of organic fertilizers decreases with an increase in the amount of rainfall, while the rate of using inorganic fertilizers increased with an increase in the amount of rainfall. The Chi-square test shows that there was a statistically significant association between the use of organic and inorganic fertilizers, and the amount of rainfall. These results are consistent with Kassie et al. (2013) and Alem et al. (2008) who found that adoption of SWCEC and inorganic fertilizer was more common in areas and during years with unreliable and high rainfall, respectively. It is also argued that the use of organic manure and SWCEC technologies have a higher impact on crop yield in moisture-stressed (low rainfall) areas than in high rainfall areas, and vice versa for inorganic fertilizer (Kassie et al. 2008, Benin 2006, Alem et al. 2008,Ministry of Agriculture Food Security and Cooperatives URT 2013). This implies that smallholder farmers have an accumulative knowledge of the nature and effectiveness of LMCTs specific to their immediate environments. Hence any initiatives that aim to achieve sustainable increase of crop productivity through adoption of LMCTs should take into account the local knowledge of farmers in the region of their application.

4.3 Crop yield differences across gender and LMCTs

Descriptive analysis was done to show the relationship between gender and productivity. The t-test results in Table 3 indicate that the male headed households had higher significant mean maize yield (407.9kg/acre and 379.3kg/acre) than female headed households (395.5kg/acre and 330.0kg/acre) in all years. The difference of crop yield across gender has been also reported by Pender and Gebremedhi (2007), Kassie et al. (2010) and Hepelwa (2013). The mean yield difference between male and female headed households is attributed to differences between males and females in resource endowments, exposure to extension services and general access to information about innovations. The literature shows the fact that female headed households in sub Saharan Africa have relatively lower average income than the male headed households and that males' access production skills and information is more feasible than females' access (Kulindwa et al. 2009, Hepelwa 2013, Kidane et al. 2015). Therefore, the low income and exposure (skills and access to information) constrain the female headed households from using improved agricultural inputs, hired labour, and investing in costly, labour-intensive LMCTs for raising their crop productivity.

Table 3: Maize mean yield across Gender and Age groups

Variable	**Maize mean yield (Kg/acre)***		
	2008	**2010**	**Panel**
Gender			
Female	395.462 (30.298)	329.950 (19.287)	366.3005 (17.269)
Male	407.853 (14.243)	379.336 (10.300)	379.0782 (8.581)
t-value	***-0.4019***	***-2.3127***	***-1.8194***

* Numbers in brackets are standard errors

The analysis further shows that there is a mean difference in yields between adopters and non-adopters of LMCTs across all technologies. The t-test results in Table 4 reveal that the mean maize yield was significantly different between the adopters and non-adopters of organic manure, inorganic fertilizers, and overall conservation at one per cent level of significance. The significant mean yield difference between adopters and non-adopters of SWCEC is noticed at 5 per cent level of significance. Plots with inorganic fertilizers had highest yield (551.5kg/acre) followed by plots with organic manure (515.8kg/acre). The plots without inorganic and organic fertilizers had mean yields of 403.0kg/acre and 410.5kg/acre, respectively. The low mean maize yield difference is notable between the adopters and non-adopters of SWCEC compared to other technologies: yield difference between the adopters and non-adopters of SWCEC is 83.0kg/acre compared to the maize mean yield of 148.4kg/acre between adopters and non-adopters of inorganic fertilizers. This suggests that inorganic fertilizers have a higher and quicker impact on maize yield than other technologies, provided a conducive environment prevails. Hepelwa (2013), Baltzer and Hansen (2012), and Selejio (2016) also found that inorganic fertilizer increases the maize yield by three times in some areas of Tanzania.

Table 4: The Maize Mean Yield (Kg/acre) Between Adopters and Non-Adopters of LMCTs for panel data

LMCTs	Adopters	Non-adopters	t-value
	515.8412	410.5443	
Organic Manure	(31.90896)	(15.32768)	0.0035
	551.493	403.061	
Inorganic Fertilizer	(39.33426)	(14.41751)	0.0000
	498.7189	415.6632	
Soil water conservation & erosion control	(37.97414)	(14.77502)	0.0256
	511.6398	374.2233	
Overall conservation	(23.36233)	(16.71859)	0.0000

Numbers in brackets are standard errors

Source: Author's computations from NPS (2008/09, 2010/11 and 2012/13) data

4.4 The static panel model results

Following the descriptive results in preceding discussion, this section presents the results of static panel models that estimate the impact of the LMCTs on panel data. The panel models estimate the impact of the overall conservation and impact of individual main LMCTs (use of organic manures, inorganic fertilizers, and SWCEC) for panel data.

As discussed above in section 3, before deciding between fixed-effect and random-effect as the appropriate static panel model, a Hausman test is performed. The results of the Hausman test for overall conservation model and individual land management and conservation technologies show that the p-values range between 0.4738 and 0.9103, which are different from zero and hence insignificant. This leads to acceptance of the null hypothesis that the FEM and REM estimators do not differ substantially, i.e. coefficients estimated by the efficient random-effects estimator are the same as those estimated by the consistent fixed-effects estimator. Hence the results of Hausman test suggest that a random model is appropriate for this analysis.

The results of the random-effect model are presented in Table 5 for overall conservation and individual LMCTs (SWCEC, organic and inorganic fertilizers). The random-effect models estimate the effect of each LMCT in pooled sample, low and high rainfall areas. The results reveal that there is positive significant effect of overall conservation on maize yield for two-period panel (2008 and 2010). The effect of SWCEC and organic fertilizers on crop yield is significantly positive in pooled sample and low rainfall areas. Unlike the SWCEC and organic fertilizers, the inorganic fertilizer effect is significantly positive in pooled sample and high rainfall areas. The highest impact of overall conservation, SWCEC, organic fertilizers and inorganic fertilizers on crop (maize) yield was 36 per cent, 39 per cent, and 39 per cent, respectively, in low rainfall areas. The highest impact of inorganic fertilizers was 36 per cent in high rainfall areas, implying that the use of inorganic fertilizers increased the maize yield by 36 per cent.

These results suggest that the best performance of SWCEC and organic fertilizers is realized in moisture-stressed areas, while the best performance for inorganic fertilizers is realized in areas with high moisture. This is because SWCEC and organic fertilizers, such as composite manure and animal manure, have high moisture retention capacity when applied in sandy soil and dry areas. The best performance of overall conservation in low rainfall areas is due to the fact that in aggregate, the majority of plots were managed and conserved with organic fertilizers (manure and composites) and with SWCEC – these make a good impact on yield in low rainfall areas due to their capacity to conserve moisture.

The current results from panel data analysis concur with the most recent previous results from cross sectional data analyses which showed a high increase return on adoption of inorganic fertilizers in high moisture soils, and on soil water conservation technologies (SWCEC) and organic manures in moisture-stressed soils (Pender and Gebremedhin 2007, Alem et al. 2008,Kassie et al. 2010). Those studies resulting in conclusions that differ from the current research (e.g. Hazell1993, Shiferaw and Holden

2001, and Tengeet al. 2004) may be due either to the nature of the data (cross-sectional) and the methodology used, or to improper adoption of the technologies under study (Pascual 2001, Kassie *et al.* 2007, Medhin and Kohlin2011, Kabubo-Mariara and Linderh of 2011, Wooldridge 2012). Therefore the use of SWCEC technologies and organic fertilizers (organic manure, composite and related manures) should be encouraged and promoted among smallholder farmers in arid and semi-arid areas of Tanzania e.g. Dodoma, Singida, parts of Manyara, and Arusha, for the purpose of increasing crop yield.

Table 5: Effect of Lana Management and Conservation Technologies on Crop Yield

Variables	Overall Conservation			SWCEC			Organic fertilizers			Inorganic fertilizers		
	All areas	**Low rainfall areas**	**High rainfall areas**	**All areas**	**Low rainfall areas**	**High rainfall areas**	**All areas**	**Low rainfall areas**	**High rainfall areas**	**All areas**	**Low rainfall areas**	**High rainfall areas**
LMCTs	0.308***	0.365***	0.222**	0.255***	0.392***	0.112	0.192**	0.390***	-0.069	0.324***	0.244	0.356***
	(0.070)	(0.097)	(0.108)	(0.097)	(0.129)	(0.148)	(0.089)	(0.116)	(0.141)	(0.086)	(0.150)	(0.109)
y2	-0.045	-0.020	-0.052	-0.025	0.010	-0.040	-0.047	-0.038	-0.047	-0.062	-0.048	-0.059
	(0.072)	(0.096)	(0.114)	(0.073)	(0.098)	(0.114)	(0.072)	(0.096)	(0.113)	(0.072)	(0.096)	(0.113)
Age	-0.007**	-0.006	-0.008**	-0.006**	-0.006	-0.007*	-0.007**	-0.006	-0.006	-0.006**	-0.006	-0.008*
	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)
hhsize	0.000	0.004	-0.008	0.004	0.008	-0.007	0.002	0.005	-0.007	0.006	0.012	-0.004
	(0.011)	(0.014)	(0.021)	(0.011)	(0.014)	(0.021)	(0.012)	(0.014)	(0.021)	(0.011)	(0.014)	(0.020)
offinco	-0.054	-0.129	0.078	-0.041	-0.131	0.093	-0.056	-0.147	0.083	-0.061	-0.135	0.061
	(0.095)	(0.131)	(0.147)	(0.096)	(0.131)	(0.149)	(0.096)	(0.131)	(0.148)	(0.096)	(0.133)	(0.145)
pltirrgt	0.646***	0.559**	0.816*	0.663***	0.509*	0.916**	0.678***	0.524*	0.933**	0.647***	0.539*	0.774*
	(0.226)	(0.268)	(0.444)	(0.230)	(0.270)	(0.447)	(0.230)	(0.271)	(0.448)	(0.228)	(0.278)	(0.437)
tfsize	0.007	0.004	0.011	0.007	0.004	0.011	0.007	0.004	0.011	0.005	0.002	0.010
	(0.005)	(0.006)	(0.007)	(0.005)	(0.006)	(0.007)	(0.005)	(0.006)	(0.007)	(0.005)	(0.007)	(0.007)
tenure	-0.149	-0.139	-0.177	-0.137	-0.123	-0.170	-0.149	-0.162	-0.156	-0.107	-0.082	-0.155

Variables	Overall Conservation			SWCEC			Organic fertilizers			Inorganic fertilizers		
	All areas	**Low rainfall areas**	**High rainfall areas**	**All areas**	**Low rainfall areas**	**High rainfall areas**	**All areas**	**Low rainfall areas**	**High rainfall areas**	**All areas**	**Low rainfall areas**	**High rainfall areas**
	(0.117)	(0.154)	(0.184)	(0.118)	(0.155)	(0.186)	(0.119)	(0.155)	(0.187)	(0.118)	(0.158)	(0.182)
pltdistrd	-0.017*	-0.015	-0.017	-0.017*	-0.018	-0.017	-0.017*	-0.016	-0.017	-0.017*	-0.014	-0.020
	(0.010)	(0.014)	(0.015)	(0.010)	(0.014)	(0.015)	(0.010)	(0.014)	(0.015)	(0.010)	(0.014)	(0.015)
soileros	-0.070	-0.009	-0.203	-0.109	-0.089	-0.220	-0.009	0.065	-0.179	-0.032	0.061	-0.215
	(0.096)	(0.122)	(0.163)	(0.103)	(0.132)	(0.173)	(0.096)	(0.121)	(0.163)	(0.095)	(0.123)	(0.161)
plotgood	0.099	0.136	0.063	0.090	0.082	0.115	0.087	0.107	0.135	0.120	0.102	0.105
	(0.171)	(0.207)	(0.323)	(0.173)	(0.208)	(0.324)	(0.173)	(0.207)	(0.326)	(0.172)	(0.210)	(0.318)
fallowplt	0.282**	0.184	0.463**	0.278**	0.162	0.481***	0.327***	0.248	0.503***	0.300**	0.207	0.468***
	(0.120)	(0.165)	(0.180)	(0.121)	(0.167)	(0.183)	(0.121)	(0.166)	(0.181)	(0.120)	(0.168)	(0.178)
larain	0.234*	0.034	0.143	0.295**	0.005	0.132	0.298**	-0.022	0.134	0.181	-0.057	0.092
	(0.129)	(0.278)	(0.343)	(0.131)	(0.280)	(0.349)	(0.131)	(0.280)	(0.350)	(0.133)	(0.288)	(0.338)
gender	0.060	0.195*	-0.069	0.052	0.196*	-0.075	0.054	0.197*	-0.079	0.068	0.214*	-0.070
	(0.084)	(0.117)	(0.124)	(0.086)	(0.118)	(0.126)	(0.086)	(0.118)	(0.127)	(0.085)	(0.122)	(0.122)
Educ	-0.006	0.030	-0.037*	-0.001	0.033	-0.031	-0.003	0.029	-0.024	0.000	0.034	-0.033
	(0.015)	(0.022)	(0.022)	(0.015)	(0.022)	(0.022)	(0.016)	(0.022)	(0.023)	(0.015)	(0.023)	(0.021)
slgsloptt	0.287***	0.226*	0.254**	0.300***	0.258*	0.256**	0.304***	0.243*	0.260**	0.290***	0.257*	0.244*

Variables	**Overall Conservation**			**SWCEC**			**Organic fertilizers**			**Inorganic fertilizers**		
	All areas	**Low rainfall areas**	**High rainfall areas**	**All areas**	**Low rainfall areas**	**High rainfall areas**	**All areas**	**Low rainfall areas**	**High rainfall areas**	**All areas**	**Low rainfall areas**	**High rainfall areas**
	(0.090)	(0.136)	(0.129)	(0.091)	(0.136)	(0.129)	(0.091)	(0.136)	(0.129)	(0.090)	(0.138)	(0.128)
typsoil_l	0.161**	0.295***	-0.001	0.158**	0.293***	0.001	0.169**	0.292***	0.000	0.158**	0.288***	-0.006
	(0.075)	(0.098)	(0.120)	(0.076)	(0.099)	(0.121)	(0.076)	(0.099)	(0.121)	(0.075)	(0.100)	(0.119)
_cons	4.151***	4.924***	5.397**	3.709***	5.163***	5.398**	3.743***	5.385***	5.314**	4.425***	5.516***	5.661**
	(0.897)	(1.896)	(2.430)	(0.908)	(1.910)	(2.468)	(0.911)	(1.908)	(2.478)	(0.921)	(1.964)	(2.391)
r2	0.108	0.134	0.104				0.0859	0.1265	0.0901	0.0994	0.1019	0.1252
Prob> F/χ^2	0.0000	0.0001	0.0029				0.0000	0.0003	0.0095	0.0000	0.0077	0.0037
N	647.000	355.000	292.000	647.000	355.000	292.000	647.000	355.000	292.000	647.000	355.000	292.000

Other factors that were discovered to influence crop yield significantly and positively, in the pooled sample or in areas with low and high rainfall common to most of LMCTs, are: the use of irrigation, fallowing of the plots, amount of rainfall, slightly sloped plots, and the presence of loam soil. Conversely, the age of the household head, farm size and distance to roads, were found to be negatively significant in their effects upon crop yield. Apparently, the influence of most of the factors and their significance for crop yield is consistent with economic theory and prediction. For example, use of irrigation made the highest contribution to crop yield, impacting significantly (51-92 per cent) upon crop yield across all land management and conservation technologies and conditions (pooled, low, and high rainfall). Fallowing of the plot contributed 50 per cent to maize yield in high rainfall areas with use of organic manure, but had an insignificant impact in low rainfall areas, for all LMCTs. This suggests that land management and conservation practices should be complemented with irrigation for better crop yield results where rainfall is not reliable.

On other hand, the results show that an increase of distance between farm and road reduces the crop yield. For example, the increase of one kilometre from plot to road reduces maize yield by 2.0 per cent in high rainfall areas with the use of inorganic fertilizers. This implies that poor accessibility to farm or plot undermines the potential productivity of the area or land, since it is difficult to conduct farm operations, including investment in adopting LMCTs. It has been noted that transportation of inputs and outputs to and from the farm becomes prohibitively expensive when the farm is poorly accessible (Pender and Gebremedhin 2007, Ministry of Agriculture Food Security and Cooperatives URT 2013).

4.5 Conclusion and policy implications

The objective of this empirical study was to investigate the impact upon agricultural productivity of adopting land management and conservation technologies in Tanzanian panel data. Results have shown that the major land management and conservation technologies that were adopted widely by a majority of households were three, namely, use of organic fertilizer, use of inorganic fertilizer, and soil erosion control and water conservation measures.

The panel data results have shown that the adoption of LMCTs makes a positive and significant contribution to increased crop yield. The results have shown, further, that this impact varies across the technologies with rainfall amount and years of application. Inorganic fertilizer had the highest significant impact on maize yield in high rainfall areas, while SWCEC and organic manure had the highest positive impact on crop yield in low rainfall areas. These results support previous studies with the same results culled from cross-sectional data analysis. In contrast, this study challenges the nature of data and the methodologies used by some previous studies. These current results also challenge the correctness of adopting land conservation technologies in areas where no measurable gains appeared to be related to adoption of LMCTs.

It has also been found that there is a close association between the type of land management and conservation technologies adopted and the amount of rainfall present (the agro-ecological zone) – implying that different technologies make significantly different impacts across ecological zones. These findings suggest that policy makers should refrain from recommending a blanket land management and conservation programme for all agro-ecological zones indiscriminately. The recommendation of the technology in a given zone should always be supported by research findings and directed by smallholder farmers' experiences and the accumulation of local knowledge in the area targeted for innovative intervention.

It is worth noting that the observed impact of adopting land management and conservation technologies on crop yield from descriptive statistics and econometric results may not influence a poor smallholder farmer to invest in costly technologies, since the study has not extended to any cost-benefit analysis. It is true that if the benefit does not justify the investment into LMCTs, the smallholder farmers will continue to clear forest to acquire new virgin land if such an option is available. Therefore subsidized improved farm input programmes like the Agricultural Input Voucher System and other supported land management conservation projects for smallholder farmers are critically important in Tanzania.

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