Productivity and Efficiency Analysis of Maize under Conservation Agriculture in Zimbabwe

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Abstract

This study sought to evaluate the performance of conservation agriculture (CA) technology-essentially comparing productivity and efficiency levels in maize production in CA and conventional farming. The analysis is based on a three year panel sample of smallholder farming households and employing a stochastic production frontier model compare productivity and technical efficiency between CA and conventional farming. Study results indicate that CA technology is implemented in relatively smaller plots than conventional farming (0.36ha compared to 0.85ha) but has a significant contribution to total maize production, on average 50% of output share. Output elasticities indicate positive responses for labor and seed in CA, and negative responses in conventional farming. On the other hand, there are negative responses to land and draft in CA. Fertilizer has a greater positive response in CA than in conventional farming. Overall returns to scale are similar for CA and conventional farming (0.84 and0.89 respectively). There is evidence of technical progress in CA for the three year panel period. Technical progress has been land-saving but seed and fertilizer-using in CA, while land-using and seed-saving in conventional farming. Joint frontier estimates indicate that farmers will produce 39% more in CA compared to conventional farming. Technical efficiency levels are generally the same (about 68%) for both technologies. Two-thirds of farmers achieve efficiency scores in the 60-80% range both CA and conventional farming technologies. These results show significant yield gains in CA practices and significant contributions to food production. CA is land-saving, and this is an important issue for land constrained farmers because they can still have viable food production on smaller area. But high labor demands in CA present some problems in adoption, particularly for the poorer farmers.

Key words: *Conservation agriculture, productivity, efficiency, technical change*

I. Introduction

Maize production is an important component of food security and livelihood for smallholder farming communities of Zimbabwe. The majority of smallholder farmers grow maize primarily for subsistence using conventional farming technology based on ox-drawn plow for tillage purposes. The challenge in Zimbabwe´s smallholder agricultural sector is to raise the productivity of the staple cereal as a way of solving food insecurity problems. The per capita maize production is steadily declining, and this has been attributed to significant decline in yields over the years from 1500 kg/ha in the early 1990s to 500kg/ha after 2000 (Government of Zimbabwe, 2002). Similar to most parts of sub-Saharan Africa, agricultural productivity levels in Zimbabwe have fallen due to land degradation as a result of many years of erosive cultivation, declining soil fertility as farmers fail to replenish soil fertility (Mano, 2006).

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The response to this food crisis in Zimbabwe has been the wide scale relief distribution of food aid and direct agricultural input assistance without an exit strategy for sustaining some of the new technologies promoted within the context of relief aid (Rohrbach et al, 2005; DFID, 2009). As part of these relief and recovery programs, research and development initiatives have seen the introduction of a specific set of technology options that aim to improve and stabilize crop yields while preserving soil and water, while using precision methods to apply inputs. These set of technology options is defined as conservation agriculture (Thierfelder and Wall, 2010; Twomlow et al., 2008). But, the key to a prolonged increase in agricultural production is to improve productivity, which can be achieved through better technology and efficiency.

In Zimbabwe there has been major investments and policy drive towards CA as a way of improving productivity through efficient use of production inputs, improved management, timeliness of operations and conserving the soil. However, in the past increase in land productivity has come from intensification of agricultural production and the adoption of yield enhancing technologies especially modern high yielding varieties and fertilisers. Higher efficiency gives subsistence farmers the opportunity to produce more output using the current level of inputs especially land which is limited in supply. Gains in output through productivity growth have become increasingly important in Zimbabwe as opportunities to bring additional virgin land into cultivation have significantly diminished in recent years.

So far there is no empirical evidence to show that CA can indeed lead to efficiency gains which can increase productivity that is crucial for improving livelihoods of smallholder farmers in Zimbabwe. The few studies that have assessed the effect of CA adoption on production efficiency (Solis, 2005, Oduol et al., 2011, Musara et al., 2012) have used cross sectional data. The studies have concluded that adoption of CA practices push smallholder farmers closer to their production frontier and an improvement of human capital variables such as access to extension and education can significantly reduce inefficiencies.

Given the nature of CA and the fact that agronomic benefits from soil improvement are only realised in the long term, the use of panel data is more appropriate for a realistic assessment of impact. Through monitoring farmers who have adopted CA over time, the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT) has created a database upon which this study will be based.

The paper is structured as follows: Section II is a review of the literature on productivity measurement and section III develops the theoretical and econometric model for estimating productivity impacts. Section IV describes the data used in the study including sample selection issues. Section V is a discussion of diagnostic and model specification issues in the econometric model. Section VI reports the major empirical findings. The summary follows in the last section.

Section II. Literature review

CA practices in Africa

A comprehensive review of conservation CA practices in Zimbabwe, and other Southern African countries is given by Mazvimavi (2011). CA in Zimbabwe is largely practiced by smallholder farmers using small farm implements such as the hand hoe to create planting basins. Though specifications may vary, CA technologies typically involve agricultural management practices that prevent degradation of soil and water resources and thereby permit sustainable farm productivity without environmental degradation (Haggblade et al., 2004; Wysocki, 1990; ECAF, 2002).

Farmers and agencies working to improve farm productivity have experimented with a broad range of these soil and water conservation technologies that are collectively known as CA. Tsegaye et al., (2008) assess the impacts of conservation agriculture on land and labor productivity in Ethiopia. Their study analyzes the adoption of the different components of CA and finds that the initial decision to adopt CA is influenced by regional location, family size, access to extension, and formal education. They also find a positive relationship between land productivity and use of CA components such as herbicide application.

Hassane et al., (2000) evaluate the impact of planting basin, and use of fertilizer and manure on millet crops in Niger. Their study finds that over a five year period from 1991 to 1996, farmers experienced yield gains of up to 511%. Similarly, significant yield gains are also noted in a study in Zambia by Haggblade and Tembo (2003) who note that farmers who dug planting basins and applied crop residues and fertilizer achieved 56% yield gains in their cotton fields and 100% yield gains in their maize fields.

Gowing and Palmer (2008) examine evidence of CA benefits amongst small-scale farmers in Africa and conclude that CA does not overcome constraints on low-external-input systems. They note that CA will deliver the productivity gains that are required to achieve food security and poverty targets only if farmers have access to fertilizers and herbicides. They further asset that adoption of CA by small-scale farmers is likely going to be partial as opposed to full adoption.

While there is evidence of CA gains in the literature, there are also studies that present a sharply contrasting assessment of CA impacts. Giller et al. (2009) suggests that empirical evidence is not clear and consistent on CA contributions to yield gains. Their study notes concerns that include decreasing yield in CA, increased labor requirements when herbicides are not used, a shift of the labor burden to women, and problems with mulching requirements due to its shortage or competing use as livestock feed. They also note that there are many cases where adoption of CA was temporary and only lasted for the course of active promotion of the technology by NGOs and research but was not sustained beyond that.

Technical Efficiency and Productivity Growth

The measurement of technical efficiency and productivity growth is an area of study that has attracted the interest of a number of researchers since the work of Farrell in 1957 (Farrell, 1957). Technical efficiency is just one component of overall economic efficiency, i.e. producing maximum output given the level of inputs employed (Kumbhakar and Lovell 2000). Efficiency change essentially contributes to productivity growth. Efficiency can be considered in terms of the optimal combination of inputs to achieve a given level of output, that is input-orientation efficiency, or the optimal output that could be produced given a set of inputs, that is output-orientation efficiency.

Productivity assessment is often associated with measurement of technical change. The work of Battese and Coelli (1988, 1992, 1995) has made notable contributions on measurement of production efficiency using stochastic production frontier approach. Khumbakar and Lovell (2000) proposes an econometric method that is based on a primal approach where shifts in the production frontier are due to technical change. It is often important to interpret results of efficiency and productivity analysis in the context of the time period analyzed, and also consider issues such as the degree of sample homogeneity, output aggregation, and use of different methodologies in the analytical process.

Total factor productivity growth is defined as growth in output that is not explained by change in inputs. Following this definition and assuming that production is not always on the frontier, change in productivity can be decomposed into two separate components: a) movements towards or away from the frontier due to changes in technical efficiency; and b) shifts in the frontier due to the effect of technological innovations or progress. Effects of scale changes can also be incorporated in this measure (Coeli et al.,2005)

Parametric and non parametric approaches

A non-parametric approach to frontier, the Data Envelopment Approach (DEA) was developed by Charnes, Coopers and Rhodes (1978). The parametric approach was developed simultaneously by Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broek (1977) who proposed the stochastic frontier production function. Both approaches are used in empirical work. However, a weakness associated with the DEA approach is that all deviations from the frontier are associated with inefficiency. In agriculture this assumption is restrictive considering that production is variable due to factors such as weather, pests and diseases. The stochastic production frontier on the other hand allows for error in measurement.

Section III: Development of theoretical and econometric model

This study uses a stochastic production frontier to estimate productivity and technical efficiency. To estimate technical efficiency, a joint frontier is used since this is a comparative analysis of two technologies. Data for the two technologies is pooled so that technical efficiency predictions are derived from the same data. This is based on discussions by Battese et al., (2004) on comparing different groups in technical efficiency estimation.

OLS regressions and Stochastic frontier models

The study will use OLS regressions to model maize production and retrieve output elasticities and returns to scale associated with CA and conventional farming. Two separate models are estimated (for CA and non CA) using a structural form indicated in the translog production function in equation 1.

$$y_{it} = \beta_0 + \sum_{j}^{J} \beta_j x_{jit} + \frac{1}{2}\sum_{j}^{J}\sum_{k}^{J} \beta_{jk} x_{jit} x_{kit} + \beta_t t + \frac{1}{2}\beta_{tt} t^2 + \sum_{j}^{J} \beta_{jt} x_{jit} t + e_{it} \qquad (1)$$

where y_{it} is the log of the output produced, the subscript i = 1, 2, …, N denotes households in the panel data, t = 1, 2, …, T are time periods, and j, k = 1, 2, …, J are the inputs used, represented by vector $\boldsymbol{x}$ in farm production. Technical change is neutral with respect to inputs if, and only if, $\beta_{jt} = 0\ \forall j$, and absent if, and only if, $\beta_t=\beta_{tt}=\beta_{jt}=0\ \forall j$.

The panel stochastic frontier model to predict technical efficiency is given in equation 2, with the same specification as equation 1 except that the error term is composed of two independent elements: $v_{it} \sim$ iid $N(0, \sigma_v^2)$ is the random noise error component and $u_{it} \geq 0$ is the technical inefficiency error component. In the econometric estimation, a joint panel is used, pooling observations for CA and conventional farming, and incorporating a dummy variable to control for these technologies.

$$y_{it} = \beta_0 + \sum_{j}^{J} \beta_j x_{jit} + \frac{1}{2}\sum_{j}^{J}\sum_{k}^{J} \beta_{jk} x_{jit} x_{kit} + \beta_t t + \frac{1}{2}\beta_{tt} t^2 + \sum_{j}^{J} \beta_{jt} x_{jit} t + v_{it} - u_{it} \qquad (2)$$

The inefficiency effects model provides some explanations for the variations in efficiency levels among farmers. Following the stochastic production frontier model in Equation 2, it is assumed that the inefficiency effects are independently distributed and u_{it} arises by truncation at zero of the normal distribution with mean, μ_t, and variance, σ_u^2, where μ_t is defined by

$$\mu_t = \delta_0 + \sum_{m=1}^{M} \delta_m z_{mt} + \delta_t t \qquad (3)$$

where z is a vector of farm specific inefficiency related variables (m=1, …, M), at time period t, and δ coefficient are unknown parameters to be estimated. Since the dependent variable in the inefficiency model is a measure of inefficiency, a positive sign on a parameter indicates a negative efficiency effect. A one stage approach that uses a maximum likelihood estimator is used to estimate the production and inefficiency effects simultaneously.

Variables for the direct factors of production are land (A), labor (L), draft animals (K), fertilizer (F), and seed (S). The output (Y) for the production function is maize produced in kgs. Land is total cultivated area in hectares. Labor is total farm labor available in the household, expressed in male adult equivalent units. Variables hypothesized to be explanatory factors of technical efficiency include ; gender (dummy variable taking the value of 1 if male headed household, zero if female headed), age and education of household head, asset endowments, and access to draft power. A time variable is included to estimate the effect of time on technical efficiency. Land and labor are also included in the efficiency model. The model used in the study assumes time varying technical efficiency, using a truncated frontier model.

Section IV: Data

This study makes use of ICRISAT panel data from household surveys collected since 2008 in Zimbabwe. The panel study aimed to examine CA adoption practices including labor allocation, technology adoption determinants, and productivity impacts observing the same farmers in successive seasons of real CA practice in non experimental setting. The study makes comparison of CA technology with alternative conventional farming practices for the same households (i.e. a household practices both technologies).

The data was collected in 15 rural districts in Zimbabwe. Table 1 shows the average number of households interviewed in the full survey sample and the selected sample (used for this particular study). During the panel period, there were incidences of attrition as some households could not be re-interviewed in successive seasons of the surveys. As a consequence, the panel data used in this study is un-balanced. This may open doors to some econometric problems associated with attrition bias. A possible solution to attrition bias is to use dynamic panel data models. However, this study does not tests for attrition bias nor make use of dynamic panel data models.

There were instances where some farmers did not produce maize in particular seasons, or where the maize crop was completely wiped out by drought. As a result, this study makes use of a sub sample of the original panel household sample. This sub sample considers maize producing households and excludes observations where no maize was produced. Further details on sample selection are discussed in the proceeding sub-section.

Table 1. Survey sample and selected sample for study

Technology	Survey sample			Selected sample		
	CA	*Conventional*	*Combined*	*CA*	*Conventional*	*Combined*
2008	322	176	498	265	155	420
2009	306	286	592	291	270	561
2010	287	258	545	200	229	429
2008-10	**305**	**240**	**545**	**252**	**218**	**470**
Total observation			**1635**			**1410**

Source: ICRISAT Conservation Agriculture panel data 2008-2010.

Table 2 gives some descriptive statistics of the production variables and factors hypothesized to explain technical efficiency in maize production. Output refers to total maize produced in kilograms. In this study, aggregation of output from different plots, as well as aggregation of inputs is done. Aggregation is used in this case by making implicit assumptions on seperability.

Table 2. Summary Statistics for factors of production and efficiency factors

		Production variables						Efficiency variables					
	Year	Output	Area	Labor	Draft	Seed	Fertilizer	Gender	Age	School	Experience	Ill	Assets
CA	2008	362.40	0.36	3.69	0.74	8.05	35.46	0.63	50.48	6.50	24.86	0.24	72.98
	2009	484.25	0.36	3.66	0.62	9.19	33.84	0.68	55.79	6.53	30.83	0.22	97.04
	2010	501.69	0.37	2.54	1.24	9.13	53.53	0.59	54.03	6.91	97.71	0.19	287.95
	average	**449.45**	**0.36**	**3.30**	**0.87**	**8.79**	**40.94**	**0.63**	**53.43**	**6.65**	**51.13**	**0.22**	**152.66**
Conventional	2008	325.09	0.94	3.84	0.90	19.27	38.68	0.63	50.75	6.57	25.37	0.25	84.00
	2009	575.07	0.75	2.93	0.64	17.20	33.52	0.69	54.53	6.79	29.90	0.18	91.74
	2010	649.29	0.85	2.63	1.39	19.03	62.64	0.65	54.21	6.81	26.72	0.21	356.20
	average	**516.48**	**0.85**	**3.14**	**0.98**	**18.50**	**44.95**	**0.66**	**53.16**	**6.73**	**27.33**	**0.21**	**177.31**
Average	2008	348.63	0.57	3.74	0.80	12.19	36.65	0.63	50.58	6.53	25.05	0.25	77.05
	2009	527.96	0.55	3.31	0.63	13.05	33.69	0.69	55.20	6.65	30.39	0.20	94.49
	2010	580.48	0.63	2.59	1.32	14.42	58.39	0.62	54.13	6.86	59.81	0.20	324.38
	average	**485.69**	**0.58**	**3.21**	**0.92**	**13.22**	**42.91**	**0.65**	**53.30**	**6.68**	**38.42**	**0.21**	**165.31**

Source: ICRISAT Conservation Agriculture panel data 2008-2010.

The efficiency variables include gender, age, education level, farming experience of the household head, and presence of chronically ill persons in the household (dummy variable proxy for impact of HIV/AIDS, named Ill). Gender and illness are proportion of households (multiply by 100 to express as percentage). Asset endowments are expressed as an index which captures information on the availability of farming implements e.g. plows, cultivators, hoes, in a household. In general there is not a lot of variation in input use for the three year period. Further discussion of input allocation is covered in a later section. Averages values for the efficiency variables are generally the same for both technologies because these averages are based on the same farmers practicing both technologies.

Sample selection

There are instances in the survey data set were households did not produce maize in a particular year. These observations were excluded from the analysis carried out in the study. This raises the concern of sample selection bias as also 13.8% of observations were excluded from the analysis. If the excluded farmers had particular characteristics specific to them and not observed in the included sample (e.g. non beneficiaries are likely to be less vulnerable households), then the sample used for analysis would not be random but rather biased. Households that did not receive input subsidies were more likely to be excluded from the sample. The full sample consisted of 1635 observations and the proportion of households that were non beneficiaries (of input subsidies) in this sample is 20.6%. Beneficiary households are households that received input support mainly through NGOs. In many instances these were free gifts of seed and fertilizer targeted at vulnerable households. In the selected sample, about 20% of non beneficiaries were excluded, compared to 11% of beneficiaries being excluded.

To explore the potential problem of sample selection bias, a Heckman's sample selection model is implemented. In the model the probability of being a maize producer for a particular year is modeled as a function of whether or not a household received input subsidies (dummy variable taking the value 1 if beneficiary and 0 otherwise). An assumption is made that receiving input subsidies will have an effect on whether a household produced or not, but will not have a direct effect on levels of production. Within reason, this assumption seems plausible. The results of the model are presented in Table 3. Draft access is incorporated as a dummy variable as a strategy to deal with zero values in computing the log for number of draft animals. This is further discussed in section V.

The probit model for participation in the sample indicates that there is a greater probability for participation if a household is a beneficiary (coefficient on beneficiary is positive and statistically significant). To evaluate if there is sample selection bias, we look at the RHO(1,2) coefficient in the corrected model. The Rho(1,2) coefficient is not statistically significant at 10% level, which suggests that there is no sample selection bias. The translog specification of the sample selection model yields even stronger results for non bias in the selected sample i.e. RHO coefficient =0.185 and it's p value =0.675

Table 3. Heckman's sample selection model

Probit model of participation in sample			**OLS Corrected Regression for the selected sample**		
Variable	Coefficient	Standard Error	Variable	Coefficient	Standard Error
Constant	-1.332	0.631***	Constant	2.528	0.321***
Area	0.458	0.062***	Area	0.313	0.050***
Labor	0.061	0.117	Labor	0.059	0.041
Daft access	0.124	0.130	Draft	0.137	0.054
Time	3.391	0.779***	Seed	0.327	0.042***
Time*Time	-0.864	0.194***	Fertilizer	0.146	0.013***
Region	0.201	0.129	Draft access	0.140	0.057**
Benefit	0.228	0.139*	Time	2.085	0.311***
			Time*Time	-0.486	0.079***
			Region	0.040	0.048
			Technology	0.336	0.052***
			σ (1)	0.797	0.023***
			RHO(1,2)	0.249	0.351
			Log likelihood	-2206.438	
			N total sample	1635	
			N selected sample	1410	

Stars indicate statistical significance: * for the 10 % significance level, ** for the 5 % significance level, and ***for the 1 % significance level.

Section V: Model specification and diagnostic issues

Dealing with zero values for input use

A challenge that had to be dealt with in the data is the presence of zero values for inputs, in particular in constructing the variable for number of draft animals where some households had no draft animals. Battese (1997) devises a method to get around this problem, where all zero values for an input are assigned a value of one to enable computation of the log, then an dummy variable is added to the regression capturing whether the input was applied or not. This method ensures that efficient estimators are obtained using the full data set but no bias is introduced.

Choosing between fixed effects and random effects

The availability of panel data makes it possible to control for individual household specific effects which may potentially bias or make regression estimators inconsistent. For example differences in plot characteristics, or any other unobservable or hard to measure characteristics can be controlled for with panel data. Alternative panel specifications to control for these farmer specific characteristics are fixed effects and random effects models. In this paper, panel specification tests are carried out to choose between fixed effects and random effects.

OLS regressions were run to test for the ideal panel specification for the data using a Huasman's test. Table 4 shows results from the regressions and the associated p values form the Huasman's test. Both the translog and Cobb Douglas models favour fixed effects over random effects (significant p values for Hausman's statistic). Fixed effects are strongly favoured in the translog model. For the rest of the analysis, fixed effects models are used as the panel specification. Interpretation of model parameters will be done with the stochastic frontier model which will be presented in a later section of the paper.

Choosing functional form

The choice of functional form to model the frontier and inefficiency effects was of interest in this study. In the literature, the translog has commonly been preferred as a more flexible functional form that allows for interaction of inputs, unlike the Cobb Douglas which does not allow for input interactions and assumes elasticity of substitution between inputs equals one. To tests for functional forms a likelihood ratio (LR) tests is used. The LR test is only valid for nested models. The LR test statistic is $\lambda = -2[L(H_0) - L(H_1)]$, where $L(H_0)$ and $L(H_1)$ are the values of the log-likelihood function under the specifications of the null and alternative hypotheses, H_0 and H_1, respectively. If the null hypothesis is true, then λ has approximately a Chi-square (or mixed Chi-square) distribution with degrees of freedom equal to the number of restrictions. The assumption that the maize production in this sample follows Cobb-Douglas estimations (β_{jk}=0, $\forall$ j, k and β_{jt} =0 $\forall$ j, t) are strongly rejected at 1 percent significance level (Chi calculated =63.691, with 35df).

Diagnostic problems

The chosen translog model has 30 variables and this is likely to lead to problems caused by correlation among the independent variables, which results in an inability to identify individual parameters of interest, and problems in statistical inference due to inflated standard errors and low t stats. This problem is caused partly by multicollinearity of the independent variables (Wooldridge 2002, Greene 2003). However, it will be beyond the scope of this study to use alternative models that might limit the effects of multicollinearity of independent variables. Heteroskedasticity is tested for using the Breush Pagan tests in the parsimonious Cobb Douglas specification. This is done by running an OLS regression and using the residuals to run an auxiliary regression with the original model regressors. The R squared from the auxillary regression =0.533 (sample size is 1410). The test statistic (Lagrange Multiplier) is 747.72, with a Chi square distribution (10df). Given these values, the null hypothesis of Homoskedasticity is rejected at the 1 percent level of alpha. Therefore results from the Breush Pagan tests indicate that there is Heteroskedasticity in the data. A challenge arises in the determination of the form of Heteroskedasticity in order to correct for it in the frontier model. So the frontier model is run without making a correction for Heteroskedasticity. Autocorrelation is not anticipated to be a problem in the panel data where the modeling uses fixed effects. In this regard, neither tests nor corrections are made for autocorrelation.

Table 4. OLS regressions to test fixed effects versus random effects

OLS Translog Model				**OLS Cobb Douglas**			
Variables		Coefficient	Standard Error	Variables		Coefficient	Standard Error
Constant	β_0	2.200	0.583***	Constant	γ_0	2.682	0.208***
Land	β_A	-0.209	0.217	Land	γ_A	0.298	0.041***
Labor	β_L	0.464	0.275**	Labor	γ_L	-0.012	0.054
Draft Animal	β_K	0.440	0.370	Draft Animal	γ_K	-0.001	0.084
Seed	β_S	0.390	0.261	Seed	γ_S	0.273	0.049***
Fertilizer	β_F	0.083	0.094	Fertilizer	γ_F	0.145	0.016***
Land*Land	β_{AA}	-0.010	0.057	Draft	γ_D	0.163	0.087**
Labor*Labor	β_{LL}	0.002	0.096	Time	γ_T	1.622	0.262***
Draft*Draft	β_{KK}	0.210	0.172	Time*Time	γ_{TT}	-0.377	0.066***
Seed*Seed	β_{SS}	0.058	0.082	Region	γ_R	0.074	0.056
Fertilizer*Fertilizer	β_{FF}	0.091	0.018***	Technology	γ_{RT}	0.301	0.057***
Land*Labor	β_{AL}	0.127	0.065**				
Land*Draft	β_{AK}	0.163	0.084**				
Land* Seed	β_{AS}	0.028	0.057				
Land* Fertilizer	β_{AF}	0.029	0.022				
Labor*Draft	β_{LK}	-0.020	0.091				
Labor* Seed	β_{LF}	-0.139	0.078**				
Labor* Fertilizer	β_{LS}	0.010	0.024				
Draft* Seed	β_{KS}	-0.165	0.089**				
Draft* Fertilizer	β_{KF}	0.034	0.027				
Seed* Fertilizer	β_{SF}	-0.058	0.026**				
Land*Time	β_{AT}	0.086	0.048**				
Labor*Time	β_{LT}	-0.011	0.055				
Draft*Time	β_{KT}	-0.046	0.058				
Seed *Time	β_{ST}	0.056	0.056				
Fertilizer *Time	β_{FT}	-0.005	0.018				
Time	β_T	1.809	0.257***				
Time*Time	β_{TT}	-0.852	0.086***				
Draft access	β_{DD}	0.182	0.067***				
Region	β_R	-0.012	0.047				
Technology	β_{RT}	0.336	0.046***				
R^2		0.427				0.634	
Huasman p value		0.000				0.098	
Observations		1410				1470	
Households		470				470	

Stars indicate statistical significance: * for the 10 % significance level, ** for the 5 % significance level, and ***for the 1 % significance level.

Section VI: Main results

Factor allocation

A look into how farmers allocate factors of production gives an idea of factor allocative efficiency i.e the use of the right mix of inputs in light of the relative price of each input. (Kumbhakar and Lovell 2000). In this study information on prices is not available, hence no direct interpretation of allocative efficiency is made. However, the analysis takes a look at physical levels of input use. Table 5 shows land allocation in hectares, and on average conventional farming has a significantly larger area (0.85ha compared to 0.35ha for CA). Reasons for this include the fact that farmers are likely to allocate most of their land to the more familiar technology-which is also relatively easier to implement in larger tracts of land as it makes more use of draft animals for tillage. CA is generally implemented in smaller tracts of land due to labor constraints in digging planting basins-in most instances hand hoes being used for tillage. Fertilizer application rates on the other hand are significantly higher in CA (on average 155kgs compared to 83 kg in conventional). This is partly due to greater availability of fertilizer subsidies for CA plots through input relief programs.

Table 5. Input allocations for CA and conventional farming

Technology	Year	Land	Fertilizer(kg/ha)	Seed (kg/ha)	Yield (kg/ha)
CA	2008	0.36	143.68	33.23	1474.80
	2009	0.36	142.09	37.71	1747.56
	2010	0.37	187.52	29.79	1607.37
	2008-10	**0.36**	**154.66**	**34.04**	**1614.86**
Conventional	2008	0.94	85.14	29.53	517.34
	2009	0.75	68.94	33.44	1070.37
	2010	0.85	97.26	25.33	857.02
	2008-10	**0.85**	**82.69**	**29.67**	**864.60**
Combined	2008	0.57	122.07	31.86	1121.45
	2009	0.55	106.88	35.66	1421.64
	2010	0.63	139.34	27.41	1206.83
	2008-10	**0.58**	**121.28**	**32.02**	**1266.87**

Source: ICRISAT Conservation Agriculture panel data 2008-2010.

The main types of fertilizer are basal and top dressing. The former is recommended before planting and the latter is recommended during crop growth. Farmers commonly substitute basal fertilizer with manure- which is readily available (from livestock). On the other hand, top dress fertilizers are more limiting, and it is likely that the big difference in yields between the two technologies is partly being driven by higher fertilizer application rates in CA. Seed application rates are higher in CA, and this is possibly due to CA planting recommendations that generally use more seed per planting station. In terms of general input use, CA is not necessarily associated with conservative input levels. One can think of the conservation attributes of the technology as mainly in the agronomic aspects such as conserving soil structure, soil moisture through use of mulch, and precision application of inputs. Mulching is more rigorously done in CA as a strategy to conserve soil moisture and suppress weeds. This paper however does not quantify mulch input levels.

Output shares

A question of interest is to look at the contribution of the alternative technologies to total maize production in a household. The output share of each technology gives a reasonably good indication of its impact on production. Figure 1 shows that CA contribution to total output in high rainfall areas is on average 63.93%, 50.17%, and 52.42% for the periods 2008, 2009, and 2010 respectively. In low rainfall areas CA average contribution to total output is 38.01%, 40.41%, and 38.96 for the respective time periods. These are interesting findings as they give a strong indication that CA technology, although implemented in relatively smaller plots, still contributes equally or more than conventional farming. A more complete analysis would require a look at the cost and revenue implications of CA technology. Tshuma et al., (2010) in their study note that CA technology generally has significantly higher gross margins and returns to input use than conventional farming. This study is based on a sub sample of the data used in this paper. The study primarily evaluates labor and time allocation in CA versus conventional farming.

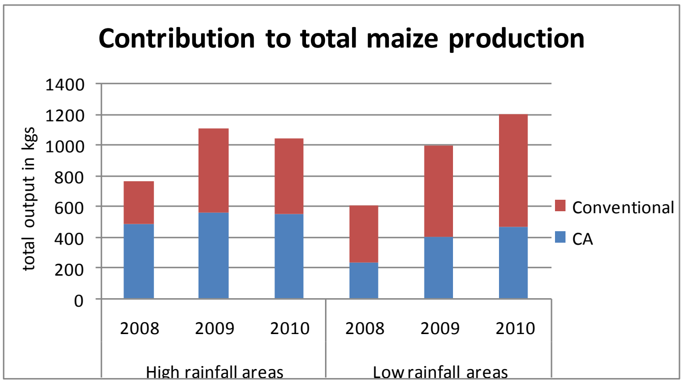

Figure 1 Output shares for alternative technologies

Partial factor productivity

A partial productivity index that takes the ratio of a single input over output is used in this study. These input output (IO) ratios allow for comparison of factor productivity. Table 6 shows mean differences in input output ratios between conservation agriculture and conventional farming. Lower IO ratios indicate higher factor productivity. In each year, CA has higher factor productivity for all the inputs except draft. CA technology by design avoids the use of draft as a coping strategy for households with no draft animals. These households can carry out land preparation and plant on time without having to wait to borrow draft animals from neighbours. Fertilizer productivity is however only significantly higher in 2008. Surprisingly, the significantly higher fertilizer regimes on CA do not yield corresponding higher productivity for this factor. A common concern with subsidized inputs is that in some instances it is overused, hence marginal productivity diminishes. It is however important to note that these productivity measures (IO ratios) are limited in providing indications of overall productivity and can be misleading when considered in isolation (Kalirajan and Wu 1999). The subsequent sections of the paper discuss more complete measures of productivity.

Table 6. Input output ratios for conservation and conventional agriculture

Year	Area		Labor		Draft		Seed		Fertilizer	
	CA	*Conv.*	*CA*	*Conv.*	*CA*	*Conv.*	*CA*	*Conv.*	*CA*	*Conv.*
2008	0.002***	0.005	0.023**	0.027	0.013	0.011	0.046***	0.111	0.189***	0.264
2009	0.001***	0.002	0.017***	0.012	0.007	0.006	0.029***	0.049	0.116	0.123
2010	0.002***	0.003	0.014	0.014	0.012	0.011	0.040***	0.073	0.230	0.225
2008-10	0.002***	0.003	0.018	0.016	0.011	0.009	0.037***	0.072	0.174	0.201

T tests for equality of means are conducted, and the significance levels indicated by *** for 1% alpha, and ** for 10% alpha.

Productivity in alternative technologies

Table 7 presents results from the OLS regressions used to compare output elasticities and returns to scale between CA and conventional farming. A time variable is incorporated to measure disembodied technical change. The models also include a time squared variable that allows for non monotonic technical change (Coeli, et al., 2005). Rainfall region is a dummy variable that controls for rainfall (1 if high rainfall and 0 if low rainfall area). There is evidence of technical progress in CA (46% on average) for the three year panel period. The coefficient on time squared is negative and statistically significant which indicates that the rate of technical change increases at a decreasing rate through time. The time squared coefficient is particularly large in the conventional farming model and as a consequence, mean technical progress in subsequent years rapidly declines for conventional farming.

Time is also interacted with each (log) input variable to allow for non neutral technical change. The positive coefficient of time interacted with land (in CA model) implies that technical change has been land saving. A geometric interpretation of the results is that the Isoquant is shifting inwards at a faster rate over time in the land-intensive part of the input space. This is possibly a results of less land being allocated for production due to input shortages in recent years. There are many instances where farmers leave some of their cropping land fallow due to inadequate access to inputs. Similarly, technical change has also been draft saving, but this is not statistically significant. Coefficients of time interactions with labor, seed, and fertilizer are negative implying factor using technical change for these inputs. These relationships are statistically significant for seed and fertilizer. On the other hand, for conventional farming, technical change has been land (significant) and draft-using, and seed-saving. Direct interpretation of output responses to factors of production will be covered in the proceeding sub-section on elasticities.

Table 7. Translog production functions for CA and conventional farming

OLS regression for CA				OLS regression for non CA			
	Variables	Coefficient	Standard Error	Variables		Coefficient	Standard Error
Land	β_A	-0.307	0.254	Land	β_A	0.956	0.534*
Labor	β_L	0.739	0.337**	Labor	β_L	-0.651	0.621
Draft Animal	β_K	-1.023	0.488**	Draft Animal	β_K	2.292	0.741***
Seed	β_S	0.008	0.305	Seed	β_S	-0.532	0.741
Fertilizer	β_F	0.338	0.138**	Fertilizer	β_F	-0.081	0.184
Land*Land	β_{AA}	0.068	0.084	Land*Land	β_{AA}	0.097	0.114
Labor*Labor	β_{LL}	-0.124	0.138	Labor*Labor	β_{LL}	0.203	0.176
Draft*Draft	β_{KK}	0.205	0.348	Draft*Draft	β_{KK}	0.896	0.285***
Seed*Seed	β_{SS}	0.294	0.091***	Seed*Seed	β_{SS}	0.169	0.227
Fertilizer*Fertilizer	β_{FF}	0.022	0.028	Fertilizer*Fertilizer	β_{FF}	0.168	0.031***
Land*Labor	β_{AL}	0.170	0.088*	Land*Labor	β_{AL}	-0.082	0.157
Land*Draft	β_{AK}	-0.131	0.097	Land*Draft	β_{AK}	0.766	0.162***
Land* Seed	β_{AS}	-0.137	0.081*	Land* Seed	β_{AS}	-0.171	0.131
Land* Fertilizer	β_{AF}	0.062	0.031**	Land* Fertilizer	β_{AF}	0.055	0.043
Labor*Draft	β_{LK}	0.127	0.109	Labor*Draft	β_{LK}	-0.468	0.191**
Labor* Seed	β_{LF}	-0.172	0.098	Labor* Seed	β_{LF}	0.001	0.166
Labor* Fertilizer	β_{LS}	0.026	0.036	Labor* Fertilizer	β_{LS}	0.079	0.042*
Draft* Seed	β_{KS}	0.106	0.134	Draft* Seed	β_{KS}	-0.695	0.202
Draft* Fertilizer	β_{KF}	0.060	0.060	Draft* Fertilizer	β_{KF}	-0.088	0.044**
Seed* Fertilizer	β_{SF}	-0.026	0.042	Seed* Fertilizer	β_{SF}	-0.118	0.051**
Land*Time	β_{AT}	0.296	0.062***	Land*Time	β_{AT}	-0.173	0.098*
Labor*Time	β_{LT}	-0.072	0.060	Labor*Time	β_{LT}	0.040	0.090
Draft*Time	β_{KT}	0.096	0.067	Draft*Time	β_{KT}	-0.096	0.085
Seed *Time	β_{ST}	-0.155	0.069**	Seed *Time	β_{ST}	0.259	0.105**
Fertilizer *Time	β_{FT}	-0.111	0.031***	Fertilizer *Time	β_{FT}	0.022	0.025
Time	β_T	2.312	0.321***	Time	β_T	1.183	0.464**
Time*Time	β_{TT}	-0.615	0.100***	Time*Time	β_{TT}	-0.927	0.129***
Draft access	β_{DD}	0.135	0.125	Draft access	β_{DD}	0.310	0.133**
Rainfall region	β_R	-0.231	0.078***	Rainfall region	β_R	-0.211	0.093**
Observations		756				654	
Households		392				405	
R squared		0.800				0.860	
Adj R squared		0.548				0.583	

Stars indicate statistical significance: * for the 10 % significance level, ** for the 5 % significance level, and ***for the 1 % significance level.

Elasticities

Elasticities of output with respect to each of the inputs are calculated as first derivatives of the output with respect to each input:

$$\frac{\partial \ln y}{\partial \ln x_j} = \varepsilon_j = \beta_j + \sum_k \beta_{jk} \ln x_k + \beta_{jt} t \qquad (3)$$

where y is output, x is vector of inputs j, k = 1,…, J inputs, ε_j is input elasticity, t is time period, and β are the parameters from the estimated translog function. Elasticity estimates are evaluated at the mean of the data for the different panel periods. The indicator of returns to scale (RTSC) is calculated from the sum of the input elasticities

$$RTSC = \sum_j \frac{\partial \ln y}{\partial \ln x_j} = \sum_j \varepsilon_j = \sum_j \left\{ \beta_j + \sum_k \beta_{jk} \ln x_k + \beta_{jt} t \right\}. \qquad (4)$$

In table 8, output elasticity with respect to land is negative for CA and positive for conventional farming (but inelastic for both). The negative response to land expansion ceteris paribus in CA seems plausible since CA is best suited to small plots.

Table 8. Elasticities and returns to scale estimates

Technology	Year	Land	Labor	Draft	Fertilizer	Seed	RTSC
CA	2008	-0.147	0.553	-0.830	0.735	0.518	0.829
	2009	-0.153	0.554	-0.845	0.668	0.539	0.763
	2010	-0.137	0.590	-0.747	0.668	0.564	0.938
	2008-10	**-0.146**	**0.566**	**-0.807**	**0.690**	**0.540**	**0.844**
Conventional	2008	0.422	-0.690	2.527	0.692	-1.986	0.965
	2009	0.232	-0.670	2.439	0.448	-1.903	0.547
	2010	0.393	-0.665	2.759	0.623	-1.967	1.144
	2008-10	**0.349**	**-0.675**	**2.575**	**0.588**	**-1.952**	**0.885**

Labor has a positive elasticity in CA, indicating greater returns to labor under CA. This is an interesting result within the context of discussions and debates on the dilemma of high labor requirements but greater returns to labor in CA. Draft is expected to be more important in conventional farming as shown by the positive elasticities compared to negative responses in CA. Output response to fertilizer is positive for both technologies but greater in CA. Output elasticity with respect to seed is positive in CA but negative in conventional farming. Overall, returns to scale is similar in CA and conventional farming (0.84 and 0.89 respectively).

Technical efficiency

Results of the stochastic frontier and inefficiency effects are presented in Table 9. Technology is a dummy variable (1 if CA and 0 if conventional). Holding all other factors constant, a farmer will produce 39% more maize output in CA than in conventional farming (technology coefficient =0.39 and is statistically significant). This indicates greater productivity in CA technology.

Table 9. Stochastic production frontier estimates

Translog Stochastic Frontier Model				Inefficiency Effects Model			
	Variables	Coefficient	Standard Error	Variables		Coefficient	Standard Error
Constant	β_0	2.855	0.497***	Age	γ_{AG}	-0.003	0.013
Land	β_A	-0.076	0.188	Education	γ_E	0.000	0.086
Labor	β_L	0.665	0.2255***	Gender	γ_G	-0.001	0.632
Draft Animal	β_K	0.236	0.299	Asset value	γ_{AV}	-0.003	0.001**
Seed	β_S	0.320	0.233	Draft	γ_D	0.430	0.628
Fertilizer	β_F	0.05	0.078	Time	γ_T	-4.383	1.654***
Land*Land	β_{AA}	0.059	0.054	Time*Time	γ_{TT}	1.389	0.470***
Labor*Labor	β_{LL}	0.055	0.093	Area	γ_A	1.404	0.380***
Draft*Draft	β_{KK}	0.229	0.135	Labor	γ_L	0.263	0.571
Seed*Seed	β_{SS}	0.078	0.079	Region	γ_R	0.009	0.570
Fertilizer*Fertilizer	β_{FF}	0.090	0.015***	Technology	γ_{TC}	0.416	0.730
Land*Labor	β_{AL}	0.185	0.062***				
Land*Draft	β_{AK}	0.143	0.079**				
Land* Seed	β_{AS}	0.023	0.056				
Land* Fertilizer	β_{AF}	0.003	0.021				
Labor*Draft	β_{LK}	-0.028	0.069				
Labor* Seed	β_{LF}	-0.196	0.069***				
Labor* Fertilizer	β_{LS}	0.005	0.021				
Draft* Seed	β_{KS}	-0.112	0.081				
Draft* Fertilizer	β_{KF}	0.049	0.021**				
Seed* Fertilizer	β_{SF}	-0.057	0.023**				
Land*Time	β_{AT}	0.132	0.038***				
Labor*Time	β_{LT}	-0.017	0.047				
Draft*Time	β_{KT}	-0.043	0.050				
Seed *Time	β_{ST}	0.073	0.045				
Fertilizer *Time	β_{FT}	-0.011	0.014				
Time	β_T	1.394	0.231***				
Time*Time	β_{TT}	-0.573	0.091***				
Draft access	β_{DD}	0.244	0.057***				
Rainfall region	β_R	0.001	0.040				
Technology	β_{RT}	0.394	0.048***				
λ		1.916	0.735				
Sigma u		1.232	0.337				
σ^2 v		0.413					
σ^2 u		1.517					
Likelihood ratio		-1549.7					
Observations		1410					
Households		470					

Stars indicate statistical significance: * for the 10 % significance level, ** for the 5 % significance level, and ***for the 1 % significance level.

Technical efficiency predictions are derived from this model. In the inefficiency model, a positive sign indicates that the variable increases inefficiency. In general, demographic factors (gender, education, labor availability) have no effect on inefficiency. Inefficiency is also not affected by the type of technology that farmers use (no statistical significance in technology coefficient). Households with high asset levels are likely to be more efficient. This is expected since higher asset values imply greater availability of farming implements-which translates to more timely and effective farming operations. Farmer efficiency is generally increasing (at a decreasing rate) over time. Farmers operating on relatively large tracts of land are likely to be less efficient. This seems plausible in the context of a production environment characterised by limited inputs-hence increasing land while holding other direct factors (draft and labor) constant will lead to inefficiency in production.

Technical efficiency scores are reported in table 10. Average efficiency levels in both high and low rainfall areas are not statistically different between CA and conventional farming. (70% and 68% in CA, 68% in conventional, in high and low rainfall areas respectively. Just fewer than 25% of household have average efficiency scores below 60%. The majority of households (62% under both technologies) have average efficiency scores of in the range 61-80%. In CA about 16.5% of households achieve technical efficiency levels greater than 80% while 14% of households achieve the same range in conventional farming.

Table 10. Distribution of efficiency scores (percentage of households)

Technology	Year	<0.40	0.41 -0.60	0.61 -0.80	>0.80	TE	N
CA	2008	1.89	21.13	60.00	16.98	0.681	265
	2009	0.69	19.59	64.60	15.12	0.684	291
	2010	1.00	22.50	59.00	17.50	0.687	200
	2008-10	**1.19**	**21.07**	**61.20**	**16.53**	**0.684**	**252**
Conventional	2008	1.29	24.52	63.87	10.32	0.664	155
	2009	0.76	19.70	65.53	14.02	0.684	264
	2010	2.18	21.40	58.08	18.34	0.677	229
	2008-10	**1.41**	**21.87**	**62.49**	**14.23**	**0.677**	**216**

Figure 2a and 2b shows efficiency levels for the alternative technologies in high and low rainfall areas. Technical efficiency tends to vary more in high rainfall areas compared to low rainfall- areas under both technologies.

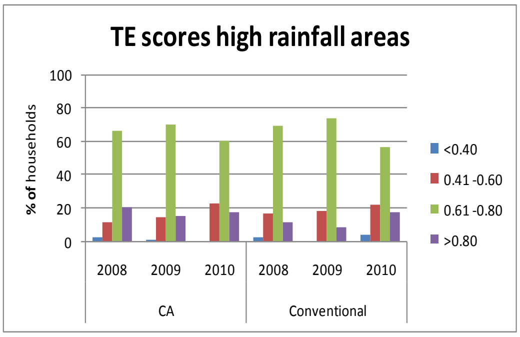

Figure 2a TE scores high rainfall

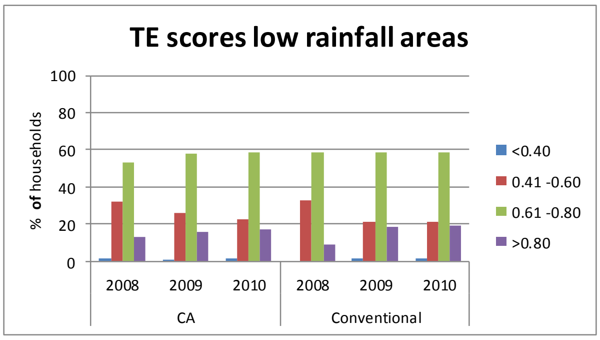

Figure 2b TE scores low rainfall

Section VII. Policy insights

Interesting policy insights can be drawn from these results. First, it is clear that CA results in significant yield gains and significant contributions to food production although it is implemented on small pieces of land. CA is land saving, and this is an important issue for land constrained farmers because they can still have viable food production with limited land. On the other hand, high labor demands in CA present some problems in adoption. NGOs promoting CA commonly target vulnerable farmers such as women famers, the elderly and households affected by HIV/AIDS. NGO targeting of vulnerable households may impact negatively on labor availability for CA practices. There is a need to include better resourced farmers as technology innovators.

CA requires higher quantities of seed and fertilizer. These inputs are not readily available to most small holder farmers hence adoption may be stalled by that fact. However, there are opportunities to counter this problem if CA farmers can achieve a marketed surplus, which can generate money to buy the seed and fertilizer. It is therefore important for functional output markets to be in place to complement technology adoption.

Section VIII. Conclusion

CA technology is implemented in relatively smaller plots than conventional farming. However, there is evidence of significant contribution of CA technology to total maize production amongst households. Our results show that productivity is greater in CA for all inputs except draft. Estimated output elasticities show that positive responses for labor and seed in CA, and negative responses in conventional farming. On the other hand, there are negative responses to land and draft in CA. Fertilizer has a greater positive response in CA than in conventional farming. Overall returns to scale are similar for CA and conventional farming. There is also evidence of technical progress in CA for the three year panel period. Technical progress has been land-saving but seed and fertilizer-using in CA, while land-using and seed-saving in conventional farming. Joint frontier estimates indicate greater productivity gains in CA (39% more than conventional farming-ceteris paribus). Technical efficiency levels are generally the same for both technologies. The majority of farmers achieve efficiency scores in the 60-80% range under both technologies.

Some limitations to this study include the short panel period, which limits observing long term trends, as well as the unavailability of price information to do a more complete economic analysis. It would also be interesting to look at adoption intensity, in terms of what components of CA are being practiced more and the relationship to efficiency and productivity gains.

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