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Agrekon

Agricultural Economics Research, Policy and Practice in Southern Africa



ISSN: 0303-1853 (Print) 2078-0400 (Online) Journal homepage: www.tandfonline.com/journals/ragr20

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To cite this article: Clifton Makate, Rongchang Wang, Marshall Makate & Nelson Mango (2017) Impact of drought tolerant maize adoption on maize productivity, sales and consumption in rural Zimbabwe, *Agrekon*, 56:1, 67-81, DOI: [10.1080/03031853.2017.1283241](https://doi.org/10.1080/03031853.2017.1283241)

To link to this article: <https://doi.org/10.1080/03031853.2017.1283241>



Published online: 16 Feb 2017.



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Impact of drought tolerant maize adoption on maize productivity, sales and consumption in rural Zimbabwe

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ABSTRACT

Increased frequency of droughts (especially mid-season dry spells), higher than normal temperatures and altered patterns of precipitation and intensity are some of the extreme weather events evident in southern Africa. These extreme weather events present a threat to livelihoods and sustainability of agricultural production in the region. However, several climate-smart agricultural technologies (including drought-tolerant maize) believed to offer adaptation to climate variability in maize-based farming systems have been widely adopted. Moreover, empirical work on these technologies is limited. This paper demonstrates how by adopting drought-tolerant maize, a climate-smart agricultural technology impacts on the quantities of maize produced, sold and consumed in Zimbabwe. Using primary data on smallholder farmers collected in 2011 in Zimbabwe's four districts, we employed propensity score matching techniques to construct a suitable comparison group and calculate the average treatment effect on the treated sample. We find that, the adoption of drought-tolerant maize (DTM) in rural Zimbabwe significantly enhances overall maize productivity and consequently the quantities set aside for sale and personal household consumption. Our study therefore suggests that, systematic expansion of climate-smart agricultural technologies such as adoption of drought-tolerant maize can significantly improve maize yields, sales and consumption in rural Zimbabwe. Our empirical results, robust to sensitivity checks, strongly point to the overall importance of DTM adoption in Zimbabwe. The findings from this paper also have very important implications for overall efforts on the promotion of climate-smart agriculture technologies in Africa and other developing countries.

ARTICLE HISTORY

Received 20 May 2016
Accepted 11 November 2016

KEYWORDS

Climate variability and change; drought-tolerant maize; productivity and livelihood outcomes; propensity score matching; smallholder farmers

1. Introduction and background

Agriculture in the developing world must undergo a substantial transformation to meet the related challenges of food security and climate change. The effects of climate change have never been as obvious and intense as in recent years (Siopongco, 2013).

A wide range of literature has documented many ways through which climate change has adversely impacted the lives of many people in southern Africa. First, climate variability and change has mainly manifested itself in the form of higher than average normal temperatures, altered patterns of precipitation and intensity, increased frequency of extreme events such as

droughts (especially mid-season droughts) and floods (Archer *et al.*, 2007, Arslan *et al.*, 2014, Field *et al.*, 2014). These changes are reportedly associated with significant reductions in crop yields, elevated agricultural risks, and subsequent increases in chronic poverty, as well as food and nutrition insecurity. Second, climate variability and change pose a huge risk to livelihoods in the region given that the majority of the population, especially rural households, rely on agriculture as their main source of livelihood (Archer *et al.*, 2007). In Zimbabwe, for example, agriculture contributes significantly to livelihoods especially among the rural dwellers which make up nearly 70% of Zimbabwe's population (ZIMSTAT, 2012). Precisely, for these rural dwellers agriculture and farming is an integral part of their social, economic and environmental well-being. On the macro-economic front, agriculture also contributes significantly to overall gross domestic product (GDP), livelihoods, food, income and nutrition security (Juana & Mabugu, 2005). Furthermore climate variability and change also present a severe threat to livelihoods. This is because many households rely on rain-fed agriculture, thus making them more vulnerable (Runge *et al.*, 2004). According to Rockstrom (2000) the effects of climate variability and change are worse in southern Africa, including Zimbabwe. These risks are made worse because of weak institutional capacities, limited know-how, inadequate technical skills and financial resources necessary for disaster management. Also poor production techniques including incompetent policies regarding the use of agricultural chemicals such as fertilisers has further exacerbated the situation (Clay *et al.*, 2003).

With the recognition of climate variability and change effects on farming and livelihoods, many of the programmes from the government, non-governmental organisations and research institutions have been initiated that specifically target smallholder agriculture. In Zimbabwe and other southern African countries, such programmes have been targeted to building resilience in significant agricultural value chains such as staple cereal maize. Maize is the staple cereal and most important crop for Zimbabwe. However, production and productivity of the crop are largely influenced by severe fluctuations in climate in southern African (Fisher *et al.*, 2015). Frequent droughts have often been cited as the cause of deterioration in yield and production outputs in Zimbabwe (Abate *et al.*, 2015). According to the International Maize and Wheat and Improvement Centre (CIMMYT), approximately 25% of the maize crop suffers frequent drought, with losses of up to half the harvest (Abate *et al.*, 2015). However, programmes are continuously being developed to improve household adaptive capabilities to the ever-changing climatic conditions. Agricultural experts and policy makers among other stakeholders concerned with rural livelihoods, poverty alleviation and food security have recommended the adoption of climate-smart agriculture¹ (CSA) and its associated technologies as a means of diminishing the likely effects of climate change on smallholder farming practices (Nhemachena & Hassan, 2007; Hassan & Nhemachena, 2008; FANRPAN, 2012; Lipper *et al.*, 2014; NEPAD, 2014)

One of the most popular climate-smart maize farming system technologies that have become widespread among smallholder farmers in Zimbabwe is that of improved maize varieties, i.e., drought-tolerant maize (DTM). DTM is a product of a project (Drought-tolerant Maize for Africa) that has released more than 160 drought-tolerant maize varieties between 2007 and 2013. The project covers Zimbabwe and another 12 African countries (Angola, Benin, Ethiopia, Ghana, Kenya, Malawi, Mozambique, Nigeria, Tanzania, Uganda and Zambia). More information on DTM can be found in Abate *et al.* (2015) and Fisher *et al.* (2015).

DTM is considered climate-smart since its adoption can potentially improve maize yields, the resilience of maize farming systems and most importantly the promotion of food security in Zimbabwe. Moreover, DTM is free from genetic modification and has additional traits such as disease resistance to major maize diseases, high protein content and high efficiency in nitrogen utilization (Fisher *et al.*, 2015). In addition, DTM varieties are believed to build resilience in maize farming systems through reducing the need for harmful post-failure coping strategies, such as reducing food consumption, borrowing, taking children out of school and selling household assets. According to Rovere *et al.* (2014) DTM varieties are mostly expected to build resilience through increasing yields and reducing vulnerability. Numerous DTM seed varieties have been released since 2007 with suitability to different agro-ecological regions in Zimbabwe (see Abate *et al.*, 2015).

Since nearly two-thirds of Zimbabwe comprises arid and semi-arid farming land (Abate *et al.*, 2015), the adaptation to climate variability and change in maize-based farming systems through the adoption of DTM varieties is a welcome initiative. Farming households are expected to be more resilient to drought-related crop failures and subsequent effects. Despite, the relevance of DTM varieties to developing countries like Zimbabwe, which are susceptible to erratic weather patterns, empirical research assessing the impacts and benefits of adopting DTM varieties in smallholder farming communities is surprisingly scarce. Probably this is due to lack of socio-economic research in this area as most emphasis is still being put on the biophysical work. Assessing progress made by farmers who have adopted the technology already and sharing their experiences is one way to improve adoption and impact. Previous DTM-based studies in Africa have mainly focused on examining the determinants of DTM adoption (Fisher *et al.*, 2015; Fisher and Carr, 2015). Rovere *et al.* (2014) utilised an economic surplus method to predict the size of the impact of DTM technologies in 13 countries in eastern, southern and western Africa. However, none of these studies have examined the ex-post impact of DTM on maize productivity and household livelihoods.

Against this background, the primary goal of this paper is to examine the impact of DTM adoption by smallholder farmers in four districts of Zimbabwe; namely, Goromonzi, Mudzi, Hwedza and Guruve. We focus on inspecting the effect of DTM adoption on selected outcome variables such as maize productivity, consumption and maize quantities set aside for future sales. Our contribution is threefold. First we use a unique cross-sectional, household-level dataset collected in the four Zimbabwe districts named above. Second, we utilise propensity score matching techniques to create a suitable comparison group and calculate the average treatment effects of adopting DTM seed varieties on maize productivity and consequently, quantities for future sales and personal consumption. Third, we contribute to the very thin literature on the evaluation of DTM technologies and create awareness of their importance on farmer livelihoods in Africa. To the best of our knowledge, this study is one of the first papers to examine the impact of DTM in a country like Zimbabwe which relies heavily on agriculture and on maize as the main staple crop. The rest of the paper is organised as follows: section 2 presents the empirical model followed by a description of the study sites in section 3 while section 4 deals with the research methodology followed by a variable description and the summary statistics in section 5. Section 6 gives the results and discussions whilst conclusions and recommendations are presented in section 7.

2. Empirical model

Our empirical model seeks to estimate the impact of adopting climate-smart agriculture (CSA) technologies such as the growing of drought-tolerant maize seed varieties (DTM) on smallholder farm productivity measured by per capita maize production and yields per hectare and on livelihood outcomes measured by quantities of maize set aside for personal consumption and future sales in Zimbabwe. We seek to estimate the average treatment effect (ATT). Since one can only observe whether an individual participated or never participated, it is usually the case in observational studies to randomly assign individuals to either treatment (adopters) or control (non-adopters) groups to successfully estimate the ATT. However, since we use cross-sectional survey data instead of experimental data, assignment into treatment is not randomly distributed. This observation implies that the outcomes for adopters and non-adopters might be systematically different (Smith & Todd, 2005). As highlighted in Mapila *et al.* (2012) and Akinola and Sofoluwe (2012), the observed differences between the two groups in the absence of randomization might be mistaken for the impacts of DTM.

To address the potential self-selection bias mentioned above, we rely on propensity score matching (PSM) techniques to estimate the average treatment effect (ATT). ATT has been shown to be a better indicator for measuring the appropriateness of intervention strategies on smaller groups of interest such as smallholder farmers than the population-wide average treatment effects calculated via probit models (Rosenbaum and Rubin, 1983, 1985; Heckman, 1995; Rosenbaum, 2002). Numerous studies in the agriculture economics literature have relied on PSM to control for self-selection

bias (Faltermeier and Abdulai, 2009; Akinola and Sofoluwe, 2012; Amare *et al.*, 2012; Mapila *et al.*, 2012; Matchaya and Perotin, 2013). In essence, the PSM technique assumes that each farmer belongs to either the group of DTM adopters (treatment) or group on non-DTM adopters (control/comparison group) but not both. Borrowing some of the terminologies in Heckman *et al.* (1997), let Y_1 denote the productivity or livelihood outcome of a farmer i after adopting DTM ($T = 1$) and Y_0 denoting the productivity or livelihood outcome of the same farmer when they do not adopt DTM ($T = 0$). The observed productivity or livelihood outcome Y can thus be calculated as follows:

$$Y = TY_1 + (1-T)Y_0 \quad (1)$$

where Y_1 is the productivity or livelihood outcome of farmer i when they adopt DTM ($T = 1$); Y_0 is farmer i 's productivity or livelihood outcome when they do not adopt DTM ($T = 0$). The average treatment effect on the treated (ATT) can be calculated as follows:

$$ATT = E(Y_1 - Y_0 | T = 1) = E(Y_1 | T = 1) - E(Y_0 | T = 1) \quad (2)$$

In equation (2) above, the only observable productivity or livelihood outcome is for those farmers who adopted DTM $E(Y_1 | T = 1)$ and not the productivity or livelihood outcome of non-adopting DTM farmers $E(Y_0 | T = 1)$. As mentioned earlier, we match DTM adopting farmers to non-adopting farmers via PSM. Central to PSM is the conditional independence assumption which assumes random participation conditional on observed covariates (Wooldridge, 2002). Assuming that the conditional independence assumption is satisfied, the ATT can then be specified as follows:

$$ATT = E(Y_1 - Y_0 | X, T = 1) = E(Y_1, | X, T = 1) - E(Y_0 | X, T = 1) \quad (3)$$

As suggested in Rosenbaum and Rubin (1983), matching the DTM adopting farmers to the non-adopting farmers based on the observed covariates X might potentially result in the curse of dimensionality problem especially when the number of covariates is large (Rosenbaum and Rubin, 1983). Following Rosenbaum and Rubin (1983) we therefore match the treatment group participants to the control group based on the propensity score $p(X)$ and not on the observed covariates. The propensity score is defined as the conditional possibility that farmer i implements a climate-smart agriculture technology (i.e. DTM) and is expressed as follows:

$$p(X) \equiv \text{prob}(T = 1 | X) = E(T | X) \quad (4)$$

where $T = \{0, 1\}$ is the binary indicator representing the treatment group. One important condition that has to be satisfied in PSM is the balancing property. The balancing property expressed as $T \perp\!\!\!\perp X | p(X)$ (Lee, 2011) states that, the conditional distribution of X , given the propensity score $p(X)$ is the same in the DTM adopting and non-adopting groups. In our case, the balancing property is indeed satisfied and the results are shown in Figure 2 later.

Considering the propensity score and the conditional independence assumption, the ATT specified in equation (2) above can thus be rewritten as follows:

$$ATT = E(Y_1 - Y_0 | p(X), T = 1) = E(Y_1, | p(X), T = 1) - E(Y_0 | p(X), T = 1) \quad (5)$$

where the first term on the right-hand side of equation (5) above measures the observable productivity or livelihood outcome of the treated farmers (DTM adopters) and the second term $E(Y_0 | p(X), T = 1)$ measures the productivity or livelihood outcome of the same farmers had they failed to adopt the climate-smart agriculture technology (DTM), the counterfactual.

The PSM technique is a two-step process that involves estimating a probit or logit regression on the first step to calculate the probability $p(X)$ that farmer i is in the DTM adopting group conditional on observed covariates as given in equation (4) above. The covariates vector X includes all the variables associated with DTM adoption. After calculating the propensity score in equation (4) above, the second step involves matching DTM and non-DTM farmers based on the similarities or closeness of

the propensity scores. At this stage, different matching methods can be utilised each resulting in an ATT value that gives the effect of DTM technology on the selected farmer productivity and livelihood outcomes. No specific matching method results in more superior result than the other, but rather it is possible to utilise more than one method as a robustness check (Becker & Ichino, 2002).

In this paper, we utilise the nearest neighbour matching technique, an algorithm that matches each DTM farmer to a non-DTM farmer on the basis of closely similar propensity scores (Becker & Ichino, 2002). To ensure a maximum covariate balance and a low conditional bias, we conduct a one-to-one matching with replacement (Abadie & Imbens, 2006). As a robustness check of our results, we also utilise the kernel matching algorithm to calculate the ATT. This algorithm involves matching all the DTM farmers with a weighted average of all the non-DTM farmers using weights that are inversely proportional to the distance between the two groups' propensity scores (Becker & Ichino, 2002).

PSM methods may be helpful in reducing, but not completely eliminating the potential endogeneity bias between the DTM adoption decision and maize productivity or livelihood outcome measures. Thus, in evaluation studies, estimates from PSM provide insightful information with respect to the direction and strength of the relationships, but not necessarily implying causality (Balsa & French, 2010). To further examine the sensitivity of our results to potential unobserved bias, we computed Rosenbaum bounds (Rosenbaum, 2002). To show their procedure, suppose all the hidden bias is captured by the single variable $B \in \{0, 1\}$. Let γ be the impact of B on the adoption decision. For the case of two matched individuals, Rosenbaum (2002) shows that the ratio of their odds of participation is within the bounds $1/e^\gamma$ and e^γ . In the absence of hidden bias, $e^\gamma = 1$,² and that the odds ratios of participation are equivalent for the matched individuals. Rosenbaum's bounds evaluate the sensitivity of the computed ATTs to any variations in γ . Since our outcome measures are all continuous, we follow DiPrete and Gangl (2004) procedure and progressively increase e^γ . We then report the Wilcoxon signed rank tests for the null hypothesis of the absence of treatment effects. Increasing e^γ widens confidence intervals around the ATT, a reflection of the uncertainty in the ATT in the presence of hidden bias. The level of e^γ at which any chosen $c\%$ confidence interval starts including zero is the critical odds ratio. The higher this odds ratio, the more an unobserved confounder would have to change the odds of adoption to completely change the ATT³ and the more robust our ATT estimate is.

3. Description of the study sites

The data used in this paper is drawn from surveys of smallholder maize farmers in four Zimbabwe districts: Goromonzi, Mudzi, Hwedza and Guruve (Figure 1). A brief description of each of the four districts is given in this sub-section.

Goromonzi district lies on the periphery of Harare. It falls under agro-ecological sub-region IIa that is characterised by an annual rainfall of 750–1000 mm. The area is at least 1000 m above sea level, with temperature range of 21°C–32°C (mean 25°C). Frost occurs infrequently in low-lying areas in July and August. Soil texture ranges from sand to sandy clay. The region is suitable for both intensive cropping and livestock production. The major crops grown in Goromonzi are maize, groundnuts, soya beans and common beans.

Mudzi lies in a semi-arid region with very low potential for maize, soya bean and sugar bean production. The district is linked by a 250-km highway to Harare (the major input and output market). Agro-ecologically, the district lies in natural farming region IV which is a low-potential zone, with a high incidence of droughts and frequent, long mid-season and in-season dry spells (Mango *et al.*, 2014). The predominant soil type is the Ferric Luvisols. Annual mean rainfall ranges between 450–500 mm while the average altitude is 500–900 metres above sea level. Mean annual temperature is 23°C. The staple crops grown in this region are groundnuts and maize in order of importance.

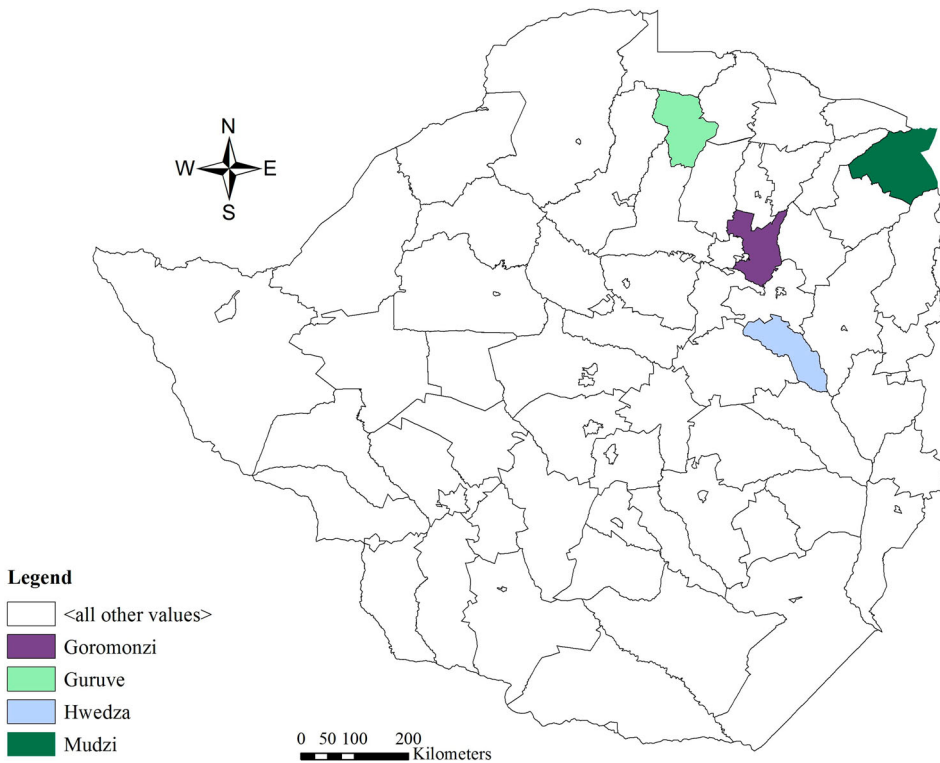


Figure 1. Map of Zimbabwe showing Goromonzi, Guruve, Hwedza and Mudzi districts.

Hwedza district lies 130 km east of Harare at an average altitude of between 900–1100 metres above sea level. The predominant soils are luvisols and cambisols while the mean annual rainfall is 700–800 mm. The major crops grown in Hwedza are maize, groundnuts, tobacco and horticultural crops, e.g., vegetables. The larger area falls in agro-ecological regions IIa and III (i.e., a transitional zone between intensive and semi-intensive farming zone).

Guruve lies in an agro-ecological zone with high potential for maize, soya bean and sugar bean production. The district lies in natural farming region II that is an intensive farming zone. It is linked to two major agricultural markets, Chinhoyi (81 km away) and Harare (151 km away), by excellent all weather tarred roads. The altitude range is 800 metres to 1500 metres above sea level. The main livelihood activity is agricultural crop production with maize being the dominant cereal crop while soya beans and sugar beans constitute the main legume cash crops.

4. Data and sampling

This study utilised cross-sectional household data collected during a survey in four districts of Zimbabwe between October and December of 2011. The simple random technique was used to select wards from a list obtained from the district extension office each of the four districts. Within the selected wards, the interviewed households were randomly chosen from household lists provided by resident agricultural extension officers. A total of 601 households (175 from Goromonzi, 187 from Guruve, 120 from Mudzi and 119 from Hwedza) were then selected for the survey. Data collection was in the form of face-to-face administration of structured questionnaires. Commissioned by the International Centre for Tropical Agriculture (CIAT), the surveys collected data on several characteristics including household composition, cereal and legume crop production and management, household market participation, access to infrastructure, household incomes, ownership of land and non-land

assets, livestock ownership,⁴ and access to agricultural inputs and technologies, extension services and market information. Maize production information was elaborately collected as part of the cereal crop production data and included information on input use in production, land area for growing maize, maize seed types sown (including drought-tolerant maize varieties and local maize varieties), crop management methods used, harvesting methods and harvest received, including post-harvest handling of the maize crop and decisions on use of the harvest at the household level.

5. Variable description and descriptive statistics

Table 1 provides the definitions, means and *t*-test results for the outcome and explanatory variables used in the study.

The data shows that about 68% of the sampled smallholder maize farmers adopted and planted DTM for the period analysed in this study. The initial comparisons of means between the DTM adopters and non-adopters appear to be significantly different for maize productivity and household livelihood outcome measures. In particular, maize output per capita, maize output set aside for household's own consumption and maize output set aside for future sale differed significantly between the two groups. Overall, the *t*-tests reveal very insignificant differences in the characteristics of covariates between the two groups of farmers. Significant differences exist with regards to whether the farmer practised conservation farming or not, whether the farmer grew maize as the major cash crop or not, dummy for asset quintile 1 and dummy variables for mean proportions of farmers from Wedza and Mudzi districts.

6. Results and discussion

The results of our empirical analysis are summarised in Tables 2 and 3. We start with a discussion of the results from the DTM adoption equation followed by the propensity score matching results. In addition, we discuss the results from the sensitivity analysis.

6.1 Factors that influence adoption of drought-tolerant maize varieties

Table 2 presents the results from the DTM adoption equation. We estimate a probit regression model to examine the socioeconomic factors influencing adoption of drought-tolerant maize seed varieties in Zimbabwe's smallholder farmers. Overall, the results show that, being a smallholder farmer practicing conservation agriculture, growing maize, of average wealth and living in drier regions such as Mudzi are some of the factors that significantly influence the adoption of drought-tolerant maize varieties. We briefly discuss the results from the probit regression since our central focus is on the evaluation of the impact of DTM adoption on farm productivity and household livelihood outcome measures.

Smallholder farmers practising conservation agriculture (CA) were found to be among the likely adopters of DTM varieties possibly because of their enlightenment through massive campaigns by various supporters of CA agriculture. Since CA is another climate-smart agriculture practice, we would have expected to see CA farmers to be among the likely adopters of yet another climate-smart technology in DTM. The ultimate goals of these climate-smart technologies are essentially similar, i.e., to increase agricultural productivity, incomes, building resilience and adapting to climate variability and change.

Our results also indicate the importance of wealth as measured by the ownership of the farm and household assets captured by the asset index on the adoption of DTM seed varieties. In our sample, wealthier households are more likely to adopt DTM varieties as opposed to their counterparts. The likelihood associating wealthier households to DTM substantiates well with the usefulness and willingness to invest in appropriate technologies, which is usually a feat for the well-resourced individuals. This result is consistent with the findings of Nkala *et al.* (2011) who in their studies found wealthier households to be amongst the likely adopters of CA as opposed to relatively poor households.

Table 1. Descriptive statistics of variables used in the analysis.

Variable	Description and measurement	DTM	Non-DTM	t-test	Full sample
<i>Outcome variables</i>					
ymaize_percap	Maize output per person (kg/person)	275.25	197.08	0.02**	250.80
ymaize_yield	Maize yield (kg/ha)	1579.07	1519.39	0.68	1560.40
ymaize_cons	Amount of maize grain for consumption (kg)	860.13	670.73	0.00***	800.88
ymaize_sold	Amount of maize grain for sale (kg)	350.16	191.81	0.05*	300.63
treatment_dtma	Binary variable = 1 if farmer adopted drought-tolerant maize (DTM) seed varieties; 0 otherwise	1.00	0.00		0.69
<i>Covariates</i>					
househ_age	Age of household head in years	51.92	50.36	0.25	51.43
househ_resp_hhead	Binary variable = 1 if respondent was the household head; 0 otherwise	0.56	0.58	0.68	0.57
househ_male	Binary variable = 1 if gender of household head is male; 0 otherwise	0.76	0.74	0.63	0.76
househ_married	Binary variable = 1 if household head is married; 0 otherwise	0.76	0.71	0.17	0.74
househ_size	Size of household	5.42	5.31	0.62	5.39
educ_secondary	Binary variable = 1 if household head reached at least secondary school; 0 otherwise	0.48	0.47	0.75	0.48
emp_farmer	Binary variable = 1 if household's main occupation is farming; 0 otherwise	0.87	0.86	0.74	0.87
ca_farmer	Binary variable = 1 if farmer practices conservation agriculture; 0 otherwise	0.33	0.25	0.04**	0.31
grow_maize	Binary variable = 1 if farmer grows maize as major cash crop; 0 otherwise	0.84	0.64	0.00***	0.78
agric_extension_freq	Extension service frequency	3.99	4.41	0.55	4.12
agric_credit	Binary variable = 1 if farmer has access to agricultural credit; 0 otherwise	0.11	0.13	0.63	0.12
dist_market	Distance to the nearest main maize market in kilometres	99.29	97.52	0.80	98.73
househ_landsize	Size of arable land in hectares	2.40	2.23	0.48	2.34
asset_quintile1	Binary variable = 1 if farmer is in asset quintile 1 (poorest); 0 otherwise	0.17	0.27	0.00***	0.20
asset_quintile2	Binary variable = 1 if farmer is in asset quintile 2; 0 otherwise	0.20	0.20	0.91	0.20
asset_quintile3	Binary variable = 1 if farmer is in asset quintile 3; 0 otherwise	0.20	0.20	0.92	0.20
asset_quintile4	Binary variable = 1 if farmer is in asset quintile 4; 0 otherwise	0.22	0.16	0.15	0.20
asset_quintile5	Binary variable = 1 if farmer is in asset quintile 5 (richest); 0 otherwise	0.22	0.16	0.15	0.20
geo_goromonzi	Binary variable = 1 if farmer lives in Wedza district; 0 otherwise	0.29	0.30	0.81	0.29
geo_guruve	Binary variable = 1 if farmer lives in Mudzi district; 0 otherwise	0.29	0.35	0.15	0.31
geo_mudzi	Binary variable = 1 if farmer lives in Guruve district; 0 otherwise	0.26	0.07	0.00***	0.20
geo_wedza	Binary variable = 1 if farmers lives in Goromonzi district; 0 otherwise	0.16	0.28	0.00***	0.20

Notes: ***Significant at 1% level; **significant at 5% level; *significant at 10% level.

Finally, we find some of the district dummy variables to be associated with adoption of DTM varieties. More specifically, maize farmers living in Zimbabwe's drier regions such as Mudzi district were found to be more likely to adopt DTM as compared to their counterparts. Essentially this is an expected result since smallholder farmers in these regions realise the need to adopt DTM varieties to enhance their chances of adapting to erratic and worsening climatic conditions such as drought (in-season, mid-season and or season-long droughts) by improving yield and reducing vulnerability linked to drought-related harvest failure. Intense DTM seed marketing campaigns are, however, required in all the districts to improve adoption.

6.2 Treatment effects from the propensity score matching methods

The propensity score matching method enables us to investigate how DTM has impacted reported changes in livelihood outcomes. The method uses propensity scores from the first stage results

Table 2. Probit regression estimates for the adoption of drought-tolerant maize.

	Maximum likelihood estimates		Marginal effects	
	Coefficient	Standard error	Coefficient	Standard error
househ_age	0.008	0.005	0.002	0.001
househ_resp_hhead	-0.051	0.121	-0.016	0.038
househ_male	-0.311	0.215	-0.098	0.067
househ_married	0.288	0.215	0.091	0.067
househ_size	-0.021	0.024	-0.007	0.008
educ_secondary	0.050	0.140	0.016	0.044
emp_farmer	-0.094	0.177	-0.030	0.056
ca_farmer	0.322*	0.130	0.101*	0.040
grow_maize	0.910***	0.224	0.286***	0.067
agric_extension_freq	-0.001	0.007	-0.000	0.002
agric_credit	0.051	0.184	0.016	0.058
dist_market	-0.001	0.001	-0.000	0.000
househ_landsize	-0.012	0.025	-0.004	0.008
2.asset_index	0.440*	0.176	0.146*	0.057
3.asset_index	0.366*	0.180	0.123*	0.059
4.asset_index	0.426*	0.185	0.141*	0.060
5.asset_index	0.503**	0.189	0.165**	0.060
geo_goromonzi	-0.377	0.259	-0.119	0.081
geo_guruve	-0.293	0.251	-0.092	0.079
geo_mudzi	0.583*	0.280	0.183*	0.088
Observations	601		601	
Log-likelihood	-333.1			

Notes: ***Significant at 1% level; **significant at 5% level; *significant at 10% level. All estimates are based on robust standard errors. Asset quintile 1 and Wedza district are the reference categories for asset index and district respectively.

Table 3. Impact of drought-tolerant maize adoption on selected variables.

Variables	Maize output per capita		Maize consumption		Maize sold (kg)		Maize yield	
	NNM	KM	NNM	KM	NNM	KM	NNM	KM
Average treatment effect	113.5*** (36.47)	96.00*** (27.56)	307.3*** (75.41)	253.3*** (65.20)	185.9*** (71.37)	202.0*** (61.33)	330.5* (171.1)	222.7* (124.8)
<i>Mean for outcome variables</i>								
DTM farmer	307.59	282.67	941.94	876.40	366.41	366.41	1741	1617
Non-DTM farmer	197.08	197.08	670.73	670.73	191.81	191.81	1519	1519
Observations	532	582	532	582	582	582	532	582

Notes: ***Significant at 1% level; **significant at 5% level; *significant at 10% level. Standard errors for the ATT in parentheses are calculated using bootstrapping. NNM = nearest neighbour matching method; KM = kernel matching method.

presented in Table 2 to generate samples of matched DTM and non-DTM groups using nearest neighbour and kernel matching methods. We impose the common support condition in the estimation by matching in the region of common support. Figure 2 shows the distribution of propensity scores and the region of common support. The bottom half of the figure shows the propensity scores distribution for the non-treated, while the upper-half refers to the treated individuals. The densities of the scores are on the vertical axis. The figure indicates that the common support condition is satisfied as there is overlap in the distribution of the propensity scores of both treated and non-treated groups. Propensity score matching results are presented in Table 3. Precisely, Table 3 presents impact estimates of adopting DTM seed varieties on changes in maize productivity, maize quantities set aside for consumption and for sale. Our primary matching method is the nearest neighbor algorithm. For robustness checks, we also present the results from the kernel matching algorithm. Both matching methods show a very strong and significant impact of DTM on our outcome measures. All the reported average treatment effects (ATT) are based on observations in the region of the common support and bootstrapped standard errors with 500 replications. For the nearest neighbour method, we utilise a caliper of size 0.00431 while for the kernel

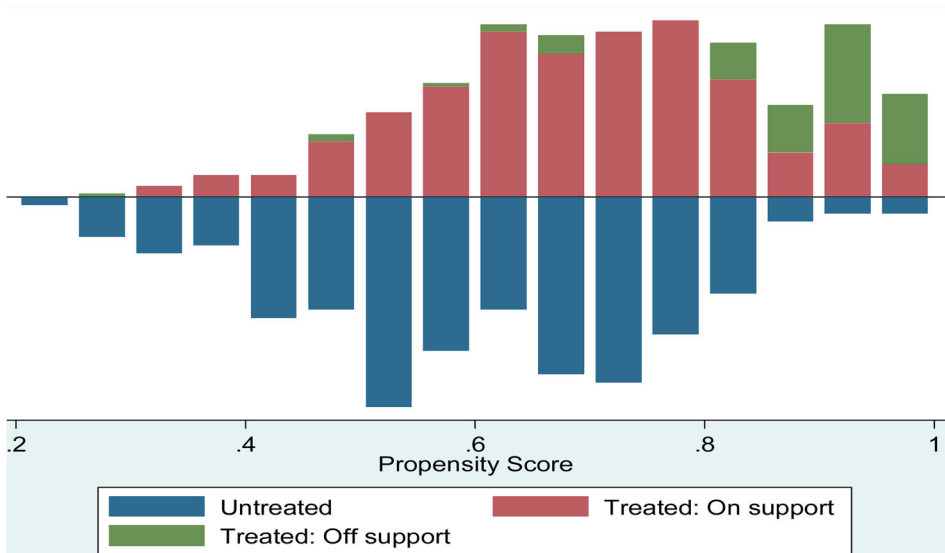


Figure 2. Distribution of propensity scores and the common support condition.

method we choose a bandwidth of 0.05. It is important to note that, our results are robust to different caliper and bandwidth sizes.

We estimate the impact of DTM on yield, per capita production and grain set aside for future sale and consumption. We include per capita output, consumption as well as maize sold to assess the possible changes in household food security and incomes associated with DTM adoption. Our results indicate a positive and very strong impact of adopting DTM varieties on maize production per capita and yield, the amount of maize grain set aside for future sale and amount of maize grain set aside for future consumption. After controlling for farmer socioeconomic and institutional characteristics, nearest neighbour matching results, show a positive significant impact of DTM varieties adoption on both maize productivity and household livelihood outcome indicators when compared to non-DTM adopters. More precisely, the nearest neighbour results show that the ATT was: 113.5 kg on maize output per capita, 307.3 kg on amount of maize grain set aside for household's own consumption, 185.9 kg on amount of maize grain set aside for future sales and 330.5 kg on maize yield are all significant at 1 per cent, and 10 per cent respectively.

The results from the kernel matching method are consistent with the nearest neighbour method and essentially tell the same story. The fact that the results from the two matching methods are not very different implies the robustness of our findings. Overall, the results obtained demonstrate the importance of going climate-smart in smallholder agriculture especially with the continuous and evident effects of climate variability and change. Adoption of drought-tolerant maize being one of the climate-smart agricultural technologies available for smallholder farmers in Zimbabwe have shown to have a positive impact on maize productivity and household welfare. Maize output per capita is a proxy measure of productivity that considers the number of individual members within each household. It suffices to infer that the adoption of climate-smart agriculture technologies such as drought-tolerant maize can potentially have significant impacts on maize output per household capita. Consequently, this increases food security within the household. A positive and statistically significant impact on maize yield highlights the observation that DTM not only reduces total harvest failure of the maize crop associated with drought stress, but can also improve its productivity.

Market participation, particularly intensity of market participation (measured by the amount of grain sold by market participants) amongst maize producers, is also another important aspect as it has a direct positive bearing on income and distribution of the crop. Our results show a positive

impact on the amount of grain set aside for future sale by the farmer which signifies that adopters of DTM varieties are more likely to sell more on the market than non-DTM adopters. This has a positive bearing on the farmer's income collected from maize grain sales *ceteris paribus*. Moreover, it can also signify the availability of surplus in maize output considering that households usually consider the household's food requirements first before deciding which portion of the harvest to sell *ceteris paribus*. The significant impact of DTM on the amount of maize grain from harvest set aside for sale therefore illustrates how important climate-smart agricultural technologies such as DTM can be on the livelihood implications of the farming household (through anticipated income from the sale of surplus) and other households through exchange on the maize market.

Maize output set aside for household's own consumption communicates access, availability and utilization of the staple cereal (maize) which can be a good proxy for household food security. Food security is recognised as a composite condition for the four key pillars of food which are access, availability, utilisation and stability (Clay, 2002; Mango *et al.*, 2014). These dimensions are closely interlinked and are all considered necessary. This finding means that *ceteris paribus*, adoption of climate smart agricultural technologies such as DTM can positively impact food security of the household. This is possible mainly through the reduced possibility of total crop failures of the maize crop (in the case of adverse droughts) due to the adoption of drought-tolerant maize. If adopting DTM varieties increases the amount of food (maize) set aside for future consumption then it also has important implications for resilience of the household's food (maize) stocks. All factors being constant, a household with more maize grain stored for future consumption in one season will be in a better position to adapt to shock in the next season say if the crop is attacked by diseases or pests. Thus, DTM adoption will have long-term effects on consumption smoothing especially in these relatively poor and drought-prone regions.

6.3 Propensity score matching (PSM) – balancing properties

To assess the quality of the matching process, we present the results from the balancing properties of the propensity score matching method in Table 4 as well as the corresponding reductions in observable differences in the baseline characteristics between the treated farmers (DTM) and non-treated farmers (non-DTM). These tests are only reported for the nearest-neighbour matching method, our main matching algorithm. These tests are critical for checking the similarities between the control and treatment in terms of observable characteristics. Table 4 shows the overall means for the treatment and control groups for the matched and unmatched samples. It is clear that balancing tests examine the percent reduction in the standardised bias achieved to attain an overall balance in the distribution of the means of covariates in both groups of DTM variety adopters and non-adopters. If matching is successful, the differences in means between the two groups should be insignificant after matching. The results in Table 4 show that nearly all the differences in observable variables between DTM variety adopters and non-adopters are all statistically insignificant except for frequency of agriculture extension services variable which is significant after the matching. Overall, the balancing test reveals that the estimated propensity score balanced the observable characteristics between the treatment and group very well.

Results of the quality assessment of the matching process suggest that the propensity score for the two groups of farmers (DTM adopters and non-DTM adopters) was balanced. Reduction in the standardised bias is substantially reduced after the matching process.

6.4 Sensitivity analysis: Rosenbaum bounds

To check the sensitivity of our results, we conducted Rosenbaum bounds analysis to assess the extent to which an unmeasured covariate would have to influence the adoption of DTM decision to undermine the findings of the propensity score matching. The sensitivity analysis results reveal that for

Table 4. Balancing tests for all matching covariates.

Variable	Sample	Mean		Standardised bias		<i>t</i> -test <i>p</i> -values
		DTM	Non-DTM	% bias	% reduction in bias	
househ_age	Unmatched	51.92	50.36	10.0		0.25
	Matched	51.37	51.14	1.5	85.20	0.85
househ_resp_hhead	Unmatched	0.56	0.58	-3.6		0.68
	Matched	0.56	0.53	5.3	-45.00	0.49
househ_male	Unmatched	0.76	0.74	4.2		0.63
	Matched	0.77	0.76	1.3	67.80	0.86
househ_married	Unmatched	0.76	0.71	12.0		0.17
	Matched	0.76	0.78	-3.3	72.50	0.65
househ_size	Unmatched	5.42	5.31	4.2		0.62
	Matched	5.37	5.45	-3.2	25.30	0.68
educ_secondary	Unmatched	0.48	0.47	2.7		0.76
	Matched	0.49	0.49	1.2	57.70	0.88
emp_farmer	Unmatched	0.87	0.86	2.9		0.74
	Matched	0.86	0.88	-7.7	-162.50	0.31
ca_farmer	Unmatched	0.33	0.25	18.5		0.04
	Matched	0.31	0.35	-9.6	48.20	0.23
grow_maize	Unmatched	0.84	0.64	46.7		0.00
	Matched	0.82	0.80	4.1	91.20	0.56
agric_extension_freq	Unmatched	3.99	4.41	-5.2		0.55
	Matched	3.98	2.28	20.9	-302.80	0.00
agric_credit	Unmatched	0.11	0.13	-4.2		0.63
	Matched	0.13	0.12	4.5	-4.90	0.56
dist_market	Unmatched	99.29	97.52	2.1		0.80
	Matched	94.55	94.93	-0.4	78.50	0.95
househ_landsize	Unmatched	2.40	2.23	5.6		0.48
	Matched	2.26	2.11	5.1	8.70	0.43
asset_quintile 2	Unmatched	0.20	0.20	1.0		0.91
	Matched	0.20	0.22	-4.4	-319.30	0.57
asset_quintile 3	Unmatched	0.20	0.20	-0.9		0.92
	Matched	0.21	0.23	-6.5	-630.70	0.41
asset_quintile 4	Unmatched	0.22	0.16	12.9		0.15
	Matched	0.21	0.16	13.3	-3.40	0.08
asset_quintile 5	Unmatched	0.22	0.16	12.9		0.15
	Matched	0.21	0.18	8.1	36.80	0.29
geo_goromonzi	Unmatched	0.29	0.30	-2.1		0.81
	Matched	0.34	0.31	5.1	-138.80	0.52
geo_guruve	Unmatched	0.29	0.35	-12.4		0.15
	Matched	0.34	0.34	0.6	95.00	0.94
geo_mudzi	Unmatched	0.26	0.07	53.0		0.00
	Matched	0.13	0.15	-4.9	90.80	0.51

most of our outcome variables, an unobserved covariate would have to exhibit a gamma (Γ) between 1.7 and 1.8 for us to question our conclusions of positive and significant ATT effects.

7. Conclusions and recommendations

This paper provides one of the very few assessments of the impact of drought-tolerant maize adoption, a climate-smart technology on livelihood outcomes. More specifically, we examine the extent to which such a climate-smart agriculture technology influence overall smallholder farmer maize productivity and consequently quantities for sale and personal consumption. We utilised the propensity score matching method based on matched observations to isolate the effect of adopting drought-tolerant maize on maize productivity, maize sold and maize consumed. Furthermore, we utilised the Rosenbaum bounds procedures for continuous outcome variables to evaluate the sensitivity of our results to violations of the conditional independence assumption.

The results from our empirical analysis shows that, adoption of climate-smart agriculture technologies such as DTM varieties is associated with significant improvements in maize productivity and

livelihood outcomes of smallholder farmers through increased maize yields, maize output per capita, maize quantities set aside for future sale on the market and amount of maize reserved for household's own consumption. The sensitivity analysis using Rosenbaum's bounds approach indicate that the computed ATTs are not at serious risk of being questionable.

Although this study makes a notable contribution to the current discussions in low-income countries on the importance of climate-smart technologies such as DTM varieties on the livelihoods of people, it is not without its limitations. We certainly acknowledge the fact that propensity score methods fail to balance the unobserved factors and potential confounders (Winkelmayr & Kurth, 2004). Thus, the unmeasured bias may still be present in our estimates. In light of this observation, future studies may focus on extending the analysis to using other robust casual inference techniques. Despite the noted limitations, our study still makes an important contribution to the relevant literature.

Our results thus support the need to push for widespread adoption of climate-smart agricultural technologies, especially drought-tolerant maize, as an adaptation strategy against undesirable maize output due to drought in smallholder maize farming areas of Zimbabwe. Adoption of drought-tolerant maize varieties will be an important alternative to mitigating the possible effects of season long or mid-season droughts on rain-fed maize crops. To a certain extent, our results have reaching implications on food security strategies in Zimbabwe.

Notes

1. Climate-smart agriculture technologies are those technologies that sustainably increases farm productivity, resilience of farming systems, reduces greenhouse gas emissions, and enhance achievement of national and household food and nutrition security and development goals (Lipper *et al.*, 2014)
2. This is the case when the conditional independence assumption holds.
3. We perform this sensitivity analysis using the user written program in Stata, *rbounds* (Diprete & Gangl, 2004).
4. We combined information on ownership of land and non-land assets, livestock ownership and household dwelling characteristics to create a living standards measure, the asset index, using principal components analysis (PCA) (Filmer & Pritchett 2001). The first principal component is then used as an overall measure of living standards. For a detailed and more technical exposition, see McKenzie (2005).

Acknowledgement

The authors would like to acknowledge the financial assistance received from the International Fund for Agricultural Development and International Centre for Tropical Agriculture (CIAT) that was used in carrying out this study.

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