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Climate Smart Agriculture? Assessing the Adaptation Implications in Zambia

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Abstract

We examine a set of potentially climate smart agricultural practices, including reduced tillage, crop rotation and legume intercropping, combined with the use of improved seeds and inorganic fertiliser, for their effects on maize yields in Zambia. We use panel data from the Rural Incomes and Livelihoods Surveys merged with a novel set of climatic variables based on geo-referenced historical rainfall and temperature data to explore the changing effects of these practices with climatic conditions. We estimate the impacts on maize yields, and also on the exhibition of very low yields and yield shortfalls from average levels, as indicators of resilience, while controlling for household characteristics. We find that minimum soil disturbance and crop rotation have no significant impact on these yield outcomes, but that legume intercropping significantly increases yields and reduces the probability of low yields even under critical weather stress during the growing season. We also find that the average positive impacts of modern input use (seeds and fertilisers) are significantly conditioned by climatic variables. Timely access to fertiliser emerges as one of the most robust determinants of yields and their resilience. These results have policy implications for targeted interventions to improve the

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productivity and the resilience of smallholder agriculture in Zambia in the face of climate change.

Keywords: *Climate change*; *climate smart agriculture*; *food security*; *maize yields*; *panel data.*

JEL classifications: *O13, Q01, Q12, Q16, Q18.*

1. Introduction

It is widely accepted that our ability to contain the pace of climate change within the 2°C threshold in the long run is now limited and we will have to deal with the consequences of this at various levels (Rogelj *et al*., 2011, 2013; IPCC, 2014). Global climate models indicate that Sub-Saharan Africa (SSA) will be one of the most affected regions, with expected agricultural yield decreases of up to 20% (for major food crops), and stubbornly high levels of poverty and food insecurity – especially in rural areas (Cline, 2008). In spite of having relatively good rainfall compared to other parts of SSA, Zambia is vulnerable to climate change due to changes in rainfall patterns and extreme weather events (NCCRS, 2010).

In the past 30 years, frequent rainfall anomalies and droughts have been observed in Zambia – especially in the southern and central regions – with resulting decreases in maize yields (Jain, 2007). Although urban poverty has decreased in the last 20 years, rural poverty has remained around 80% while the proportion of the population which is malnourished has increased by 23% since 1990 (Garrity *et al*., 2010; Chapoto *et al*., 2011). Most of the rural poor (75% of total farming population) are subsistence farmers who rely on rainfall for production (Jain, 2007). Climate smart agriculture (CSA) seeks to sustainably increase agricultural productivity and incomes by adapting and building resilience to climate change and reducing and/or removing greenhouse gas emissions relative to conventional practices (FAO, 2013). Site specific and rigorous analyses are needed to identify potential practices for a successful CSA strategy under various climatic conditions.

Most studies on climate change and productivity in Zambia have been based on simulations, which lack detail at the household level or on cross-sectional data lacking detail on climate variables. In contrast, we use large-scale household panel data from the Rural Incomes and Livelihoods Surveys (RILS) together with a novel set of climatic variables based on geo-referenced data on historical rainfall and temperature as well as soil characteristics to assess the impacts of potential CSA practices on maize yields in Zambia.

The potential CSA practices we consider are minimum soil disturbance (MSD), crop rotation and legume intercropping. We also consider the impact of the use of inorganic fertilisers and improved maize seeds on yields. Any of these practices are considered potentially CSA, based on their potential to contribute to increased productivity and incomes, adaptation and/or reduced GHG emissions from agriculture. Other practices with a CSA potential but not covered by the RILS data include (*inter alia*) agro-forestry, improved livestock/grazing management, and joint crop-livestock systems (FAO, 2014). In this paper we focus on maize yields, given the importance of the crop for the food security and incomes of smallholders in Zambia.

CSA practices affect both the levels and the variability of production through improvements in the capacity to cope with extreme weather events (e.g. droughts or late onset of rains). Empirical research on the effects of various practices on the probability of disastrous yield shortfalls is mostly absent from literature to date, a gap we address here. Since maize is a major food source for smallholders in rural Zambia, our analyses of the probability of low production are also relevant for the availability and stability dimensions of food security.[2]

We provide an overview of climate change, agriculture and food security in Zambia in the next section, before briefly reviewing the literature to date on our CSA practices in section 3. Section 4 outlines our data sources and provides descriptive statistics. We briefly explain our empirical methodology and independent variables in section 5; discuss results in section 6 and conclude with policy implications in section 7.

2. Agriculture, Food Security and Climate Change in Zambia

The agricultural sector in Zambia accounts for approximately 20% of GDP (ZDA, 2011; World Bank, 2013). 64% of Zambians live in rural areas where rain-fed subsistence agriculture is the dominant economic activity (Govereh *et al.*, 2009). Maize is the most important staple crop; over half the calories consumed in Zambia are from maize, although this proportion is decreasing (Dorosh *et al.*, 2009).

Despite rapid economic growth over the last decade, driven primarily by an expansion of mining, poverty levels are very high especially in the rural areas (around 80%; Chapoto *et al.*, 2011). 75% of Zambians earned equal to or less than USD 1.25 per day (World Bank, 2013). Agricultural commercialisation and surplus production are concentrated in the hands of a small proportion of farmers, while over half of Zambian farmers sell little or no crops, strengthening the link between productivity and food security (Hichaambwa and Jayne, 2012).

Predicted impacts of climate change in Zambia differ between the country's three agro-ecological regions (AER), defined mainly by rainfall (Figure 1). In the western and southern parts of the country (AER I), rainfall has been low, unpredictable and poorly distributed for the past 20 years, despite historically being considered a good cereal cropping area (Jain, 2007). The central part of the country (AER IIa & b) is the most populous and has the highest agricultural potential, with well distributed rainfall and fertile soil. The northern part of the country (AER III) receives the highest rainfall but has poorer soils. About 65% of this region is underutilised (Jain, 2007). Despite considerable agricultural potential, Zambia's maize harvest fails to meet national market demand in 1 year in three on average (Dorosh *et al.*, 2009).[3]

The dominance of rainfed agriculture in Zambia means that climate change poses a considerable challenge. Droughts in the 1991/1992, 1993/1995, 2001/2002 and 2004/2005 seasons had significantly large negative impacts on yields and consequently on food security (FAOSTAT, 2012). Global climate models predict that temperatures will increase in Southern Africa by 0.6–1.4°C by 2030 (Lobell *et al.*, 2008). Rainfall predictions are more ambiguous, with models suggesting either reduced or increased precipitation (Lobell *et al.*, 2008). Crop yields in the region are predicted to suffer, especially if rainfall is reduced, with maize yields predicted to fall by 30% in the

[2]In our dataset, around 60% of households did not sell any maize in both years, 54% did not buy any maize grain and around 88% did not buy maize meal. Given these numbers, household's own production addresses a significant part of the availability dimension of food security.

[3]Maize harvests in Zambia have exceeded national demand since 2009 (after the period covered by the data used in this paper) owing mainly to favourable rainfall and the government's input subsidy programme (Tembo and Sitko, 2013).

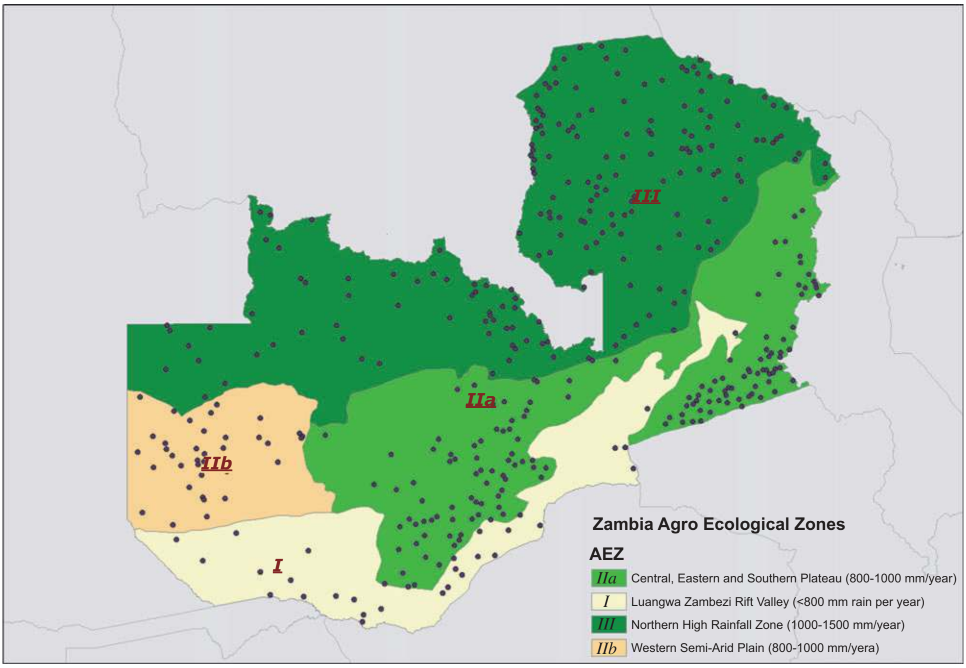

Figure 1. Agro-ecological regions (AER) of Zambia and Rural Incomes and Livelihoods Survey sites

absence of adaptation (Lobell *et al*., 2008; Müller and Robertson, 2014). Zambia-specific models predict decreased rainfall in AER I, IIa and IIb and increased rainfall in AER III, as well as significant warming in AER I (Kanyanga *et al*., 2013). Projected maize yield losses in Zambia are concentrated in regions where most of the maize production now takes place (Southern and Eastern provinces), underlining the importance of understanding how climate change affects yields and conditions the impacts of CSA practices (Kanyanga *et al*., 2013).

The impact of climate change on crop production is not limited to total rainfall and average temperature effects: intra-seasonal shocks are also important. A 'false start' to the rainy season due to erratic rainfall can be disastrous for crop establishment. Similarly, intra-seasonal dry spells may be more damaging to growth than low total rainfall (Tadross *et al*., 2009; FAO, 2011a). Very high maximum temperatures during the growing season are also significantly detrimental to yields (Thornton and Cramer, 2012). Such temporal variation is predicted to increase in many parts of Africa under most climate change scenarios (Boko *et al*., 2007).

The Government of Zambia has been promoting various agricultural practices to improve food security. One of the most important (and controversial) of these policies is the input subsidy programme, which takes around 60% of the Ministry of Agriculture's budget (Mason and Jayne, 2013). GRZ has implemented input subsidy programmes in some form since 1997 (the Fertilizer Support Programme (FSP) being the latest) with the stated goal of improving food security and reducing poverty. In spite of the long history and the scale of resources, rural poverty rates remain high (Mason *et al*., 2013). Mason *et al*. (2013) provide a detailed overview of the performance of FSP targeting of and response rates to fertilisers and conclude that most inputs are received by larger-scale farmers that are above the poverty line. In this paper we do not focus on the FSP *per se*, but investigate the impacts of improved seed and inorganic fertiliser use more generally on productivity and the probability of productivity falling below a threshold under various climatic conditions.[4]

Conservation agriculture (CA; including MSD, crop rotation and legume intercropping as well as residue retention) is another practice that has been promoted as an official priority of the Ministry of Agriculture and Livestock (MAL) since the 1990s with extensive support from international agencies (Baudron *et al*., 2007; Mazvimavi, 2011).[5] Most CA promotion programmes have also included subsidised fertiliser and seed packages. Adoption of the full CA package consisting of MSD, crop rotation and legume intercropping has been very low and unstable in most parts of the country, as the existing technologies being promoted within this package are more suitable to the low-rainfall regions with high rainfall variability (Haggblade and Tembo, 2003; Ngoma *et al*., 2014). Given these high levels of non-adoption of CA practices, their effects on yield levels and variability deserve attention, especially under different climatic conditions using large datasets (Arslan *et al*., 2014). Most literature on the impacts of CA is based on either experimental plots or data from small samples of farmers who have participated in related promotion activities, providing only suggestive evidence. We review this gap in the literature in more detail in the next section.

3. Productivity Implications in the Literature

Productivity implications of inorganic fertilisers and improved seeds are well known from the large body of literature on the impacts of green revolution technologies, and therefore are not reviewed here in detail (Desai, 1990; Byerlee *et al*., 1994; Evenson, 2003; Smale and Jayne, 2003). Other practices analysed in this paper (minimum tillage, legume intercropping and crop rotation) are associated with CA, which we review here with the more general literature on sustainable land management.

3.1. Productivity implications in general

There are a number of meta-studies which attempt to quantify the average (environmental and yield) benefits of practices associated with CA. Lal (2009) reviewed the literature on soil conservation globally and concluded that mulching and no-till clearly

[4]Around 60% of farmers who used inorganic fertilisers in our sample acquired it from channels other than FSP.

[5]Conservation Agriculture is promoted as Conservation Farming (CF) in Zambia in a package consisting of: (i) reduced tillage on no more than 15% of the field area without soil inversion, (ii) precise digging of permanent planting basins or ripping of soil with a *Magoye ripper* (the latter where draft animals are available), (iii) leaving of crop residues on the field (no burning), (iv) rotation of cereals with legumes, and (v) dry season land preparation (CFU, 2007). The Conservation Farming Unit has recently been promoting the incorporation of nitrogen fixing crops into the CF package. However the five main principals remain essential. Note the differences between this and the more general CA package that consists of three principles: minimum mechanical soil disturbance; permanent organic soil cover, and crop rotation (FAO, 2012). While these principles were treated as inseparable in the past, recent thought on CA is more flexible in acknowledging that one or more of the components may provide needed food security and adaptation benefits in many smallholder systems in Southern Africa.

improved soil health, sometimes improved yields (depending on conditions) and usually improved profits (due to lower inputs). Farooq *et al.* (2011) reviewed 25 long-term CA trials (mainly from North America, Australia and Europe) and found that crop yields showed a slight increase (that increases over time) compared to conventional tillage, especially in dry conditions. Pretty *et al.* (2006) gathered evidence on the effect of CA from 286 developing country case studies, where 'best practice' sustainable agriculture interventions had occurred. For interventions related to smallholder CA, average yield improvement was over 100%.

Branca *et al.* (2011) undertook a comprehensive, empirical meta-analysis of 217 individual studies on CA globally. Their empirical analysis showed that improved agronomic practices such as cover crops, crop rotations (especially with legumes) and improved varieties have increased cereal yields by 116% on average across the studies consulted. Similarly, reduced tillage and crop residue management is associated with a 106% increase, and agroforestry techniques with a 69% increase. Tillage management and agroforestry were found to be particularly beneficial in dry agricultural areas.

It should be noted, however, that Pretty *et al.* (2006) purposely selected 'best practice' examples, and both Pretty *et al.* (2006) and Branca *et al.* (2011) mainly consider those studies examining practices actively promoted by various CA projects, as opposed to 'spontaneous' adoption among farmers not directly involved in promotion projects.[6]

Hence, although there is general agreement that some of the CA practices can improve yields under at least some circumstances, a debate continues over what and how extensive these circumstances are in practice.

There are a number of reasons why CA may not be suitable in particular contexts (Lal *et al.*, 2004; Knowler and Bradshaw, 2007; Gowing and Palmer, 2008; Giller *et al.*, 2009; McCarthy *et al.*, 2011; Nkala *et al.*, 2011). For instance, crop residues are often used as animal feed: the benefits of mulching with crop residues may not be worth the trade-off of reduced livestock numbers. Similarly, there may be a trade-off between labour saved on tillage and labour spent on increased weeding, in the absence of herbicides. These authors also raise questions about which specific element(s) of CA drive yield improvements as many published studies do not vary only one factor, but instead examine the effects of CA overall (Gowing and Palmer, 2008; Giller *et al.*, 2009). This often includes confounding changes to herbicide and fertiliser regimes. While proponents of CA argue that the method is 'holistic', and thus cannot be reduced to a single element, such disaggregated information is necessary for refinement and extension of the CA approach.

3.2. Productivity implications in Zambia

There is a small literature that assesses the benefits of CA as practiced in Zambia.[7] Langmead (undated) analysed pooled data from five trials in AERs IIa and III during the 2002/2003 season. He finds that timely planting and weeding is the most important

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[6]Publication bias is another caveat to be kept in mind for meta-analyses, where results with positive impacts are expected to be published more than those with no/negative impacts.

[7]Although the Zambia-specific literature mostly uses the term conservation farming (CF), we stick with the more general terminology of the global literature and use CA in this section to prevent confusion.

determinant of yields and yield variability. Timely conventional farming increased yields by 50%, and CA (planting basins plus lime application) increased yields by 68%. The authors conclude that facilitating timeliness is the most important contribution of CA.

Rockström *et al.* (2009) presented results from a 2-year on-farm trial of different farming systems in Zambia, amongst other SSA countries.[8] They compared the yields of farmer managed CA plots with conventional tillage plots (both with fertiliser inputs) and found that maize yields on the CA plots (> 6 tons/ha) were double those on the conventional plots, with no significant difference between the use of planting basins and rip lines. The authors also noted that CA appeared to improve yields most directly by improving soil moisture, especially for the lowest productivity systems. They concluded that for smallholder farmers in savannah agro-ecosystems, CA is primarily a water harvesting and conservation strategy, valuable even when crop residue retention is not practiced. They also noted that the soil moisture effect works in conjunction with fertiliser application, hence, at least some fertiliser input was required for crops to take advantage of the additional soil moisture (based on data from Kenya and Ethiopia).

Similar findings with regard to soil moisture benefits were presented in two related papers by Thierfelder and Wall (2009, 2010a). The authors undertook a multi-year, researcher-managed cropping trial at Monze (in Southern Zambia with annual rainfall of 748 mm) to evaluate the impact of tillage practices on water infiltration, run-off erosion and soil water content. Infiltration rates were 57–87% higher on CA plots. Resulting higher soil moisture levels were found to improve yields in poor seasons, demonstrating that CA has the potential to reduce the risk of crop failure due to low or poorly distributed rainfall.

A third paper by Thierfelder and Wall (2010b) used data from the same experiments to assess the impact of crop rotations. Mono-cropped maize was compared to maize–cotton–sunhemp rotations under different tillage and CA regimes.[9] Soil quality, as measured by aggregate stability, total carbon and earthworm populations, was significantly improved on CA plots. Maize yields were 74–136% higher under the 3-species CA rotation regime, and even in a simple maize–cotton rotation were 38–47% higher.

FAO (2011b) indicated that CA (defined by the use of planting basins or rip lines) yielded an average of 3 tons/ha, 42% more than conventional draft tillage, in Chongwe (in south-central Zambia with rainfall between 600 and 1,000 mm). It is not clear, however, how many farmers participated in the focus group discussions, or how they were selected for the study. Due to the unfortunate lack of background information in this report, these results can only be considered indicative.

In addition to the trial-based analyses, there are also some studies based on socio-economic surveys of farmers. Haggblade and Tembo (2003) conducted a comprehensive CA assessment in central and southern provinces during the 2001/2002 cropping season. The authors assess the yield and profit impacts of CA, controlling for other variables (such as fertiliser use) that could otherwise confound findings.[10] One

[8]The Zambian trial site was in Chipata (Eastern Province), a moderate rainfall location (approximately 1,000 mm annually).

[9]Sunhemp, i.e. *Crotalaria juncea*, is a leguminous manure crop.

[10]This is particularly important given that many CA programmes in Zambia have been promoted through the provision of 'input packs' from sponsors, which contain hybrid seeds, fertiliser, lime and other productivity enhancing materials.

hundred and twenty five (125) randomly selected farmers, with both CA and conventional tillage plots, were surveyed. Average maize yields were 3.1 tons/ha under basin planting CA and 1.3 tons/ha under conventional tillage. Of this large difference, the authors found that the CA technique itself was responsible for 700 kg of yield improvement, and increased fertiliser and hybrid seed use was responsible for 300–400 kg. A large positive impact was found due to earlier planting, which is facilitated by CA. Haggblade *et al*. (2011) also confirm this using a simulation model calibrated with Post Harvest Survey data from 2004 in order to assess the productivity impact of CA for smallholder cotton farmers in AER IIa. They show that CA has the potential to increase yields (of both maize and cotton) by around 40% due to early planting and improved soil quality.

Burke (2012) uses RILS data to estimate yield response for maize. Although CA is not the focus of the analysis, he controls for various tillage methods including some components of CA. He finds no significant impact of planting basins and ripping on maize yields, and that the positive impacts disappear after controlling for unobserved heterogeneity and input use endogeneity, underlining the importance of due caution when interpreting the results of cross-sectional studies.

Umar *et al*. (2011) interviewed 129 randomly selected farmers from a CA adopters list provided by the Conservation Farming Unit in the Central and Southern provinces of Zambia. Simple univariate analysis of yields showed significantly higher yields under planting basins, whereas ripping showed no significant yield benefits. This study, however, is mainly descriptive as it cannot separate the confounding impacts of other inputs and resource bases from those of tillage practices.

A different approach is taken by FAO (2011c) in their assessment of CA and climatic risk in Southern Africa. The authors used the agricultural production systems simulator models (APSIM) and concluded that in semi-arid environments, CA can improve yields in drier seasons and thus improve climate change resilience. In sub-humid environments, they found that CA offered little yield benefit at least in the short term. A key reason for this is the danger of water logging which can occur in wet seasons, as also mentioned by Thierfelder and Wall (2009, 2010a,b).

Based on the literature reviewed above, the evidence for improved yields from the use of CA practices is positive but weak, as some of the studies are subject to endogeneity or selection bias, some conduct only simple comparisons confounding impacts of CA with other variables (e.g. input use), some lack adequate background information to assess the quality of the research, and others rely on simulations rather than observed data. While it is clear that CA practices have the technical potential to increase yields, particularly in drier parts of Zambia, how large this effect is, how much of that can be attributed to the practice itself (rather than changes in inputs and timing of cropping operations) and how it interacts with climatic variables requires further research.

We use a novel dataset that combines large-scale panel data from households with geo-referenced data on historical rainfall and temperature as well as soil characteristics at the standard enumeration area (SEA) level to estimate the impacts of various potential CSA practices on maize yields, while also controlling for unobserved household heterogeneity that may confound the analyses based on cross-sectional data. We also explicitly analyse the use of fertilisers and improved seeds to identify their impacts on productivity and resilience, as well as how these impacts are changed by climatic stress.

4. Data and Descriptive Statistics

Our socio-economic data come from two rounds of RILS conducted in 2004 and 2008. These surveys are the second and third supplemental surveys to the nationally representative 1999/2000 Post-Harvest Survey (PHS). The supplemental surveys, carried out by the Central Statistical Office in conjunction with the Ministry of Agriculture, Food and Fisheries (MAFF) and commissioned by the Food Security Research Project (FSRP) of Michigan State University, were designed to study options to improve crop production, marketing and food consumption among small-scale farmers.[11] The first panel captured data from 5,358 households for the 2002/2003 cropping season; 4,286 of these households were re-interviewed in the second panel (gathering data on the 2006/2007 season) that extended the total sample size to around 8,000 households.[12] We use plot-level data from households that are interviewed in both surveys, covering 4,107 and 4,317 maize plots in the first and second panels, respectively.

We merge RILS data with a novel set of climatic variables based on historical rainfall and temperature data at the SEA level to control for the effects of the levels and variations in rainfall and temperature on productivity. Rainfall data come from the Africa Rainfall Climatology version 2 (ARC2) of the National Oceanic and Atmospheric Administration's Climate Prediction Center (NOAA-CPC) for the period of 1983–2012. ARC2 data are based on the latest estimation techniques on a daily basis and have a spatial resolution of 0.1 degrees (~10 km).[13] Our temperature data are surface temperature measurements at 10-day intervals (i.e. dekad) for the period of 1989–2010 obtained from the European Centre for Medium-Range Weather Forecasts (ECMWF). We also use data from the Harmonized World Soil Database (HWSD) to control for the effects of soil nutrient availability and soil pH levels on productivity. The HWSD has a resolution of 30 arc-seconds and combines existing regional and national updates of soil information worldwide.[14]

Using the ARC2 data, we created the following variables relevant for maize yields: total rainfall; average and maximum daily temperatures; an indicator variable for false onset of the rains[15] – all for the growing seasons covered by the RILS (i.e. 2002/2003 and 2006/2007), and the coefficient of variation (CoV) of rainfall in the growing season since 1983. Maize yields are shown to decrease significantly when the growing season maximum temperatures exceed 28°C, as well as with false onsets and dry spells (Tadross *et al.*, 2009; Thornton and Cramer, 2012). The CoV of rainfall during the growing season captures the (scale invariant) variation in rainfall that is expected to

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[11]MAFF was called Ministry of Agriculture and Cooperatives (MACO) during the 2008 surveys, and is now called Ministry of Agriculture and Livestock (MAL). FSRP has recently been transformed into a local institute called Indaba Agricultural Policy Research Institute (IAPRI).

[12]For more details about the surveys and other published work based on RILS see CSO (2004, 2008), Megill (2005) and Mason and Jayne (2013).

[13]See http://www.cpc.ncep.noaa.gov/products/fews/AFR_CLIM/AMS_ARC2a.pdf for more information on ARC2 algorithms.

[14]See http://webarchive.iiasa.ac.at/Research/LUC/External-World-soil-database/HTML/ for more information.

[15]False onset is defined as an onset (two consecutive dekads of at least 50 mm rain starting in October), followed by a dry dekad (< 20 mm rainfall) within 20 days of the onset (Tadross *et al.*, 2009).

affect yields through adoption of practices that help farmers deal with climate stress (Arslan *et al*., 2014; Asfaw *et al*., 2014). We also include two categories of soil nutrient availability constraints using the HWSD: moderate and severe/very severe. To the best of our knowledge, this is the first study to combine nationally representative household panel data with such a rich set of geo-referenced climatic and agro-ecological indicators to analyse the impacts of agricultural practices.

Table 1 reports the total rainfall, average and maximum temperatures and the percentage of SEAs with a false rainy season onset by AER for two seasons (2002/3 and 2006/7). The growing season rainfall in our data conforms with the AER standards shown in Figure 1, with rainfall increasing from southern to northern regions. Growing season rainfall between the two seasons slightly decreased in all but one AER, whereas both the average and the maximum temperatures slightly increased. AER I is the region with the highest share of SEAs with a false onset, and this share decreased in all AERs except in IIb (where it increased from 6% to 14%) between the two seasons.

Our remaining geo-referenced variables are not time-varying including soil nutrient constraints, soil pH levels, and the coefficient of variation in the growing season rainfall since 1983.[16] Thirty six percent (36%) of the SEAs in the whole country face severe/very severe soil nutrient availability constraint. AER I has the lowest share of severe soil nutrient constraints with 6%, whereas this proportion is around 40% in the rest of the country, as well as the best soil pH levels for maize cultivation (maize grows best in soils with pH levels between 5.8 and 6.5).[17] AER I, however, has the highest rainfall variability. Both pH levels and rainfall variability decrease from south to north, with expected opposing correlations with productivity.

Our adoption variable for MSD equals one for plots that have been treated with planting basins, zero tillage[18] or ripping. Crop rotation variable (CR) indicates maize plots that have been rotated with different crops during the 3 years around each survey,[19] legume intercropping (LEGINT) indicates plots intercropped with legumes,

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[16]The averages of these variables for each AER are reported in Table S1 of the supporting information to this paper (available online).

[17]Note that, taking into account all other plant nutrients (Nitrogen, Phosphorus and Potassium), AER I is classified as only marginally suitable for maize and many other crops by Zambia's Ministry of Agriculture and Cooperatives (MACO, 2003).

[18]An anonymous referee has mentioned that in 2004 the traditional practice of shifting cultivation (*chitemene)* may have been coded as zero tillage. We investigated the implications of this potential error on maize plots. *Chitemene* is traditionally practiced in cassava, finger millet and bean systems in the Northern and Luapula provinces (Chidumayo, 1999; Kapekele, 2006). Most households that reported zero tillage are in the Eastern province where *chitemen*e is not the tradition. In 2008, when *chitemene* was coded explicitly, only seven maize plots in Luapula and three maize plots in Northern province have been coded under *chitemene*. We have excluded the corresponding nine households from our analyses to prevent any potential confusion this issue could introduce.

[19]Plot histories are covered in different ways in each RILS survey used here. We define rotation using the information on crops planted on each plot one season before and one season after the survey season in 2004, and the two previous seasons before the season covered in 2008. Most common maize rotations in our data include groundnuts, cotton and cassava. In total, 58% of maize plots are rotated with non-leguminous crops. The results remain the same when we restrict the rotation indicator to legume rotations only.

Table 1

Growing season rainfall (mm), temperature (°C) and false onset (% of SEAs) by AER and year

	Rainfall		Avg. temp.		Max. temp.		False onset	
AER	02/03	06/07	02/03	06/07	02/03	06/07	02/03	06/07
I	614.8	658.9	23.8	24.1	28.7	28.8	71	51
IIa	813.2	766.2	22.1	22.4	26.8	27.1	71	24
IIb	893.0	854.8	22.9	23.0	28.0	28.3	6	14
III	1008.3	985.4	21.1	21.3	25.9	26.3	67	2
Average	893.8	869.7	21.9	22.1	26.6	26.9	63	17

Note: AER, agro-ecological regions; SEA, standard enumeration area.

and inorganic fertiliser (INOF) and improved seed (IMPS) indicate plots that have been cultivated using these modern inputs.[20]

MSD was practiced on 6% of all maize plots in 2008 (up from 4%) and the majority of plots under MSD were cultivated with zero tillage, followed by planting basins and ripping.[21] These figures are similar to those in Ngoma *et al*. (2014) based on Crop Forecast Surveys.[22] CR was practiced on 37% of plots in 2008 (up from 24%) and LEGINT was practiced on 2% of plots (down from 4%). AERs I and IIa have the highest percentage of plots with MSD (6% and 9%, respectively), whereas AER III has the smallest percentage (1%). Basins are the most practiced in AER I and zero-till is the most practiced in AER IIa. CR is most commonly practiced in AERs IIa and III, whereas LEGINT is mostly practiced in AER III, followed by AER I.

The most common practice is IMPS, which was used on around 40% (52% in AER I) of plots in the 2006/2007 season with a significant increase over time. This is followed by INOF, which was used on around 34% (46% in AER IIa) of plots in both years. AER IIb shows the lowest levels of INOF and IMPS use in both years with a decrease over time. The most common combinations include CR, INOF and IMPS, where 25% of plots were cultivated with INOF and IMPS at the same time. Around 15% and 14% were cultivated with CR in combination with IMPS and INOF, respectively, in 2008. All other combinations are practiced on very small numbers of plots preventing econometric analyses of the effects of different combinations of practices on productivity.

Given the very low numbers of observations on various combinations of practices, we analyse the impacts of each of these five practices in what follows, holding everything else constant at their sample average levels. Table 2 shows maize yields by

[20]Tables S2 and S3 in the supporting information to this paper (available online) summarise the shares of maize plots cultivated with the five practices analysed in this paper in the whole sample and by AER, respectively. Table S2 also presents key combinations among practices.

[21]All descriptive statistics based on RILS data are weighed using sampling weights to produce representative summary statistics.

[22]Adoption figures related to CA practices in Zambia have been subject to a recent debate in the country. While nationally representative data provide figures similar to those in RILS (Ngoma *et al*., 2014), data from small-scale surveys clustered around CA promotion provide much higher figures (around 20% in Kasanga and Daka, 2013). We do not further investigate this issue, as our focus is on estimating impact in RILS data taking into account different climatic conditions. We refer interested readers to these papers for further information.

Table 2

Maize yields (kg/ha) by practice and year

	2004		2008	
	No	Yes	No	Yes
MSD	1,524	1,573	*1,474*	*1,308*
CR	*1,497*	*1,614*	1,446	1,496
LEGINT	1,514	1,817	1,461	1,625
INOF	*1,314*	*1,957*	*1,208*	*1,957*
IMPS	*1,390*	*1,728*	*1,216*	*1,787*

Notes: Differences between the two groups within a year are significant if italic. CR, Crop rotation; IMPS, improved seed; INOF, inorganic fertilise; LEGINT, legume intercropping; MSD, minimum soil disturbance.

practice and year. Average maize yields are consistently (and statistically significantly) higher for households that use INOF and IMPS in both years. Yields were (statistically significantly) higher for those who practiced CR in 2004 (not significant in 2008) and lower for those who practiced MSD in 2008 (they were higher but not significantly in 2004).

In addition to maize yields, we also analyse the impacts of these practices on the probability of very low yield and percentage yield shortfall. We use the long-term (2002–2008) provincial averages of maize yields reported in Tembo and Sitko (2013) to calculate these variables. Our low yield variable equals one if the yield on that plot is more than one standard deviation below the long-term provincial average yield, and the yield shortfall variable is the percentage difference between provincial average yield and the yield for plots (this variable is zero for plots that have yields equal to or greater than the provincial average).

Table 3 summarises all dependent variables by AER. Overall average maize yields were around 1.5 tons/ha in both years. Although AER III has the highest average yields, it also has the highest share of plots with yields lower than the long-term averages and the highest average yield shortfall. Lowest average yields as well as the highest average percentage yield shortfall are found in AER IIb.

5. Empirical Models

5.1. Maize yields

Modelling the effects of agricultural practices on agricultural production is inherently subject to various endogeneity problems, as adoption behaviour is not random and farmers that adopt a given technology are likely to have unobserved characteristics that are correlated with their productivity (Mundlak, 2001). This constitutes the standard self-selection problem causing bias in estimated parameters of the production function. An instrumental variables approach is usually used to address this problem. However, finding variables that satisfy the necessary IV requirements is frequently a challenge, which is further complicated when there are multiple endogenous variables and panel data methods are used, as in our study.

Alternatively, panel data (fixed or random effects) models control for unobserved time invariant household variables and can address this endogeneity inasmuch as the selection into adoption is caused by household characteristics that do not change over

Table 3
Dependent variables by AER and year

AER	Maize yield (kg/ha)		Share with low yield		Yield shortfall (%)	
	2004	2008	2004	2008	2004	2008
I	1,081.8	1,269.6	0.36	0.31	47.61	48.58
IIa	1,655.0	1,464.9	0.28	0.34	42.43	44.45
IIb	736.3	911.7	0.38	0.24	56.93	54.77
III	1,714.6	1,723.6	0.50	0.49	43.90	44.94
Total	1,525.9	1,464.4	0.37	0.37	45.04	45.64

Note: AER, agro-ecological regions.

time. Most common forms of selection arise due to our inability to observe farmer 'ability' or 'openness to innovation', which can be expected to change little over short periods of time. Given that our data cover two seasons that are only 4 years apart from each other, we use panel data methods to control for the unobserved household characteristics in order to identify the impacts of these practices on maize yields.

We model the maize yield by using the following reduced form equation:

$$Y_{pit} = \alpha_1 \mathbf{X}_{pit} + \alpha_2 \mathbf{C}_{ikt} + \beta MSD_{pit} + \chi CR_{pit} + \delta LEGINT_{pit} + \gamma INOF_{pit} + \theta IMPS_{pit} + e_{pit} \quad (1)$$

where Y_{pit} is the maize yield on plot p of household i at time t; $\mathbf{X}$ is a vector of variables including household and plot characteristics as well as provincial controls; $\mathbf{C}$ is a vector of geo-referenced variables including climatic and agro-ecological variables in enumeration area k where household resides; *MSD, CR, LEGINT, INOF* and *IMPS* are dummy variables indicating maize plots that have been cultivated with the corresponding practice in year t; and e is a normally distributed error term. Two potential econometric challenges arise. First, all adoption variables are potentially endogenous causing the error term to be correlated with the right-hand side (rhs) variables. However, in our case, as noted above, it is practically impossible to deal with this using an IV approach, so we note its potential difficulties, but hope that our explanatory variables can be treated as approximately exogenous over this limited time period. Second, the error term is not *iid* as it includes time-invariant unobservables that are correlated with yields (i.e. $e_{pit} = u_{pit} + v_i$, where u_{pit} is a normally distributed error term independent of the rhs, and v_i are time-invariant unobserved effects (Wooldridge, 2002, Ch. 15).

This problem is addressed by modeling the unobserved time-invariant heterogeneity using fixed or random effects methods. Fixed effects (FE) models treat the unobservables as parameters to be estimated that can be correlated with the rhs, whereas the random effects (RE) models treat them as a random variable uncorrelated with the rhs, whose probability distribution can be estimated from data (Wooldridge, 2002). FE models are usually not consistent in short panels (e.g. with only two time periods) and can only estimate the effects of time-varying variables, hence time-invariant agro-ecological variables cannot be included in the analysis. We reject the unrelatedness assumption of RE using the Hausman test, but given our short panel and interest in time-invariant variables, we apply a Chamberlain-like correction to the RE model to estimate a correlated random effects (CRE) model.

The CRE allows v_i and rhs variables to be correlated using a Chamberlain-like model by assuming $v_i|X_i \sim N(\phi + \overline{\mathbf{X}}_i\xi, \sigma_a^2)$, where σ_a^2 is the variance of a_i in the equation $v_i = \psi + \overline{\mathbf{X}}_i\xi + a_i$, and $\overline{\mathbf{X}}_i = T^{-1}\sum_{t=1}^{T}\mathbf{X}_{it}$ is the $1 \times K$ vector of time averages of all time-varying variables on the rhs (Chamberlain, 1980). The estimation amounts to including all time averages as explanatory variables and one can test the unconditional normality of v_i by testing whether $\xi = 0$ (Wooldridge, 2009). We reject this hypothesis in all specifications and use CRE to consistently estimate the partial effects of rhs in our models.

5.2. Low yields and yield shortfalls

We also analyse the impacts of the practices on the occurrence of both low yields (at least one SD below the provincial average) and on yield shortfall (as a percentage shortfall from the provincial average).

$$D_{pit} = 1 \quad \text{if } Y_{pit} \leq (\overline{Y}_j - SD_j),\ 0 \text{ otherwise.} \tag{2}$$

D_{pit} is the low yield indicator on plot p of household i at time t, Y_{pit} is the yield on plot p of household i at time t, $\overline{Y}_j$ is the long-run (2002–2008) average maize yield in province j (where the plot p is) reported in Tembo and Sitko (2013) and SD_j is the long-run standard deviation of yield in province j. Assuming a normal distribution for this probability, we estimate its determinants using a probit model in CRE framework to model the unobservable effects.

The probability model does not tell us how far below the provincial yield the maize production is on that plot (i.e. yield shortfall), which can provide valuable information as some practices may decrease the yield shortfall more than others under certain circumstances. We express the yield shortfall in percentages and define S_{pit} on plot p of farmer i at time t as:

$$S_{pit} = (\overline{Y}_j - Y_{pit}) \times 100/\overline{Y}_j \quad \text{if } Y_{pit} \leq \overline{Y}_j,\ 0 \text{ otherwise.} \tag{3}$$

This variable is by definition between zero (for observations that do not have a shortfall) and one hundred, hence we use a tobit model to account for censoring and estimate the determinants of percentage shortfall using CRE. The addition of time averages on the right hand side of the CRE tobit model takes care of the unobserved heterogeneity problem allowing us to estimate $\sqrt{N}$ -consistent estimates of rhs variables (Wooldridge, 2002, Ch. 16).

5.3. Independent variables

The set of independent variables we use are intended to identify the average impacts of agricultural practices on outcome variables and their interactions with climatic variables, rather than estimating input response functions. Moreover, the only inputs that are available in quantities per plot are land size, seeds and inorganic fertilisers. Given that we need to use proxies for other inputs and labour, which is one of the most important inputs, and the well-known challenges created by conversion factors to aggregate seeds and fertilisers, we use a reduced form specification to model maize yields. All agricultural practices analysed here enter the regressions as indicator variables, which are also interacted with a set of climatic variables, since these interactions are a major focus of our study. Table 4 summarises the variables that are hypothesised to affect maize yields.

We use the number of adults and the share of chronically ill adults as a proxy for household labour availability. In addition to the standard variables of household human capital (age and education), productive capital (wealth index,[23] oxen holdings and land size) and gender, we also use controls for production-specific variables on each plot. These include: organic fertiliser application, number of complete weedings applied, and whether it was tilled before the rains started. The timing of fertiliser access is an indicator for households that reported having had timely access to fertilisers. This variable is only observed for those that have acquired fertiliser, therefore we also include an interaction variable between the inorganic fertiliser use and timely access. Thirty percent (30%) of households reported timely access to fertilisers (up from 28%), and 37% had acquired some in 2008 (up from 34%). Timely access to fertiliser is an important determinant of whether farmers can realise full yield benefits from fertiliser use as well as from other practices, and has been found to increase yields significantly (Rockström *et al.*, 2009; Xu *et al.*, 2009).

The bottom part of Table 4 presents the SEA level geo-referenced variables included in our models.[24] The season rainfall was significantly smaller and average temperature was significantly higher in 2008 than 2004. A much smaller percentage suffered from a false rainfall onset in 2008 compared to 2004 (19% and 59%, respectively). The CoV variable captures the long-term variation, hence is time-invariant and drops out of FE models, however its effects are captured in CRE models.

Variables on soil nutrient availability and pH levels are expected to impact yields in opposing ways: whereas higher nutrient constraints would decrease yields, higher pH levels (less acidity) would increase them. These variables are also time-invariant, hence drop out of FE models, providing another motivation to use CRE models in addition to its empirical and theoretical appeal given our short panel. Nonetheless, we present OLS and FE models below for robustness checks and comparison.

6. Results

6.1. *Yield models*

Table 5 presents the results of yield models with a simple OLS, an FE and a CRE model, in order to check for the robustness of CRE coefficients under different specifications.[25] The estimated coefficients are robust to various specifications, and given the challenges of FE models mentioned above we focus on the CRE specification in what follows.[26]

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[23]The wealth index is created using principal component analysis based on the number of bikes, motorcycles, cars, lorries, trucks, televisions and wells owned by the household.

[24]We provide descriptive statistics for all temperature variables, but given the high correlation between average and maximum temperature we only use the indicator variable for maximum growing season temperatures above 28°C in regressions.

[25]In all yield models, maize yields and the land size are used in logarithms to decrease the influence of outliers. Using levels does not change the results significantly.

[26]All results presented are average partial effects of control variables. These are obtained using the **margins** command in Stata 13 with proper attention paid to interaction variables and time averages in CRE models as suggested in Pinzon (2014) and Wooldridge (2013).

Table 4
Mean values of independent variables used in empirical models

Variables	2004		2008
Age of household head	48.56		51.49
Education (average)	5.01		5.24
No. of adults (age ≥ 15 years)	4.20		3.66
Share of ill adults	0.07		0.02
Female headed	0.20		0.22
Total maize area (ha)	1.06		1.41
Wealth index	0.04		0.05
No. of oxen owned	0.61		0.91
Organic fertiliser applied	0.11		0.12
No. of weedings applied	1.73		1.71
Tilled before rainy season	0.39		0.33
Policy variables			
Had fertiliser on time	0.28		0.30
Acquired fertiliser	0.34		0.37
Geo-referenced variables			
Growing season rainfall (100 mm)	8.64		8.15
CoV of growing season rainfall (1983–2012)		0.20	
False onset of rainy season	0.59		0.19
Growing season avg. temperature (°C)	22.04		22.34
Growing season max. temperature ≥ 28°C	0.16		0.20
Moderate nutrient constraint		0.36	
Severe/very severe nutrient constraint		0.36	
Average soil pH		5.60	
Observations (no. of maize plots)	4,134		4,344

Note: CoV, coefficient of variation.

We find no significant effect of MSD and CR on maize yields controlling for the use of all other practices and the large set of control variables (the negative effect of CR is only observed in the FE model). LEGINT, INOF and IMPS all have highly significant positive effects on yields, increasing yields by 36%, 23% and 16%, respectively. Having access to timely fertiliser significantly increases yields by 21%. As expected the growing season rainfall has a significant and positive coefficient, however the negative and significant coefficient of the indicator variable for maximum temperatures higher than 28°C loses its significance once we control for unobserved heterogeneity in FE and CRE models.

The coefficient of the total maize area cultivated remains strongly significant (at around 27%), providing support for the inverse farm-size-productivity (IR) hypothesis.[27] The standard socio-economic variables are mostly significant in OLS model,

[27]The main reasons for IR in the literature are market failures, omitted variables and measurement errors. Carletto *et al.* (2013) recently showed that accounting for measurement error strengthens, rather than weakens, the IR relationship. See Binswanger *et al.* (1995) and Eastwood *et al.* (2010) for a comprehensive review of the IR debate.

Table 5
Determinants of (log) maize yields (OLS, FE and CRE models)

	OLS Coef.	FE Coef.	CRE Coef.
Potential CSA indicators			
MSD	−0.049	−0.009	−0.048
CR	−0.012	−0.106**	−0.013
LEGINT	0.198**	0.356***	0.229**
INOF	0.368***	0.370***	0.358***
IMPS	0.182***	0.061	0.164***
Production and household variables			
Organic fertiliser	−0.046	−0.046	−0.019
No. of complete weedings	0.011	0.037	0.025
Tilled before rains	−0.029	0.058	0.039
Log(total maize area)	−0.116***	−0.257***	−0.273***
No. of adults (age ≥ 15 years)	0.022***	0.003	0.009
Age (head)	−0.002***	−0.003	−0.006***
Education (avg.)	0.025***	0.013	0.018
Share of ill adults	−0.245**	−0.181	−0.240
Female head	−0.032	0.006	−0.028
Wealth index	0.025***	0.025**	0.026***
No. of oxen owned	0.029***	0.022**	0.023**
Policy variables			
Fertiliser on time	0.241***	0.152	0.216**
Timely fertiliser × INOF	0.06	0.073	0.06
Geo-referenced variables			
Growing season rain	0.045***	0.115***	0.051**
False onset	0.119***	0.003	0.097*
Max temp ≥ 28°C	−0.341***	−0.203	−0.275
CoV of rainfall	1.977		0.720
Moderate soil constraint	0.075		0.075
Severe/very severe soil constraint	0.018		0.026
Soil pH (SEA avg.)	−0.053		−0.046
2008 Dummy	0.077	0.056	0.085
Constant	5.690***	5.783***	6.282***
No. of observations	8,424	8,424	8,424
R^2/between (overall) R^2 for CRE	0.16	0.06	0.23 (0.17)
AIC	25,574	14,686	25,498

Notes: ****P* < 0.01, ***P* < 0.05, **P* < 0.1. AIC is the akaike information criteria to compare the model fit across specifications. AIC is obtained using an MLE specification in the CRE model. CoV, coefficient of variation; CR, Crop rotation; CRE, correlated random effects; FE, Fixed effects; IMPS, improved seed; INOF, inorganic fertilise; LEGINT, legume intercropping; MSD, minimum soil disturbance; OLS, ordinary least square; SEA, standard enumeration area.

however all lose significance after controlling for FE and only household head's age and wealth indicators remain significant in CRE models, underlining the importance of controlling for unobserved heterogeneity using panel data methods.

The CSA practices analysed here are hypothesised to increase yields especially under rainfall or temperature stress (Rockström *et al.*, 2009; Thierfelder and Wall, 2009, 2010a,b; FAO, 2011c). These types of effects can be captured using interaction terms between the indicator variables for each practice and variables that represent climate stress. We use two sets of interaction terms between the practice indicators and: (i) the false rainy season onset indicator, and (ii) the indicator for greater than 28°C growing season maximum temperature, in order to identify the differing effect of a practice according to these climatic conditions (Table 6).[28]

False onset interactions show that the impacts of MSD and CR do not depend on this variable. The average productivity increasing effect of and LEGINT is slightly higher under false onset shock than the impact under no shock (24% vs. 23%). The impact of INOF following a false onset is significantly less than its impact under normal onset (26% vs. 43%). On the other hand, IMPS increases yields more after a false onset (22% vs. 13%), perhaps reflecting the performance of IMPS in shorter growing seasons following a false onset. We note that the coefficients with and without shocks differ significantly which underlines the effects of the interactions between practices and critical climatic variables.

Interactions with the indicator of very hot growing season (Tmax28) show that the positive effect of LEGINT increases significantly under this shock, whereas that of INOF decreases significantly. The impact of IMPS, however, disappears if the growing season maximum temperatures are 28°C or more, underlining the potential vulnerability of the positive impact of improved seeds. This finding is in line with maize breeding literature where high temperatures are recognised as one of the most detrimental variables to maize growth during critical periods, especially for improved varieties (JAICAF, 2008; Cairns *et al.*, 2012). Given that heat stress is predicted to intensify with climate change, plant breeding literature is continuously expanding to improve the heat stress tolerance of maize (Bita and Gerats, 2013), to offset the increased riskiness of seed improvement (Just and Pope, 1979). The risk-increasing nature of modern inputs can be expected to intensify affecting adoption behaviour and yield outcomes, underlining the importance of integrating climate stress response in promoting improved seeds under different environments.[29]

Having had timely access to fertiliser is still one of the most consistent determinants of productivity in these specifications. Maize yields on average are 21% higher for those that have timely access to fertilisers, *ceteris paribus*.

6.2. Probabilities of low yields and yield shortfalls

Table 7 reports the results of low yield probability models that control for time-invariant unobserved heterogeneity using CRE models with and without interaction variables.

[28]We only present the coefficients of practices we focus on, their interactions with climate shock variables and geo-referenced variables in the rest of the paper for the sake of brevity. The coefficients of other variables remain virtually unchanged compared to those presented in Table 7. Full results can be obtained from the authors upon request.

[29]We have also experimented with CoV interactions but the results were mostly not significant. This result can be expected as the impact of long-term shocks on yields are mostly captured by adoption of practices that have the potential to increase yields and decrease their variability over time as a response to long-term variation (Arslan *et al.*, 2014; Asfaw *et al.*, 2014).

Table 6
Determinants of (log) maize yield with interaction terms

	False onset interactions Coef.	Tmax28 interactions Coef.
MSD		
Without shock	−0.10	−0.06
With shock	0.08	0.08
CR		
Without shock	0.00	−0.01
With shock	−0.02	−0.003
LEGINT		
Without shock	0.225**	0.134**
With shock	0.244***	0.884***
INOF		
Without shock	0.429***	0.346***
With shock	0.266***	0.30*
IMPS		
Without shock	0.131***	0.227***
With shock	0.222***	−0.11
Fertiliser on time	0.213***	0.213**
Timely fertiliser × INOF	0.06	0.06
Growing season rain	0.052**	0.059***
False onset	0.11*	0.09
Max temp ≥ 28°C	−0.255	−0.124
CoV of rain 1983–2012	0.814	0.934
No. of observations	8,424	8,424
Between (overall) R^2	0.20 (0.17)	0.20 (0.17)
AIC	25,499	25,482

Notes: ***$P < 0.01$, **$P < 0.05$, *$P < 0.1$. The AIC reported are based on an MLE model to facilitate comparison between models. AIC, akaike information criteria; CoV, coefficient of variation; CR, Crop rotation; IMPS, improved seed; INOF, inorganic fertilise; LEGINT, legume intercropping; MSD, minimum soil disturbance.

While MSD and CR do not have a significant impact on the probability of obtaining low yields, LEGINT, INOF and IMPS decrease this probability significantly when no climate shock occurs (INOF has the highest effect at 20%, followed by LEGINT at 10% and IMPS at 9%). A false onset to the rainy season on a plot treated with these practices, however, decreases the magnitudes of their impacts significantly (e.g. INOF decreases the yield loss probability by 25% without the shock but by 14% with the shock). More importantly, plots cultivated with INOF and IMPS have a significantly higher probability of low yields if the growing season maximum temperatures exceed 28°C, as these modern inputs decrease the probability of low yields only if the temperatures remain below this threshold. LEGINT, on the other hand, decreases low yield probability even more under a temperature shock. Timely fertiliser access significantly decreases the probability of obtaining low yields as expected.

Table 8 presents the results of percentage yield shortfall models using the same specifications as in Table 7.

The yield shortfall results closely mirror low yield probability results with a couple of exceptions. LEGINT decreases the percentage shortfall only if there is no false

Table 7

Determinants of probability of maize yields falling below LR provincial averages

	No interactions Coef	False onset interactions Coef	Tmax28 interactions Coef
MSD	0.018		
Without shock		0.025	0.07
With shock		−0.021	−0.182
CR	0.008		
Without shock		0.007	0.044
With shock		0.005	−0.2
LEGINT	−0.101***		
Without shock		−0.117***	−0.187*
With shock		−0.088**	−1.059***
INOF	−0.195***		
Without shock		−0.245***	−0.545***
With shock		−0.135***	−0.22
IMPS	−0.087***		
Without shock		−0.098***	−0.278***
With shock		−0.076***	−0.073
Fertiliser on time	−0.135	−0.132***	−0.315***
Timely fertiliser × INOF	−0.031*	−0.030*	−0.132*
Growing season rain	−0.047***	−0.047***	−0.138***
False onset	−0.032**	−0.039**	−0.081
Max temp ≥ 28°C	0.034	0.028	0.158
CoV of rainfall (LR)	−0.329	−0.465	−0.504
No. of observations	8,424	8,424	8,424
ROC area	0.74	0.74	0.75
AIC	9,715	9,712	9,692

Notes: ***$P < 0.01$, **$P < 0.05$, *$P < 0.1$. ROC area is the area under the ROC curve and the closer this number is to 1, the better the performance of the model in correctly predicting probabilities (Cleves, 2002). AIC, akaike information criteria; CoV, coefficient of variation; CR, Crop rotation; IMPS, improved seed; INOF, inorganic fertilise; LEGINT, legume intercropping; MSD, minimum soil disturbance.

onset, but it decreases the shortfall by around half in very hot growing seasons. Plots have smaller yield shortfalls after a false rainy season onset if they use IMPS and under temperature shock if they are treated with INOF – conditional on yields being already below the long-term average. Given that very low yields were defined as those that are more than one standard deviation below the long-term average (in the low yield probability models above), modern inputs seem to have a yield shortfall decreasing impact only around the long-term averages under climate shocks, whereas they have no impact on the probability of low yields towards the lower end of the yield distribution.

Consistent with the findings from the yield models, having had access to timely fertiliser is one of the most robust determinants of low yield probabilities and shortfalls: timely fertiliser significantly decreases both of these outcomes in all specifications. Timely access to fertiliser has also been identified as an important determinant of yields in Zambia by Xu *et al.* (2009), who used a smaller and older dataset to analyse impacts of fertilisers on yields. We note here that in our data, fertiliser acquisition is

Table 8
Determinants of yield shortfall (measured as % of LR average)

	No interactions Coef	False onset interactions Coef	Tmax28 interactions Coef
MSD	1.51		
Without shock		2.54	3.93
With shock		−1.65	−10.2
CR	0.46		
Without shock		0.22	0.98
With shock		0.39	−1.69
LEGINT	−5.76***		
Without shock		−6.72***	−5.61
With shock		−4.74	−48.42
INOF	−11.84***		
Without shock		−14.60***	−20.35
With shock		−8.52***	−14.42
IMPS	−5.09***		
Without shock		−4.70***	−11.54
With shock		−5.83***	2.29
Fertiliser on time	−9.77***	−9.52***	−12.27
Timely fertiliser × INOF	−1.52***	−1.50***	−6.47
Growing season rain	−2.51***	−2.53***	−4.79
False onset	−2.01	−2.15**	−3.24
Max temp ≥ 28°C	4.78***	4.32***	7.68
CoV of rainfall (LR)	−48.65	−53.79	−58.02
No. of observations	8,424	8,424	8,424
Model χ^2 (*P*-value)	1,209.8 (0.00)	1,240.6 (0.00)	1,255.6 (0.00)
AIC	49,353.40	49,339.00	49,318.70

Notes: ***$P < 0.01$, **$P < 0.05$, *$P < 0.1$. We report the model Chi-squared and its *P*-value instead of pseudo-R^2, as pseudo-R^2 in panel tobit models does not provide a meaningful measure of model fit. AIC, akaike information criteria; CoV, coefficient of variation; CR, Crop rotation; IMPS, improved seed; INOF, inorganic fertilise; LEGINT, legume intercropping; MSD, minimum soil disturbance.

strongly correlated with land size: at least 57% of households with landholdings > 5 ha have acquired fertilisers, whereas this share is only 30% for those that have < 1.5 ha of land. Although the timeliness for those that acquired seem to have improved between 2004 and 2008, acquisition itself seems to have stagnated to the disadvantage of smallest landholders over the period covered by our data.

One caveat in interpreting our results is that the models estimated here cannot control for potential endogeneity of adoption of these practices that may be caused by unobservable variables that are not constant over time. Panel data spanning longer time periods to ensure enough climate variability is observed, a large and valid set of instruments to capture time-varying unobserved heterogeneity and a system of equations including adoption and yield models with high computing power requirements would be needed to control for this potential endogeneity. These types of analyses could also benefit from considerations of other staple crops important for food security, as well as from physical input response models under various climatic shocks.

Future research should try to address these caveats if data and computing power permit.

7. Conclusions

Our analysis indicates there are a set of agricultural practices with CSA potential that increase yields and help farmers adapt to climate change in Zambia and these vary by the types of climate impacts and AER. Some of the practices analysed here form part of the CA package, whose impacts on production have been extensively researched in the literature (Haggblade and Tembo, 2003; FAO, 2011b; Haggblade *et al.*, 2011; Umar *et al.*, 2011 among others). However, most of this literature deals with data from experimental plots or small datasets from a non-representative group of farmers. Studies that control for rainfall, temperature and soil quality variables in a panel setting are rare. We examine the impacts of a set of potentially CSA practices (including some CA practices) on maize yield and its probability of falling below a low threshold using nationally representative panel data on rural households merged with novel geo-referenced climate and soil quality data from Zambia. We also control for the impacts of modern inputs that otherwise confound the impacts of other practices.

Controlling for a large set of variables that affect production, we find no significant impact of minimum soil disturbance and crop rotation, and a positive impact of legume intercropping on maize yields over the 2004–2008 time period. The positive impact of legume intercropping remains positive even under climate shocks. We find that the average positive impacts of modern input use are also conditioned by climatic variables: inorganic fertilisers have a much smaller impact under false rainfall onsets, and improved seeds have no impact on yields under very high growing season temperatures. Combined with the results from recent literature documenting the role of climatic variables in shaping agricultural technology adoption decisions (Asfaw *et al.,* 2014; Arslan *et al.*, 2014), our results underline the importance of careful consideration of site-specific climatic conditions for policy design and targeting.

One of the most robust findings is that having timely access to fertilisers increases maize yields, and decreases low yield probability and yield shortfall significantly in all specifications, similar to Xu *et al.* (2009), who report a similar finding from AER IIa using an older dataset. Delays in fertiliser delivery through government programmes are well known in Zambia, causing further delays due to the uncertainty created for private distributors (Xu *et al.*, 2009). Most smallholders in Zambia do not have access to fertilisers at all, and those that do have disproportionately late access compared to larger landholders (Mason *et al.*, 2013). Given the fact that some fertiliser application is required to realise the benefits of most CSA practices and improved seed use, and that timeliness adds to these benefits, this finding indicates a relatively easy policy entry point to improve food security in the country.

Applying inorganic fertiliser and using improved seeds increases yields and reduces the probability of a shortfall. However, both these positive effects are contingent on not having a false onset of the rains (for fertiliser) or not having high temperatures (for improved seeds), while the positive impacts of traditional legume intercropping are robust to these shocks, indeed being of even more benefit in seasons with very high temperatures. Our results indicate that climate change impacts are heterogeneous across AER, implying that effective adaptation strategies are also varied.

In the case of Zambia, we find that timely access to fertiliser is a consistently important element in determining yields and targeting smallholders, who are universally found to have low levels of access, is an important policy measure needed to increased productivity amongst the highly food insecure agricultural population of Zambia. We also find that other interventions that are robust to climate shocks could be adopted, such as increasing legume intercropping to increase yields and limit the extent of yield shortfalls. The sensitivity of the effectiveness of improved seeds and inorganic fertiliser application to false onsets of the rainy season and high temperatures indicates that better information to farmers on how to deal with these climatic shocks could help in retaining the positive effects of these practices on yields, which otherwise risk being lost.

Supporting Information

Additional Supporting Information may be found in the online version of this article:

Table S1. Time-invariant geo-referenced variables by AER.

Table S2. Population shares of adoption of agricultural practices and key combinations.

Table S3. Adoption of agricultural practices by AER.

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