Food and Agriculture Organization of the United Nations

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Abstract

This paper examines the impacts of the El Niño during the 2015/2016 season on maize productivity and income in rural Zambia. The analysis aims at identifying whether and how sustainable land management (SLM) practices and livelihood diversification strategies have contributed to moderate the impacts of such a weather shock. The analysis was conducted using a specifically designed survey called the El Niño Impact Assessment Survey (ENIAS), which is combined with the 2015 wave of the Rural Agricultural Livelihoods Surveys (RALS), as well as high resolution rainfall data from the Africa Rainfall Climatology version 2 (ARC2). This unique, integrated data set provides an opportunity to understand the impacts of shocks like El Niño that are expected to get more frequent and severe in Zambia, as well as understand the agricultural practices and livelihood strategies that can buffer household production and welfare from the impacts of such shocks to drive policy recommendations.

Results show that households affected by the drought experienced a decrease in maize yield by around 20 percent, as well as a reduction in income up to 37 percent, all else equal. Practices that moderated the impact of the drought included livestock diversification, income diversification, and the adoption of agro-forestry. Interestingly, the use of minimum soil disturbance was not effective in moderating the yield and income effects of the drought. Policies to support livestock sector development, agroforestry adoption, and off-farm diversification should be prioritized as effective drought resiliency strategies in Zambia.

Keywords: Crop productivity; risk management; vulnerability; Zambia.

JEL codes: O13, Q01; Q12; Q16.

Acknowledgements

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1 Introduction

Southern Africa experienced one of its driest cropping seasons in 2015, which coincided with the most intense period of the El Niño. Most of the region received only 50-70 percent of its regular rainfall between October and February, which caused crops to fail shortly after planting and region-wide food deficit warnings (Rembold *et al.*, 2016). In Zambia, the effects of El Niño were classified as the most severe in the last fifty years (ZVAC, 2016).

There is emerging consensus among climate scientists that extreme weather events such as El Niño are expected to get more frequent and intense, especially in Africa and South-East Asia (IPCC 2014, Table 21.7). Therefore, there is urgent need to identify agricultural practices and livelihood strategies that build the resilience of food production systems and farmers' livelihoods to these events. The main objective of this paper is to analyse the impacts of the 2015/16 El Niño induced drought on maize productivity and incomes in rural Zambia. More specially, this paper examines the extent to which sustainable land management (SLM) practices and livelihood diversification strategies influenced welfare and productivity effects of the El Niño related drought. This analysis provides a starting point for identifying policy options to increase smallholder resilience to climatic shocks in Zambia.

Data in this paper come from a unique household survey called the El Niño Impact Assessment Survey (ENIAS), which is a follow up to the 2015 wave of the Rural Agricultural Livelihoods Surveys (RALS). ENIAS covers a sub-sample of households in the RALS selected through a sampling frame that was designed to cover severely affected households and those that were not, based on Zambia Vulnerability Assessment Committee (ZVAC) Situation Report published in early 2016. Combined with the RALS 2015, as well as high resolution rainfall data from the Africa Rainfall Climatology version 2 (ARC2), the unique data set provides an opportunity to analyse the impacts of shocks like El Niño and understand the agricultural practices and livelihood strategies that can buffer household production and welfare from the impacts of such shocks to drive policy recommendations.

The paper is organized as follows. We provide a brief review of climate change and vulnerability in the literature in general and in Zambia in the next section, and discuss the agricultural practices and livelihood strategies that are intended to decrease vulnerability in rural Zambia in Section 3. We introduce our conceptual framework and empirical methodology in Section 4, provide detailed descriptive statistics in Section 5 and present our results in Section 6. We offer concluding statements and policy recommendations in Section 7.

2   Climate change and vulnerability

Severe climatic events such as droughts, floods, and extreme temperatures are expected to increase in frequency and intensity over time (Nelson and van der Mensbrugghe, 2013; IPCC, 2012). In the absence of measures to reduce the vulnerability of farmers to these events, significant negative impacts on food security are expected (FAO, 2010).

Farm households throughout Sub-Saharan Africa are particularly exposed to weather induced risks, due to the preponderance of rain-fed production systems and imperfect market conditions. Climate change exacerbates these risks by increasing the probability and severity of adverse weather conditions. Extreme weather events may directly affect agricultural productivity in terms of crops, livestock, fisheries and forestry, and affect incomes indirectly through decreased labour demand, increased local prices, as well as limited access to markets due to different constraints such as, negative impacts on infrastructure. Hence, climate change not only represents a threat to incomes today, but also makes them less predictable by changing the incomes' probability distributions in ways that are difficult for households to incorporate into decision-making (Lipper and Thornton, 2014).

Although the availability of data (especially panel data sets) is scarce, there exist several attempts aimed at estimating the impacts of extreme weather on household welfare, most often measured through consumption (or income) related variables. Wineman *et al.* (2017) find that income per adult equivalent per day decreases by 18.3 percent with very low rainfall in rural Kenya. Furthermore, while the effect on calories consumed per adult equivalent is not significant, they find that the share from own crop and livestock production is lower, and the share of purchased calories is higher when a low rainfall shock occurs. Del Ninno *et al.* (2001) show that though overall food expenditures in Bangladesh were not affected by flood intensity, expenditures on calorie-dense foods fell, as did calorie consumption per capita for most flood-affected household categories, except for the most severely hit. This is explained by the fact that food aid was delivered to households living in the most severely-hit areas.

Arouri *et al.* (2015), Baez *et al.* (2016) and Christiansen and Dercon (2007) show a decrease from 5 to 19 percent in consumption expenditures following weather shocks in Vietnam, Guatemala and Ethiopia, respectively. In Nicaragua, households that experienced a drought over three years were 10 percent more likely to remain impoverished four years later (Premand and Vakis; 2010), while after the drought that affected Burkina Faso in 1984–85, poverty rates increased from 12 to 15 percent in the Sudanian zone, and from 2 to 19 percent in the drier Sahalian region (Reardon and Taylor; 1996).

In most of these cases, extreme weather events increase vulnerability of rural households through their effects on crop production. Using a two-period panel data set, McCarthy *et al.* (2017) show that the floods that occurred during the 2014/15 growing season in Malawi dramatically reduced crop yields of affected households. However, drops in food consumption expenditures and calories per capita were less dramatic. Using panel data from Zimbabwe, Michler *et al.* (2016) find that severe climate events negatively and significantly affect crop production, with descriptive analysis showing average yields in extremely low rainfall years about 34 percent lower than in normal years. Similarly, Wineman *et al.* (2017), using panel data from Kenya, find that extremely low rainfall conditions decrease the value of crop production per adult equivalent by 29 percent. After the largescale floods of 1998 in Bangladesh, (using cross-sectional data) Del Ninno *et al.* (2001) documented crop losses

between 42 and 62 percent for the flood-affected households, with damages to the entire harvest in several cases.

Weather shocks can also indirectly affect welfare and vulnerability through prices and wages. Some evidence for Bangladesh shows that agricultural wages decrease during months with floods, especially when floods are "extreme" (Banerjee, 2007). Likewise, following the extreme flooding that occurred in the country in 1998, wage earnings fell after the floods (Del Ninno *et al.*, 2001), and wages declined 4 percent for every foot the flood deviated from normal flood depth in agricultural markets, and about 7 percent in non-agricultural markets (Mueller and Quisumbing, 2010). The impact of shocks on local grain prices in Ethiopia has been analysed by Hill and Fuje (2017) over 17 years. On average, in the months following harvest, prices were estimated to increase by 2.5 percent following a 10 percent loss in yields, but this effect dissipated until no significant effect on grain prices was observed 6 months after the drought has occurred. A higher local price after a drought-related shock would likely have a negative impact on consumption for net-food buyers.

The empirical evidence suggests that households subject to severe climate events often experience increasing levels of vulnerability related to large losses in agricultural income. The negative impact on consumption and calories tends to be lower than the impact on crop income but still significant, indicating that households are not able to perfectly smooth consumption ex-ante. However, households can react to negative impacts of weather shocks by implementing household risk-coping strategies ex-post, such as labour re-allocation, sales of durables and livestock, and access to transfers from friends and relatives. Furthermore, although theoretically, households can rely on a number of institutions, mechanisms such as access to credit, markets and social safety net programs are never more than partial and consumption shortfalls remain high when faced with extreme shocks (Baez and Mason, 2008; Dercon, 2005; Alderman and Paxson, 1994).

The impacts of climate change on rural livelihoods are not only felt through extreme weather events discussed above, but also through slow-onset changes in weather such as, changes in the time and duration of cropping seasons, increases in dry spells, hot days and warm nights (IPCC, 2014), all of which also affect the distribution of pests and diseases that affect agricultural production. The effects of slow-onset events tend to be harder to quantify as observing enough variation in data becomes more challenging, but there is a growing literature also captures these effects thanks to the improving availability of large scale agricultural household surveys and high-resolution climate data (FAO, IFAD, UNICEF, WFP and WHO, 2018; Arslan *et al.*, 2014, 2015, 2017; Asfaw *et al.*, 2015; among others).

This paper contributes to this growing literature by using a novel data set specifically collected to analyse the impacts of El Niño on livelihoods in rural Zambia in order to contribute to policies to decrease vulnerability of smallholders.

3   Agricultural policies, practices, and rural livelihood strategies

Among the African countries, Zambia is one of the most urbanized, with about 41 percent of urban population. This is mainly due to the copper mining industry, which has been the backbone of the economy in the country since the period of colonial rule. Although agriculture represents about 10 percent of the GDP (NAP, 2016) in Zambia, it remains the main economic and livelihood activity for the rural poor, who make up more than 75 percent of the rural population (LCMS, 2015). As such, improving the agricultural productivity and incomes of the rural poor is a national policy priority with many initiatives to support and increase the adoption of different agricultural practices as well as livelihood diversification strategies. Most policies focus on smallholder agriculture, nonetheless, there are few (about 740) large commercial farms who focus mainly on intensive livestock, as well as wheat, soybean and maize production (FAO, 2016).

Maize is both the primary crop grown by small-scale producers and the national staple food. As both a cause and a consequence, agricultural policy in the recent past in Zambia was focused predominantly on the maize sector. This includes significant public expenditure on output market and input subsidies, as well as frequent use of maize trade restrictions to affect prices (Sitko *et al.*, 2017).

The Farmer Input Support Programme (FISP) and the Food Reserve Agency (FRA) are the two cornerstones of Zambia's agricultural sector Poverty Reduction Programs, accounting for about 29 percent of total agricultural sector spending between 2004 and 2013 and reaching about 60 percent of the poverty reduction programme budget of the Ministry of Agriculture in most recent years (Mason and Myers, 2013).

The output market subsidies in the country were established in 1996, and have been provided through the FRA, a parastatal strategic food reserve/maize marketing board, which has become the main buyer of maize produced by smallholders in the country. The FRA buys maize at pan-territorial prices, which are frequently higher than prevailing private sector prices. It then exports the maize or resells it internally. In the case of low-harvest years, FRA imports maize and sells it to large-scale millers at prices that are below their market levels.

As a consequence of this policy, farmers are incentivized to grow maize, even in regions where it may be agro-ecologically unsuitable (Mason and Myers, 2013). Moreover, the high prices paid for maize elevate the opportunity costs of growing crops that do not receive the same support, and may act as a disincentive for diversification.

The FISP traditionally provides fertilizers and maize seeds to "vulnerable but viable" farmers (i.e., those that have the ability to cultivate maize on at least 0.5 ha of land) that are members of cooperatives/farmer groups, with around 900,000 intended number of beneficiaries (Mason *et al.*, 2013). Nonetheless, since its inception in 2010 a large body of evidence has raised concerns over the program showing its inefficiency, as well as its inability to achieve the desired objectives. On the other hand, it has created a number of negative side effects including biasing livelihood and agricultural technology adoption decisions, crowding out of alternative agricultural investments, decreasing production and productivity due to lack of transparency, corruption and delays in distribution of inputs (Mason, 2013).

Various modifications to FISP have been introduced over the years. To address the importance of and the need for crop diversification, for example, the distribution of rice, sorghum, cotton and groundnuts was added to hybrid maize seed within the FISP, the only seed crop distributed

along with fertilizers until 2009 (Mason *et al.*, 2013). Yet, quantities of seeds for these alternative crops has remained relatively low whenever it existed (FAO, 2016).

Many of the inefficiencies of the FISP program have been addressed in various national agricultural plans and policies, to end up with its more recent approach whereby an electronic voucher system has been piloted for distribution of inputs. This system utilizes Visa based vouchers that allow farmers to purchase inputs from private agro-dealers at subsidized rates. The e-voucher system was piloted in 2015/16 in 13 districts and was expanded to 39 districts in 2016/17. According to existing plans, by 2018 the FISP will totally graduate towards the e-voucher system, enabling farmers to choose their inputs and seeds.

3.1 Field level practices

Large efforts, advocacy and investments have been made in the country to promote the adoption of farming practices that would improve the traditional and natural resource intensive systems, such as the slash and burn, chitemene[1] and ox-ploughing among others, in order to help reduce the vulnerability to crop production losses. These improved practices are claimed to increase water retention capacity and soil nutrients, and reduce erosion. Among the most intensively promoted and adopted practices, Conservation Farming, Agroforestry and Improved Fallows are worth mentioning and analysing within the context of climatic shocks and production.

The Zambia National Farmers Union (ZNFU) started promoting Conservation Agriculture[2] (CA) in 1995 through the Conservation Farming Unit (CFU). In 1999 the Zambian Government endorsed the promotion of CA as a national priority and ended up including it in the Zambian National Agricultural Policy starting in 2004. This focus on CA was echoed and supported by a number of initiatives and projects supported and implemented by various NGOs, as well as international agencies and organizations including FAO and the World Bank, among others (Arslan *et al.*, 2014).

Despite the large investments towards facilitating and encouraging adoption of CA and Agroforestry, the adoption rates are still rather low. Using a rich data set that combines data from two large-scale household surveys with historical rainfall data, Arslan *et al.* (2014), found very little adoption of the entire CA package and as such analysed, the adoption of the main CA components combined: minimum/zero tillage and planting basins documenting only 5 percent of nationwide adoption in 2008, down from 13 percent in 2004 with dis-adoption rates up to 95 percent (Arslan *et al.*, 2014) although with an increase to 12 percent in the most recent panel.

The rich panel data set has allowed an analysis differentiated by geographic area as well as by climatic patterns and characteristics, which concluded that adoption of CA practices are more suited and better performing in areas of highly variable rainfall patterns, mainly in the Zambian agro-ecological region IIa (FAO, 2016). Policy recommendations included

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[1] Chitemene cultivation implies that the tree canopies are cut off by trimming branches. These are heaped in several locations in the field and burnt. Planting of crops is done in the places where burning had taken place. These areas are rich in potash from the biomass and contribute to high yields. Trees regenerate and the process is repeated year in and out. This method is common in the high rainfall northern province of Zambia (for more info see a Manual for Climate Smart Agriculture in Zambia [FAO, 2016, mimeo]).

[2] Conservation Agriculture techniques promoted in Zambia are known as Conservation Farming (CF) and include: reduced tillage, precise digging of permanent planting basisns or ripping of soil with a Mogoye ripper, keeping of crop residues, rotation of cereals with legume, dry season land preparation (Arslan et al., 2014).

suggestions to account for agro-ecology and site-specific climate shock exposure when selecting the most suitable farming practice to promote.

A number of other land management practices have been promoted or are adopted in the country, though in general with a relatively low adoption uptake. These include improved fallows and agroforestry among others.

In improved fallows, crops are grown sequentially with fertilizer trees, which are grown for one or a few seasons (depending on practice, location, and species). Improved fallows were introduced to Zambia in the late 1970s through a NORAD-funded Soil Productivity program at the Misafmu Research Station in the Northern Province.

Trees, shrubs and palms integrated into a farm can provide year-round vegetative cover that reduces soil disturbance and can often provide habitat for wild species, including crop pollinators. The practice of using perennial trees and shrubs within a farming system is referred to as "agro-forestry". Agro-forestry can improve land productivity providing a favourable micro-climate, permanent cover, improved soil structure and organic carbon content, increased infiltration and enhanced fertility, reducing the need for mineral fertilizers.

There are many trees in Zambia that farmers use on their farms to benefit their land by restoring soil fertility or indeed some have medicinal effects. Gliricidia sepium, Sesbania sesban, Leucaena leucocephala, Tephrosia vogelii, and Cajanus cajan (Pigeon pea) were the main species utilized in the fallow systems. Preferred species by farmers were Tephrosia and Cajanus, since they are good seeders, require less fallow time, are easy to manage and coppice, and can provide income (Tephrosia for seed and Cajanus for food) (FAO-EPIC, 2017).[3]

3.2   Livelihood diversification strategies

An effective way of addressing and reducing vulnerability and smooth risk is through adoption of diversified livelihood strategies.

Different livelihood diversification strategies can be adopted by households in rural economies to manage risk and smooth income ex-ante as well as ex-post (Arslan *et al*., 2017). The ability of a livelihood system to respond to shocks through coping strategies is indeed a crucial determinant of household resilience.

The extensive literature that exists on livelihood diversification strategies classifies the drivers of diversification into push and pull factors (Reardon, 1997; Barret and Reardon, 2000; Arslan *et al*., 2017), whereby push factors include imperfect credit and insurance markets, stagnation in the agricultural sector and high transaction costs in addition to natural hazards. As such, diversification choices are somewhat forced by these drivers and do not necessarily improve average incomes but rather tend to stabilize and ensure income levels (Barrett *et al*., 2001; Reardon *et al*., 2007; Lay *et al*., 2009; Arslan *et al*., 2017). Pull factors, on the other hand, are linked to a developing non-farm sector and the availability of and access to new/improved technologies in the farm sector. In this latter case, diversification choices are more likely to be correlated with improved average outcomes, as well as reduced variability of consumption (Reardon *et al*., 2007; Bandyopadhyay and Skoufias, 2013; Arslan *et al*., 2017).

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[3] For a throughout review of practices see FAO, 2016, mimeo.

The impacts of climate change can be generally classified as push factors for diversification as risk-averse farmers implement ex-ante risk management strategies (by diversifying crops, other agricultural activities or incomes) and trade a part of their expected earnings with a lower variability in income (Alderman and Paxson, 1992; Reardon *et al.*, 1998; 2007; Barrett *et al.*, 2001b).

Empirical evidence on the role of diversification as an adaptation strategy is growing and these are mainly linked to crop diversification strategies as well as to land management practices that can help smooth climatic shock and which is the subject of the present study (Di Falco and Chavas 2009; Cavatassi *et al.*, 2011).

In a recent study, Arslan *et al.* (2017) conducted an empirical analysis investigating the factors driving crop, livestock and income diversification, and their relationships with selected vulnerability indicators in Zambia. They found that diversification is mainly an adaptation response to long term trends in climatic shocks which act as push factor into livestock diversification. They also found that, in the presence of a shock (weather anomalies and long term climatic variability), households revert back to subsistence crop production activities instead of diversifying incomes.

The present study offers the opportunity to analyse whether and how diversification strategies and adoption of land management practices buffered the impacts of the drought caused by the El Niño in 2015. An assessment in southern Zambia found that 975,738 people (162,623 households) were affected by drought and required humanitarian assistance. Southern Province, for example, recorded a 48 per cent maize production decline (ZVAC, 2016). By using a rich and novel data set, we provide rigorous evidence into policies that can deal with similar shocks in the future.

4 Sampling frame and empirical strategy

Maize yields in the 2015/16 season in Zambia were expected to decrease by at least 30 percent in the most affected areas (Rembold *et al.*, 2016; ZVAC, 2016). Additional expected impacts included reduced livestock production and incomes in general, as well as impacts on energy sector and the water table. The sampling frame and the empirical strategy of this paper are designed to identify the more direct impacts of El Niño on the rural poor, i.e. maize yields and total incomes.

4.1 Sampling frame

The starting point for this analysis is the nationally representative household data from the 2015 wave of the Rural Agricultural Livelihoods Survey (RALS), collected by the Central Statistics Office (CSO) in collaboration with Michigan State University (MSU) and the Indaba Agricultural Policy Research Institute (IAPRI). The survey is designed to be representative of rural farm households at national and province levels and covers a sample of 7 934 households.[4] RALS includes detailed information on agricultural (crop and livestock) production and sales, off-farm activities and other income sources, along with household demographic characteristics as well as social capital indicators. RALS 2015 provided a rich background for the design of the ENIAS sample and questionnaire, which was initiated in response to the delayed onset of the rainy season due to the El Niño at the beginning of the 2015–16 rainy season. The FAO-EPIC programme of work, in collaboration with FAO Zambia office and IAPRI, has conducted the ENIAS to analyse the impacts of El Niño on maize yields, and to identify agricultural and livelihood strategies that successfully improve farmers' resilience to droughts, as well as to investigate the types of policies and institutions are needed to improve resilience to such shocks.

The sampling frame for ENIAS was defined by using propensity score matching (PSM) at the Standard Enumeration Area (SEA) level in order to match severely affected areas in the RALS 2015 data with those that were not severely affected to ensure that the sample has enough households in both areas for identification. The definition of "severely affected areas" is based on the most recent assessment of the ZVAC at the time of the design of the sampling frame, which was released in January 2016 (see Figure 1). Given the fact that the northern parts of the country were experiencing normal or above normal rainfall, all of Luapula, Northern and North-Western and most of Copperbelt and Muchinga provinces were excluded from the sampling frame. This choice was also driven by the significant differences between the agro-ecological and cropping systems of the excluded areas and the severely affected areas. Out of the 35 severely affected districts, 22 were covered in the RALS 2015 surveys and were used to create a sampling frame for ENIAS using PSM. Finally, 149 SEAs were selected comprising of 60 severely affected (treatment) and 89 not severely affected (control) SEAs, and a random sample of 9–10 households from the RALS 2015 roster was interviewed in each SEA, yielding a final sample of 1 311 households.

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[4] The first round of RALS was undertaken in 2012 using a new sampling frame derived from the 2010 Census. One of the most important design features is that RALS allows to track, to the maximum extent possible, the same households over time, providing a statistically valid and comprehensive means to assess trends in rural livelihoods and welfare within a consistent panel framework (IAPRI, 2012). Statistics for the Eastern province are representative at the district level due to the oversampling in the survey.

In most of the affected regions of Zambia, rainfall has finally started in February 2016 and the cumulative seasonal rainfall levels approached normal levels. Given the fact that ENIAS data was collected starting in early November 2016, we re-assessed the treated and control households using ENIAS data merged with rainfall data. This assessment indicated that the difference in terms of 2016 season rainfall and productivity between treatment and control SEAs as defined in the original sampling frame had blurred. Therefore, a second matching was conducted at the household level using the observed rainfall levels from November 2015 until the end of February 2016 as a "shock" identifier. Our shock definition based on observed rainfall data is an indicator variable equal to one in wards, where the total rainfall observed from November 1, 2015 until February 28, 2016 fell below the long-term minimum rainfall of 353 millimetres.[5]

Figure 1.   Severely affected 35 districts as reported in the Zambia Vulnerability Assessment Committee (ZVAC) Situation Report (2016)

Source: Zambia Vulnerability Assessment Committee (ZVAC) Situation Report, 2015.

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[5] In the remainder of this paper we use treated vs. control, interchangeably with shocked vs. non-shocked households based on this definition of the rainfall shock.

4.2 Empirical strategy

4.2.1 Matching methods

As a first step of our empirical strategy, using the shock variable described above and defined as "treatment" in RALS 2015 data, we used a set of matching methods to create two groups of households that are as similar to each other as possible except their exposure to the shock. In order to create the two groups, we have used various methods to match shocked and non-shocked households including the nearest neighbour (NN) matching using the estimated propensity scores (PSM) and Mahalanobis distance. The NN matching is considered the most straightforward matching estimators, in which an individual from the comparison group is chosen as a matching partner for a treated individual that is the closest in terms of propensity score (Caliendo and Kopeinig, 2008). We also test the robustness of our results correcting for standard errors as proposed by Abadie and Imbens in 2006 (see the *mahal*[6] options in Stata)[7]. Matching using Mahalanobis Distance (MHD) based on covariate matching (CVM) has been also used to calculate similarity of two households in terms of covariate values applying the matching on these distances (see also Imbens, 2004 and Zhao, 2004 and *mahapick*[8] command in Stata).

Table 1.   Summary statistics of variables selected in the matching process

Variable	Mean	Std. Dev.	Min	Max
Household characteristics				
Age of household head	48.23	15.58	21	94
Dependency ratio	1.16	0.81	0	6
Highest level of education of household head	5.67	3.77	0	19
Household wealth				
Wealth index	0.25	1.17	-0.89	12.05
Share of agriculture income	0.65	0.34	0	1
Gini-Simpson index of crop diversification	0.38	0.24	0	0.82
Gini-Simpson index of livestock diversification	0.20	0.26	0	1
Gini-Simpson index of income diversification	0.34	0.24	0	1
Number of cultivated plots	2.71	1.36	0	9
Durables and agriculture implements				
Household owns tv (1=yes)	0.24	0.43	0	1
Household owns ploughs (1=yes)	0.32	0.47	0	1
Household owns pumps (1=yes)	0.05	0.23	0	1
Social capital & market access				
Household (HH) has a coop, farmer/women/savings-loan group (1=yes)	0.60	0.49	0	1

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[6] In Stata, the programme *psmatch2* developed by Leuven and Sianesi (2003) allows to implement a variety of propensity score matching methods to adjust for pre-treatment observable differences between a group of treated and a group of untreated. Matching estimators include propensity score (PSM) and covariate (CVM) matching, including NN and caliper matching, Kernel matching (KM), local linear matching (LLM) and Mahalanobis metric (covariate) matching. The *psmatch2* routine also includes the *pstest* routine for covariate-balancing tests.

[7] Results from different matching methods are available upon request.

[8] *mahapick* in STATA seeks matching observations for a set of "treated" observations, using a Mahalanobis distance measure which it calculates (Kantor, 2008)

Variable	Mean	Std. Dev.	Min	Max
Fertilizer purchased from different sources (1=yes)	0.56	0.50	0	1
Fertilizer source: FISP (1=yes)	0.44	0.50	0	1
Dist. to the nearest agro-dealer (km)	24.78	24.58	0	160
Dist. to tarmac/tarred road (km)	21.67	24.88	0	170
District characteristics				
District poverty rate	0.52	0.10	0.23	0.71
District banks, Tobacco & cotton buyers (1=yes)	0.74	0.44	0	1

Source: Authors' elaboration.

The implementation of matching methods to create the two groups of shocked and non-shocked households using RALS 2015 requires the selection of a set of variables. During the selection process, one should avoid the omission of important covariates that would lead to increase the bias in resulting estimation (Heckman *et al.*, 1997), although including not essential variable would reduce the probability of finding common support (Bryson *et al.*, 2002). The selection of relevant variables should be guided by economic theory, other previous related findings as well as the specific context in which the analysis is performed, and the selected covariates should influence the choice to participate in a programme (i.e. the probability of participation) and should not be affected by the programme participation (Caliendo and Kopeinig, 2008).

Our setting is slightly different from the standard program evaluation literature based on quasi-experimental methods, which try to control for the potential endogeneities in household participation in a program to be evaluated and create a counterfactual to measure program impacts. Our "treatment", i.e. El Niño shock defined above, by and large is a random weather event that has affected some households severely and some not, hence there is no selection bias. Some households, however, may have adopted ex-ante strategies that has made them more resilient to the treatment, especially in areas with repeated exposure to such events. Such autonomous adaptation would lead us to underestimate the impact of treatment. Hence, we use matching to pre-process our data in order to select a sample of "shocked" and "non-shocked" households that are similar to each other in terms of a set of variables in the baseline that potentially shaped the way they were affected by the shock. By combining matching and panel data methods, we control for both observable and unobservable household characteristics that confound the impact of the shock on the outcomes we are interested in.

Table 2. Test for selection bias after matching

Variable	Matched sample		Bias		T-test p-value
	Treated	Control	% Bias	% Bias reduction	
Household characteristics					
Age of household head	48.72	48.80	-0.5	74.1	0.914
Dependency ratio	1.12	1.12	0.1	-1 675.6	0.983
Highest level of education of household head	5.72	5.90	-4.8	78.9	0.341
Household wealth					
Wealth index	0.59	0.65	-4.2	58	0.417
Share of agriculture income	0.67	0.67	0.1	96.6	0.988
Gini-Simpson index of crop diversification	0.41	0.38	13.5		0.021
Gini-Simpson index of livestock diversification	0.23	0.25	-5.9	64.5	0.258
Gini-Simpson index of income diversification	0.35	0.35	-1	88.2	0.849
Number of cultivated plots	2.85	2.84	0.8	-163.9	0.874
Durables and agriculture implements					
Household owns television	0.29	0.30	-1.5	74.3	0.771
Household owns ploughs	0.42	0.41	3.4	85.8	0.51
Household owns pumps	0.08	0.09	-3.1	51.7	0.563
Social capital and market access					
Household has a coop, farmer/women/savings-loan group	0.64	0.61	5.7	-46.8	0.257
Fertilizer purchased from different sources	0.61	0.65	-8.1	-100.6	0.101
Fertilizer source: FISP	0.45	0.45	0.7	93.8	0.893
Dist. to the nearest agro-dealer (km)	27.66	27.36	1.1	81.8	0.823
Dist. to tarmac/tarred road (km)	22.51	23.75	-4.7	-185.2	0.339
District characteristics					
District poverty rate	0.52	0.51	13	-332.2	0.009
District banks, tobacco and cotton buyers	0.75	0.76	-2	88.7	0.672

Source: Authors' elaboration.

The variables included in the matching process are listed in Table 1. We have considered those variables ensuring stronger comparability between treated and control households such as, household head's age and education, dependency ratio as socio-economic characteristics and a range of wealth and diversification indicators. These include a wealth index, the share of agricultural income in total income as well as three different diversification indices measured by the Gini-Simpson index (crop, livestock and income).[9] We also use ownership of durable assets and social capital and market access indicators as well as two district level variables (poverty rate and credit sources) for balancing.

There exist several covariate-balancing tests that can be applied to test the balance of the PSM results. In this study, we use the following method to check the selection bias before and after matching. In some cases, matching techniques may result in many individuals not being matched, which can lead to larger bias than if the matches are inexact but more individuals remain in the analysis (Rosenbaum and Rubin, 1985). The test results reported in Table 2 to assess the change in the selection bias after matching for shocked and non-shocked farmers

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[9] Gini-Simpson index is defined as $D_j = \left(1 - \sum_j w_j^2\right)$, where w_j is the number of distinct diversity units in the corresponding index j (with $j = c, l, y$ indexing crops, livestock and income, respectively).

show a reduction in the standardized percentage bias as a consequence of matching for most of the selected variables. We also find that there are almost no significant differences in matched shocked and non-shocked households for the selected covariates. Figure 2 depicts the standardized percentage bias in all the covariates, and shows a significant decrease in bias in the matched sample as opposed to the unmatched sample.

Given the results of the matching and balancing tests, we conclude that our matching methods result in a balanced sample in terms of important covariates that shape household response to shocks. This is important as, combined with panel data methods, it helps us identify the impact of El Niño in a more causal way in our analyses of maize yields and income.

Figure 2.   Balancing test before and after matching
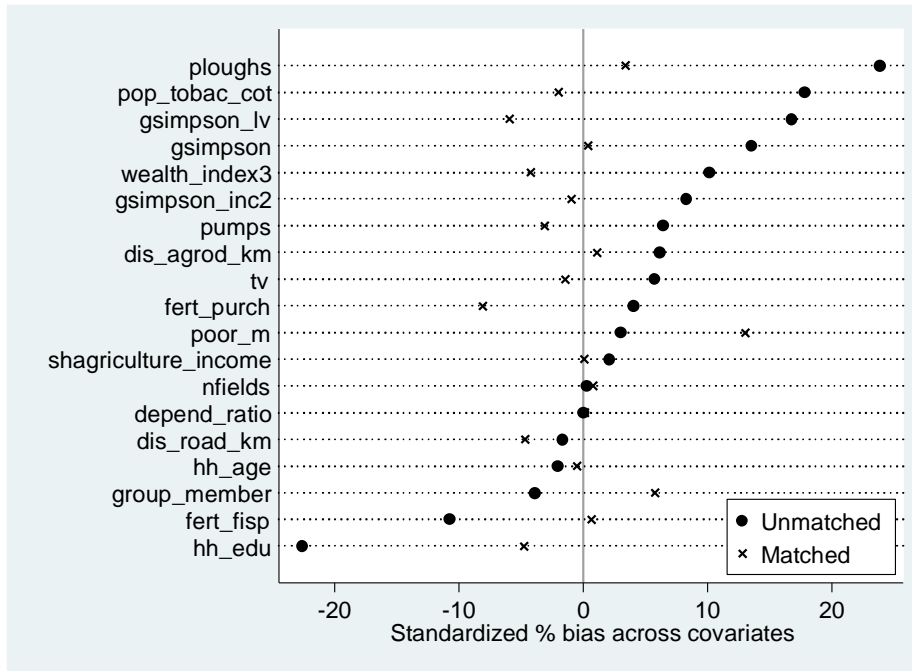
Source: Authors' elaboration.

4.2.2   Yield and income models

Using the matched sample as described above, we have defined two estimating equations, one for the maize yield and one for total gross income per capita as below.

$$Y_{it} = \alpha + \beta\, EN_{i16} + \gamma\, R_{kt} + \delta\, X_{it} + \theta\, P_{it} + \vartheta\, P_{it} * EN_{i16} + \varepsilon_{it} \qquad\qquad 1)$$

Where Y_{it} is the output variable (maize yield in kg/ha, or the value of total gross income per capita, both in logarithms) for the ith household ($i = 1, \dots, n$) at time t (t = 2015, 2016), EN is the El Niño dummy which is equal to 1 if the ward of the household has experienced rainfall in 2015-16 season that was below the long run minimum of that ward, R_{kt} are rainfall variables

at ward level[10] (k=1,…,136), X_{it} is a vector of household level variables including socio-demographic characteristics, and wealth and social capital indicators at time t, P_{it} are practice and policy variables that capture the potential ex-ante measures or policies that are expected to ameliorate the impact of the shock on the outcomes, and the $P_{it} * EN_{i16}$ are interaction terms between practice/policy variables and the shock indicator. The error term ε_{it} is composed of a normally distributed term independent of the regressors (u_{it}), and time-invariant unobserved effects v_p.

We use fixed (FE) and random (RE) effects estimation models which allow to model time-invariant heterogeneity (Wooldridge, 2002). Whereas, the FE models treat unobservables as parameters to be estimated that can be correlated with explanatory variables, RE models consider them as a random variable uncorrelated with covariates, whose probability distribution can be estimated from data. As described in Mundlak (1978), Chamberlain (1984) and Wooldridge (2009), we can control for possible additional correlations between time-varying explanatory variables and random effects, by parameterizing the distribution of v_i and including the means of the time-varying characteristics as regressors in the analysis.

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[10] Climatic variables were processed at the ward level using the boundaries to extract information from ARC2 data to be merged with RALS data. Wards are administrative units under the district and above the village levels.

5 Data and descriptive analysis

5.1 Socio-economic and climate data sources

As described in previous sections, this study makes use of two main sources of data: i) household level data based on the ENIAS and RALS surveys, and ii) historical rainfall data at high resolution from publicly available data sources.

Our socio-economic data (ENIAS sample merged with RALS 2015) includes relevant information on crop[11] and livestock production and sales, different sources of income along with household demographics and social capital information for 1 311 farmers tracked over years across seven provinces of Zambia as shown in table 3.

Rainfall information comes 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 1983–2016. ARC2 data are available on a daily basis and have a spatial resolution of 0.1 degrees (~10km).[12] We created our rainfall variables at the ward level to trace historical trends as well as current period shocks that are closely linked with agricultural production as well as the adoption of livelihood strategies with implications for vulnerability and welfare of small farmers. The ENIAS survey together with rainfall data allows us to evaluate the impacts of shocks like El Niño that are expected to get more frequent and severe in Zambia, as well as understand the agricultural practices and livelihood strategies that can buffer household production and welfare from the impacts of such shocks to drive policy recommendations.

Table 3.   Distribution of interviewed households by province and sample type

Province	Number of interviews by selected sample type		
	Selected	**Replacement**	**Total**
Central	210	23	233
Copperbelt	96	5	101
Eastern	590	66	656
Lusaka	75	12	87
Muchinga	16	1	17
Southern	150	4	154
Western	56	7	63
Total	**1 193**	**118**	**1 311**

Source: Authors' elaboration.

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[11] RALS surveys traditionally cover the cropping seasons that goes back two seasons in order to capture total value of crop production and sales that are from one particular season completely. This is especially useful as there is no detailed information on household expenditure and total income is used instead as a welfare outcome. Therefore 2015 RALS covers the 2013/14 season, whereas ENIAS covers the 2015/2016 agricultural season.

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

5.2   Descriptive analysis

Given the delayed onset of rainfall that occurred in most of the regions of Zambia in 2016 and the key role played by rainfall levels in defining the shock variable in our analysis, we first present the distribution of the observed amount of rainfall in our data. Figure 3 shows a comparison of total rainfall registered during the 2014/15 and 2015/16 cropping seasons (i.e., from November to April) as well as between November and February in the districts surveyed in the ENIAS at the district level. The reduction in the total amount of rainfall from the 2014/15 to the 2015/16 cropping season depicted in the upper maps is confirmed when we look at rainfall between November and February (lower panel of Figure 3), which show a clear decrease in the amount of rain in most of the areas during these months, based on which our shock indicator is defined.

Descriptive statistics of control variables used in the analyses are presented in Table 4 both for ENIAS and RALS. Fifty eight percent of farmers are in our shocked group, which experienced a total rainfall between November 2015 and February 2016 that was below the long-term minimum of the same period in their ward. Climate variables include rainfall deviation (in absolute value) defined as the percentage deviation of total rainfall in the season covered by each survey from the long-term (1983–2016) average, and the long-term coefficient of variation (CoV) of rainfall during the cropping season capturing the effect of year-to-year rainfall variability on maize productivity and welfare. Empirical studies have shown that climate variability significantly influences farmers' choices and consequently affects agricultural yield and incomes (e.g., Arslan *et al.*, 2015; Porter, 2008; Seo and Mendelsohn, 2006; Mano and Nhemachena, 2006; Benhin, 2007). Differences in seasonal precipitation and temperature tend to affect farmers' decisions, leading them to favour livestock production and irrigation (where possible) while reducing crop cultivation due to the effect of drier and warmer conditions (Skoufias *et al.*, 2011; Hassan and Nhemachena, 2008).

Figure 3.   Total rainfall during the cropping season (Nov-Apr) and between November and February using RALS 2015 and ENIAS 2016 data
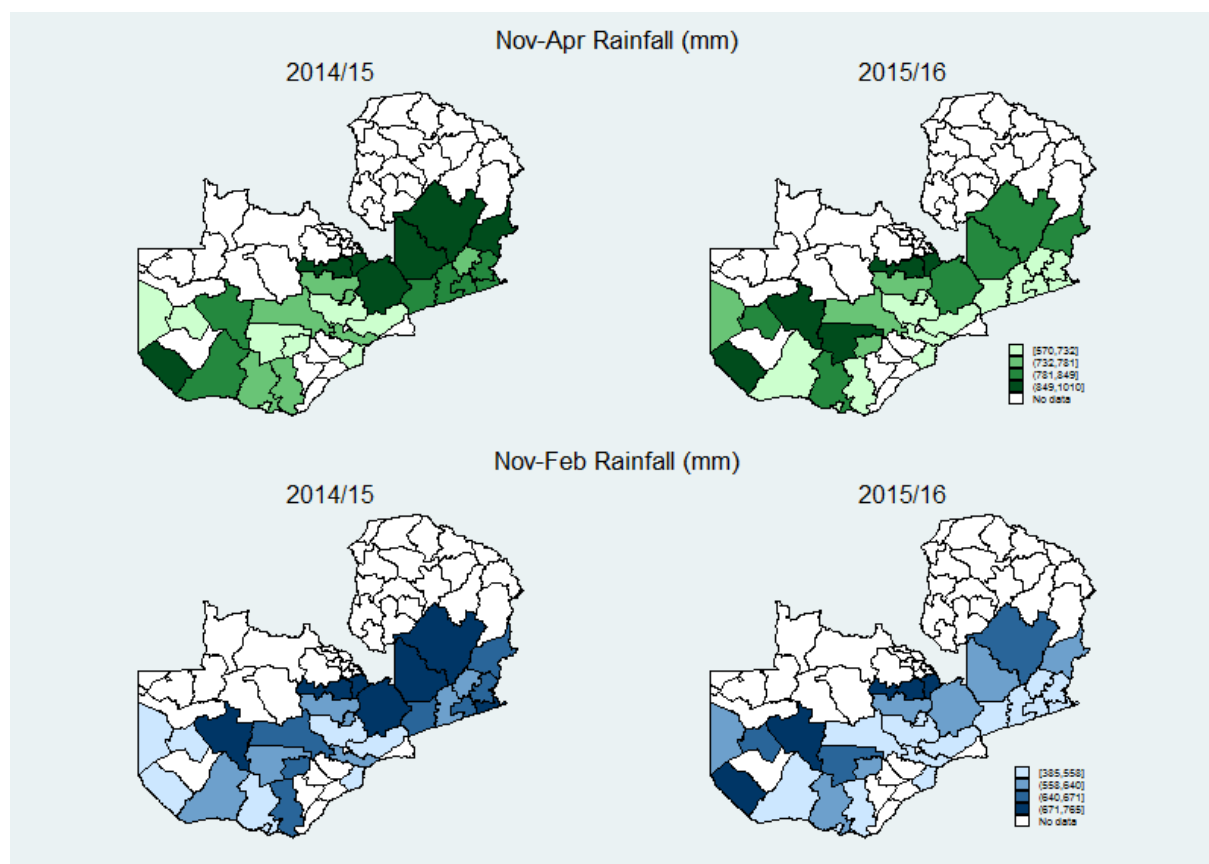
Source: Authors' elaboration based on Rural Agricultural Livelihoods Survey (RALS) 2015 and El Niño Impact Assessment Survey (ENIAS) 2016 data.

The set of socio-demographic variables includes household head's characteristics such as age, gender and educational level, and the number of household members. The effect of household size on agricultural production and income may be considered from two different perspectives. On the one hand, number of household members is a proxy for higher labour endowment that can be engaged in different agricultural tasks (Deressa *et al.*, 2009; Croppenstedt *et al.*, 2003). One the other hand, in the attempt to earn income and decrease consumption risks ex-ante, family members of large households may be forced to engage in off-farm activities, hence decreasing farm labour availability (Yirga, 2007). In our sample, the average household has 6.8 members in 2015 and 7.3 in 2016. The average age of the head, capturing farming experience is 48 years in 2014 and 50 years in 2016, and around 24 percent of households are female headed in both years. The number of years of schooling is 7.8 and 8.1 in 2015 and 2016, respectively. Some evidence suggests that female headed households have lower productivity because women face more constraints than men, such as less education, inadequate access to land, difference in input use such as improved seeds, fertilizer and production assets, as well as limited access to information and extension services (Akresh, 2008; De Groote and Coulibaly, 1998; Udry, 1996; Udry *et al.*, 1995). Regarding education, it is shown that schooling has positive effects on agricultural productivity and wealth due to the skills that more educated farmers acquire to gather and analyse information relevant to farm decisions (Reimers and Klasen, 2012; Asadullah and Rahman, 2005; Appleton and Balihuta, 1996; Feder *et al.*, 1985).

Table 4. Descriptive statistics of selected control variables

Variable	RALS 2015				ENIAS 2016			
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Household received the shock (1=yes)	**-**	**-**	**-**	**-**	**0.58**	**0.49**	**0**	**1**
Climate variables								
Rainfall deviation*	0.06	0.06	0.002	0.378	0.13	0.07	0.003	0.36
CoV of Oct-Apr rainfall 1983-2016**	0.20	0.02	0.154	0.246	0.20	0.02	0.15	0.25
Household socio-demographic								
Number of household members	6.81	3.06	1	30	7.30	3.23	1	30
Age of household head (years)	48	16	21	94	50	15	9	96
Education of household head (years)	7.82	3.54	0	19	8.16	3.39	0	19
Head is female (1=yes)	0.24	0.43	0	1	0.24	0.43	0	1
Land characteristics and agricultural practices								
Land size under maize (ha)	1.65	2.30	0	45	1.39	1.56	0	28
Inorganic fertilizer applied on maize plots (1=yes)	0.73	0.44	0	1	0.68	0.46	0	1
Household uses hybrid maize seeds (1=yes)	0.67	0.47	0	1	0.62	0.48	0	1
Adoption of minimum soil disturbance (MSD) on maize plots (1=yes)	0.09	0.29	0	1	0.10	0.29	0	1
Crop association*** on maize plots (1=yes)	0.27	0.44	0	1	0.44	0.50	0	1
Crop residue cut and spread on the field (1=yes)	0.02	0.14	0	1	0.04	0.20	0	1
Household grows trees/shrubs on plots (1=yes)	0.33	0.47	0	1	0.34	0.47	0	1
Household uses mechanical erosion control (1=yes)	0.25	0.43	0	1	0.19	0.39	0	1
Household owns agriculture implements (1=yes)	0.35	0.48	0	1	0.37	0.48	0	1
Household uses animal/mechanical tillage power (1=yes)	0.65	0.48	0	1	0.63	0.48	0	1
Household wealth, market access and social capital								
Wealth index (normalized)	0.08	0.08	0	1	0.11	0.11	0	1
Fertilizer purchased from diff. sources (1=yes)	0.56	0.50	0	1	0.43	0.49	0	1
Fertilizer source: FISP (1=yes)	0.44	0.50	0	1	0.42	0.49	0	1
Group membership (share in SEA)	0.64	0.19	0.11	0.95	0.64	0.22	0.11	1
Households receiving credit (share in Ward)	0.01	0.02	0	0.071	0.01	0.02	0	0.071

Notes: Based on 1 197 panel observations. * Rainfall deviation is calculated as the absolute value of the total rainfall deviation during the 2013–2014 and 2015-2016 cropping seasons from the long-term average. ** CoV of Oct-Apr rainfall between 1983 and 2016. *** Rotation and/or legume intercropping practiced on maize plots.

Source: Authors' elaboration.

Regressors that are the main focus of our analyses include variables related to agricultural input and practice use, such as fertilizers, hybrid maize seeds and a set of SLM practices applied to maize plots.[13]

The percentage of farmers adopting Minimum Soil Disturbance (MSD) defined as practicing zero tillage, planting basins (potholes) or ripping on at least one maize plot is quite low for the selected sample, although figures show a slight increase (from 9 to 10 percent) between the two waves. The crop association variable constructed as practicing legume intercropping and/or crop rotation on at least one plot devoted to maize, exhibits a rise from 27 to 44 percent of households. Residue retention, defined as the use of crop residues as surface mulch rather than removing or burning them, increases from 2 to 4 percent between 2014 and 2016, although its level of adoption is still low in the country.

The wealth index (normalized), constructed using principal component analysis (PCA) based on assets ownership and dwelling conditions, is used as a proxy for household wealth. Wealthier farmers are expected to be more capable of coping with shocks, hence have lower livelihood vulnerability (De Janvry et al., 1991; Kinsley et al., 1998), as well as to be more able to afford the purchase of agricultural inputs, such as chemical fertilizer and improved seeds (Arslan et al., 2015). The average wealth index increased between the two waves from 0.08 in 2015 to 0.11 in 2016. Social capital and market access may positively affect agricultural production and wealth due to the opportunity that households have of sharing information and knowledge in groups or in markets that act as main information hubs (Cavatassi et al., 2012). In this study, we use a variable indicating whether the household purchased fertilizer from different sources as a proxy for market access, and access to Farmer Input Support Subsidy Programme (FISP) to capture the role of relevant institutions given the main objective of the programme of increasing food security and income through the expansion of the market for private input suppliers in the country. Figures show that 56 and 43 percent (in 2015 and 2016, respectively) of households have access to fertilizer from different sources including governmental and commercial ones, whereas around 44 percent of farmers declared to have access to FISP in 2015 (42 percent in 2016). We also use the share of households that participate in groups such as farmer cooperatives, women's groups or savings and loan societies within a SEA as a proxy for social capital. In our sample, around 64 percent of households participate in any of the groups mentioned above in an average SEA in both waves. Furthermore, the level of households that have access to credit from formal sources in the country is extremely low. This very low share of borrowers among small farmers is due to the fact that they are not attractive for formal financial institutes because they cannot meet the minimum requirements and are perceived as high-risk borrowers (Onumah, 2003).

Figures 4 and 5 show the distribution of the two outcome variables at district level both for RALS 2015 and ENIAS 2016. From Figure 4, we see a reduction in maize productivity between the two waves in most of the ENIAS surveyed districts, whereas in terms of wealth (see Figure 5), the reduction of income per capita is not as clear as for yields. Although weather shocks may have intense effects on crop productivity, households may anticipate negative effects of climatic events by modifying agricultural plans and investing resources, labour and time in off-farm activities. Nevertheless, the unconditional averages plotted in these figures provide just suggestive

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[13] Most of the variables on land characteristics and adoption of SLM practices included in the analyses are relative to maize due to its importance in production, consumption and sales with respect to other cultivated crops.

evidence, as it has to be seen whether and how climatic conditions drive outcome variables controlling for other variables that affect livelihood decisions and risk attitudes.

Figure 4.   Maize productivity in RALS 2015 and ENIAS 2016
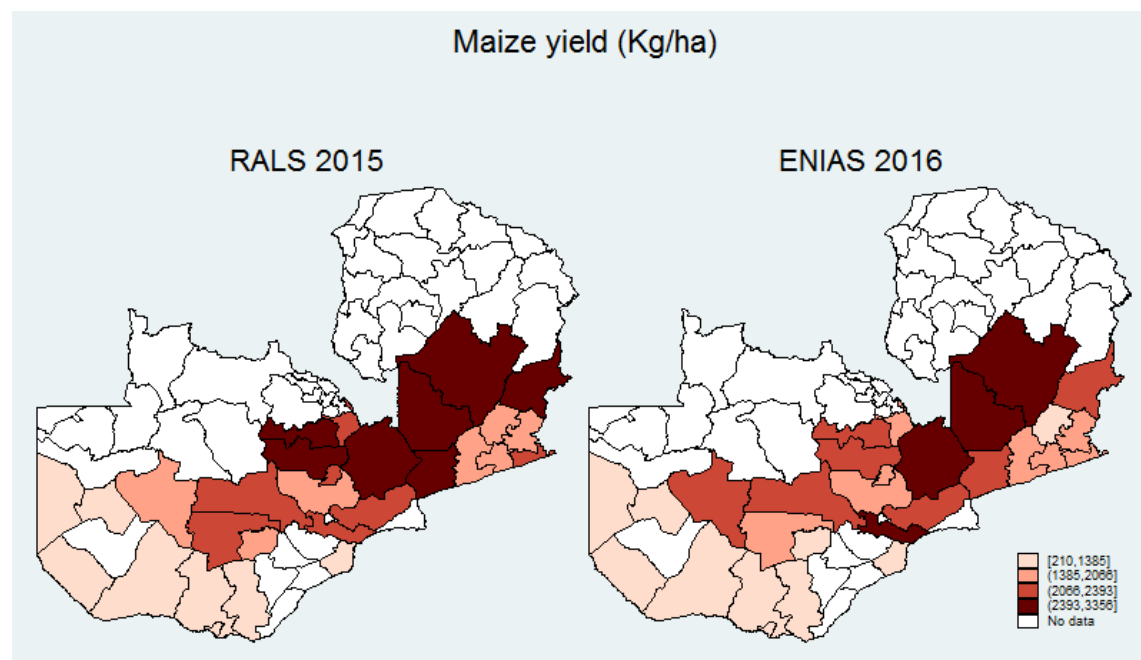
Source: Authors' elaboration based on Rural Agricultural Livelihoods Survey (RALS) 2015 and El Niño Impact Assessment Survey (ENIAS) 2016 data.

Figure 5.   Income per capita in RALS 2015 and ENIAS 2016
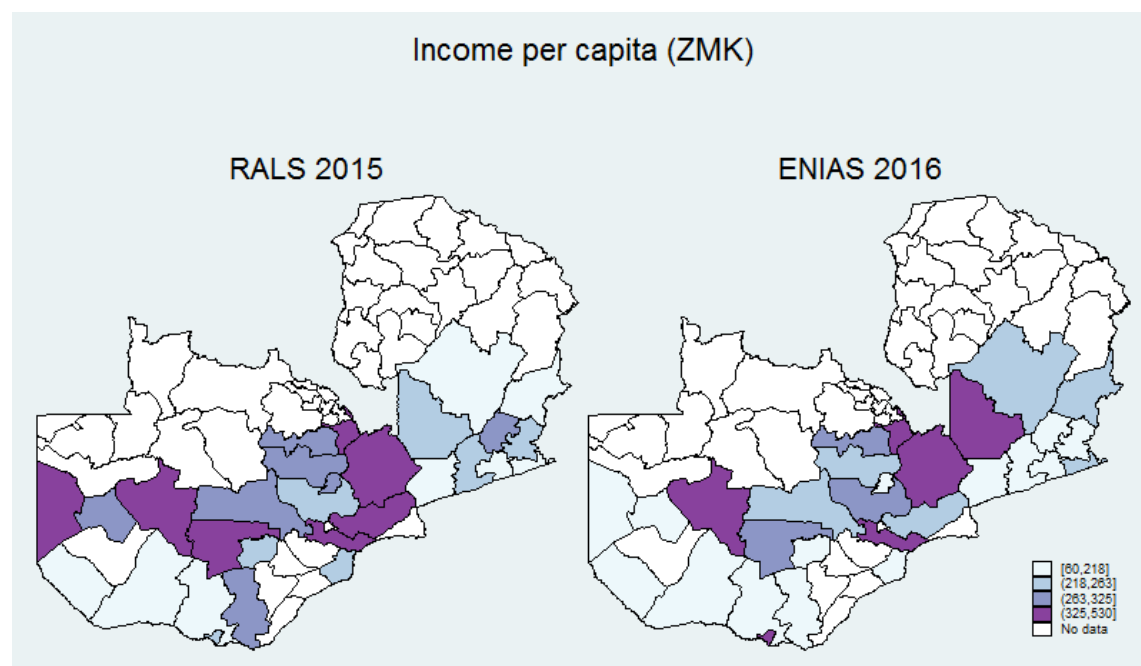
Source: Authors' elaboration based on Rural Agricultural Livelihoods Survey (RALS) 2015 and El Niño Impact Assessment Survey (ENIAS) 2016 data.

6 Results

In this section we present the results from the analysis of the impact of El Niño and other control variables on the two outcome variables of interest: maize productivity and household income per capita.

6.1 Determinants of maize productivity

Results on the determinants of maize productivity are presented in Table 5 showing estimates on the sample based on the nearest neighbour (NN) matching using the estimated propensity scores.[14] Findings from fixed effects (FE) estimation together with the correlated random effects (CRE) model obtained through the Mundlak (1978) correction are reported, although results are robust to the choice of model.[15] In addition to the simple model without interaction terms, columns (3) and (4) of Table 5 show results of models with interactions of agricultural practices with the absolute value of rainfall deviation to investigate whether a non-linear impact of practices exists that is not picked up by the shock variable.

Consistently across all the specifications, results show that being exposed to the shock negatively and significantly affected maize yields, resulting in a decrease in yield by around 20 percent. Considering that around 70 percent of total income comes from crop income and maize income makes up 80 percent of crop income, yield decreases at this level can result in serious welfare implications for smallholders, especially those not able to count on ex-post coping strategies. Other rainfall variables (rainfall deviation and the long-term variation in season rainfall measured by the CoV) are never significant controlling for the shock variable.

The coefficient of land size devoted to maize is negative and statistically significant, revealing an inverse farm-size productivity relationship. There exists an extensive literature emphasizing different explanations for this empirical regularity (Savastano and Scandizzo, 2017), going from market failures (e.g., Sen, 1966; Scandizzo and Kutcher, 1981; Feder 1985; Barrett, 1996; Binswanger *et al.*, 1995; Benjamin and Brandt 2002; Ali and Deininger, 2014) to measurement issues with land and agriculture output[16] (e.g. Goldstein and Udry, 1999; De Groote and Traorè, 2005; Barrett *et al.*, 2010) or errors in self-reported survey data (Deininger *et al.*, 2012; Kilic *et al.*, 2017).

In terms of agricultural practices, use of inorganic fertilizer, hybrid seeds, MSD on maize plots as well as crop residue retention, have all positive and statistically significant effects on maize yields. The first two results are evidence of the important role played by fertilizers and hybrid seeds in increasing maize productivity consistent with expectations and previous empirical findings (Arslan *et al.*, 2015; Smale and Mason, 2017; among others). Figures from the CRE model (column 2) show that the use of inorganic fertilizer and hybrid maize seeds increases average maize productivity of around 34 and 23 percent, respectively. Average percentage increase in maize yield is 20 percent when the farmer adopts MSD and 22 percent for residue

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[14] Results on the whole sample, as well as on other samples as described in Section 4.2, based on the nearest neighbour (NN) matching and the Mahalanobis-metric matching (*mahal* option) using the estimated propensity scores (PSM), and the Mahalanobis Distance (*mahapick* command) are presented in Annex 1 for comparison and to test the robustness of our results.

[15] All reported models are based on the sample matched by using PSM with three nearest neighbours.

[16] Carletto et al. (2013 and 2015) confirm the presence of the inverse farm-size productivity relationship even when land size is measured using GPS devices.

retention. This is in line with several studies on SLM suggesting that such management practices help farmers achieve agronomic benefits in water-limited and/or water-stressed regions (Pittelkow *et al.*, 2015). Other agricultural practices, such as crop associations, agroforestry, erosion control measures and the use of agricultural implements and animal/mechanical tillage, do not have a statistically significant effect on average maize yields in our sample.

Table 5.   Determinants of maize productivity

	Without interaction terms		With interaction terms	
	Fixed effect (1)	**Correlated random effects (2)**	**Fixed effect (3)**	**Correlated random effects (4)**
Shock received (1=yes)	-0.208***	-0.225***	-0.184***	-0.221***
Climate variables				
Rainfall Deviation	-0.186	-0.268	0.321	-0.130
CoV	-	-0.663	-	-0.754
Household socio-demographics				
(log) Nr. of household members	-0.507**	-0.084**	-0.495**	-0.084**
(log) Age of household head (years)	-0.133	-0.102	-0.083	-0.098
(log) Edu of household head (years)	0.006	-0.002	0.008	-0.001
Head is female (1=yes)	-0.303**	-0.048	-0.309**	-0.054
Land characteristics and agricultural practices				
(log) Land under maize (ha)	-0.378***	-0.385***	-0.385***	-0.394***
Inorganic fertilizer applied (1=yes)	0.284***	0.343***	0.348***	0.341***
Hybrid maize seeds (1=yes)	0.076	0.234***	0.078	0.314***
MSD on maize plots (1=yes)	0.142*	0.204***	0.362***	0.386***
Crop association*** (1=yes)	-0.024	-0.058	0.085	-0.031
Crop res. cut&spread (1=yes)	0.192*	0.222**	0.182	0.307**
Trees/shrubs grown (1=yes)	0.043	-0.030	0.016	-0.118*
Mech. erosion contr. (1=yes)	0.059	0.051	-0.047	-0.007
Agric. implements (1=yes)	0.110	0.078	0.096	0.075
Animal/mech. tillage (1=yes)	0.020	0.075	0.029	0.074
Household wealth, market access and social capital				
Wealth index (normalized)	-0.555	-0.403	-0.597	-0.326
Fertilizer Purchased (1=yes)	0.127*	0.099	0.110	0.086
Fertilizer source FISP (1=yes)	0.054	0.074	0.041	0.067
Group members (% in SEA)	0.320	0.267**	0.385*	0.275**
Credit received (% in Ward)	-2.236*	-2.515**	-2.043*	-2.405*
Agricultural practices interactions with rainfall deviation				
MSD on maize plot*RainDev			-2.211***	-1.793***
Crop association *RainDev			-0.909	-0.133
Crop residue*RainDev			0.203	-0.750
Trees/shrubs*RainDev			0.332	0.944**
Mech. erosion cont*RainDev			1.100	0.662
Inorg, fert applied*RainDev			-0.489	0.029
Hybrid maize*RainDev			-0.004	-0.757
Constant	8.434***	7.163***	8.107***	7.135***
Number of observations	2 363	2 363	2 363	2 363

Source: Authors' elaboration.
Note: Significant levels are * p<0.10, ** p<0.05, *** p<0.01.

Among variables that are indicators of wealth, social and financial capital, only group membership (to cooperatives, farmers', women's or savings and loan groups) and credit access have significant coefficients with opposing signs. While group membership significantly increases maize yields, indicating a potential risk sharing mechanism, credit access significantly decreases yields. Although credit access is very low in our sample, this suggests that households in SEA with high levels of credit access have observed lower maize yields, perhaps because they focus on other crops or income sources – which can be assessed by the income analysis in the next sub-section.

Interaction models to investigate whether the positive average effects of some of the agricultural practices obtained in simple models were robust to high levels of rainfall deviation indicate that the average positive effect of MSD on maize yield disappears when observed rainfall deviates from the long run average. MSD is considered to increase water retention, and it may look surprising that the interaction term is negative. However, based on previous literature on conservation farming (of which MSD is the main component), it is known that most farmers do not combine MSD with residue retention, which is one of the main preconditions to trap humidity in the soil. Moreover, considering that around 60 percent of the deviation in our sample is positive deviation and the fact that MSD may lead to water logging when there is too much rain, this finding is not unexpected. Agroforestry is the only practice that provides positive yield benefits even under rainfall conditions that deviate from the long run average.

6.2 Determinants of household income

Table 6 presents the results from the analysis of the determinants of household income per capita (in logarithms), specifically focusing on the role of livelihood diversification strategies, among other control variables. As in maize productivity results, we show estimates on the nearest neighbour (NN) matching sample[17] from FE and CRE estimation models, and both simple models (columns 1 and 2) and the models with interaction variables between the shock and diversification variables (columns 3 and 4).

Results show that being exposed to the shock negatively and significantly affected the level of welfare, resulting in a decrease in income per capita up to 37 percent. Nevertheless, farmers who have adopted diversifying strategies in terms of crop and income seem to have been able to compensate for part of the loss. On average, each additional type of crop cultivated contributed about 8 percent to household income, and each additional income source has contributed about 20 percent.

Rainfall deviation has surprisingly a positive and significant coefficient. On closer inspection, this finding can be explained given the fact that around 62 percent of deviation in our sample is positive. The long-term coefficient of variation of rainfall has negative coefficients, though it is not significant.

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[17] Results on other samples are presented in Annex 2 for comparison and robustness check.

In line with other findings from the literature, socio-demographic characteristics such as household size, age and education of the head tend to significantly explain the variation in welfare. In particular, larger households with older heads tend to have lower incomes, whereas households with more educated heads have significantly higher incomes. Furthermore, as expected, both household wealth indicators, i.e. land owned and the wealth index, have a significant effect on income per capita. In particular, a one hectare increase in land endowments would increase per capita income by about 20 percent.

Social capital and market access variables are not significantly correlated with household income, except selling maize to the Food Reserve Agency (FRA), which has a positive effect on income per capita.

We use the shock variable (as opposed to the rainfall deviation used in maize yield models) in the interaction models to investigate whether the average effects of diversification strategies and some policy variables in simple models hold when households faced the shock. This choice stems from the fact that total income includes all non-farm income as well, which is not expected to be affected by the rainfall shock in a non-linear way. The positive average effect of crop diversification on income disappears when interacted with the shock variable, indicating that crop diversification by itself was not able to provide additional benefits to households in shocked areas. Livestock and income diversification, on the other hand, have contributed more to household income in such areas, underlining the importance of promoting these risk management strategies as a way to reduce household vulnerability to shocks like El Niño. The interaction term between FRA and shock is not significant, suggesting that the average benefits of being able to sell maize to FRA have not specifically helped households in shocked areas.

Table 6.   Determinants of household income per capita

	Without interaction terms		With interaction terms	
	Fixed effect (1)	Correlated random effects (2)	Fixed effect (3)	Correlated random effects (4)
Shock received (1=yes)	-0.248***	-0.245***	-0.277*	-0.372***
Climate variables				
Rainfall Deviation	0.607**	0.548*	0.754**	0.594**
CoV	-	-0.276	-	-0.430
Diversification indexes				
Crops planted count index	0.097***	0.074***	0.113***	0.082***
Livestock diversity count index	0.040	0.024	0.027	0.013
Income sources count index	0.190***	0.215***	0.176***	0.201***
Household socio-demographics				
(log) Nr. of household members	-1.516***	-0.836***	-1.518***	-0.840***
(log) Age of household head (years)	0.048	-0.348***	0.071	-0.350***
(log) Edu of household head (years)	0.014	0.037***	0.014	0.038***
Head is female (1=yes)	-0.001	-0.044	0.020	-0.041
Household wealth				
(log) Land owned (ha)	0.217***	0.206***	0.222***	0.207***
Wealth index (normalized)	2.068***	1.856***	1.951***	1.759***
Market access and social capital				
Maize sold to FRA (% in SEA)	0.987***	1.073***	0.979***	1.088***
Cash received from safety net programmes (% in SEA)	0.362	0.292	0.959	0.742
Group members (% in SEA)	-0.152	-0.117	-0.130	-0.121

	Without interaction terms		With interaction terms	
	Fixed effect (1)	**Correlated** random effects **(2)**	**Fixed effect (3)**	**Correlated** random effects **(4)**
Credit received (% in Ward)	0.653	0.919	0.799	1.066
Interactions with shock				
Crops planted*Shock			-0.071**	-0.034
Livestock diversity* Shock			0.059**	0.046*
Income sources*Shock			0.047	0.052*
Maize sold to FRA*Shock			0.336	1.242
Cash from safety net prog*Shock			-2.879**	-1.763
Constant	6.376***	6.314***	6.278***	6.397***
Number of observations	2 383	2 383	2 383	2 383

Source: Authors' elaboration.
Note: Significant levels are * p<0.10, ** p<0.05, *** p<0.01.

7   Conclusions and policy recommendations

The main conclusion from the empirical results is that rural households in Zambia are very vulnerable to weather shocks. To reduce vulnerability to crop production losses, households can adopt sustainable land management practices that are hypothesized to reduce losses caused by droughts. These practices should increase water retention capacity and soil nutrients, and reduce erosion. However, though many of these practices have a positive impact on yields in general, they do not provide additional benefits for households located in drought areas. The one exception is having trees and shrubs on the plot. The direct impact on maize yields is negative but having trees and shrubs has a positive impact for those located in areas hit by the drought. Interestingly, minimum soil disturbance (MSD) has the opposite effect; those located in drought areas actually received lower yields. The agronomy literature stresses the fact that in order to improve soil quality and water retention capacity, most practices need to be adopted for a number of years before these benefits can be realized. An earlier RALS survey covering the period 2010/2011 shows that many fewer households were practicing MSD in that year. And, as highlighted in Arslan *et al.* (2014), many households adopt and dis-adopt through time, often as a result of MSD promoting projects' cycles. Thus, our results may reflect that households have not practiced MSD long enough to realize drought resilience benefits. On the other hand, bushes, and especially trees, are more likely to have been on the plot for enough years to provide resilience benefits. Overall, however, the evidence suggests that currently available and promoted sustainable land management practices are not widely adopted, and when adopted, may not have been adopted for enough years to provide resilience benefits.

Given crop production losses stemming from the drought, households can respond by drawing on risk coping mechanisms. However, our results show that households were only partially able to cover losses to income per capita due to the drought. Our most robust result is the positive impact of livestock diversification for households located in drought areas, with some evidence to suggest a positive role for income diversification to help cope with the drought as well. We have limited evidence to suggest that crop diversification reduces income risk, and in fact may have led to lower incomes for those located in drought areas. And, our social capital variables play a limited role in helping households respond to drought.

Our results suggest three policy recommendations. The first is that agro-forestry appears to be the most widely adopted sustainable land management practice, and it is the only one that provided protection against maize yield losses due to the drought. At the same time, Zambia has had some of the highest rates of deforestation in the world in the recent past (FAO, 2011). While agro-forestry has recently become a part of the "conservation farming" extension package, the emphasis on zero-tillage and other MSD practices have dominated, and continue to dominate, extension activities and large donor-funded projects. Our results suggest that actors involved in promoting sustainable land management in Zambia should re-direct more resources towards agro-forestry. Second, households need access to better risk-coping mechanisms. Evidence from other countries suggest that being able to re-allocate labour off-farm is an effective mechanism to help households cope with risk; our results suggest that there is wide scope to increase the ability of households to shift labour off-farm in response to weather shocks. Additionally, group membership was found to be an ineffective coping mechanism in this study, but participation in farmers groups and savings and loan societies has been found to be effective in other contexts. Our results reinforce the importance of

developing viable micro-finance and savings and loan societies in rural areas of Zambia. Policymakers need to consider the legal and regulatory framework that will allow for expanding access to financial institutions, including the potentially important role of mobile banking. Third, in addition to household-based risk coping mechanisms, there is clearly a role for social safety nets to play. Social safety nets in Zambia are currently very scant, reaching few rural households. Safety net programs can be designed to operate flexibly, so that more resources are available in response to weather shocks, harmonized to disaster risk management activities.

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Annexes

Annex 1. Determinants of maize productivity on different samples

Yield estimates on different samples

| | Without interaction terms | | psm2 | | | | | | With interaction terms | | psm2 | | | | | |
| | Whole sample (FE) | Whole sample (CRE) | NN matched sample (FE) | NN matched sample (CRE) | mahal matched sample (FE) | mahal matched sample (CRE) | MHD matched sample (FE) | MHD matched sample (CRE) | Whole sample (FE) | Whole sample (CRE) | NN matched sample (FE) | NN matched sample (CRE) | mahal matched sample (FE) | mahal matched sample (CRE) | MHD matched sample (FE) | MHD matched sample (CRE) |
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(1-int)	(2-int)	(3-int)	(4-int)	(5-int)	(6-int)	(7-int)	(8-int)
Shock received (1=yes)	-0.225***	-0.231***	-0.208***	-0.225***	-0.209***	-0.225***	-0.231***	-0.252***	-0.198***	-0.227***	-0.184***	-0.221***	-0.185***	-0.221***	-0.206***	-0.247***
Climate variables																
Rainfall deviation*	-0.167	-0.235	-0.186	-0.268	-0.184	-0.269	-0.232	-0.237	0.560	0.010	0.321	-0.130	0.327	-0.133	0.532	0.023
CoV**	-	-0.378	-	-0.663	-	-0.699	-	-0.905	-	-0.456	-	-0.754	-	-0.789	-	-0.982
Household socio-demographic																
(log) Nr. of household members	-0.357	-0.053	-0.507**	-0.084**	-0.506**	-0.085**	-0.341	-0.042	-0.365	-0.054	-0.495**	-0.084**	-0.494**	-0.085**	-0.354	-0.044
(log) Age of household head (years)	-0.026	-0.113*	-0.133	-0.102	-0.135	-0.103	-0.047	-0.131**	0.037	-0.109*	-0.083	-0.098	-0.086	-0.099	0.012	-0.126*
(log) Edu of household head (years)	0.006	-0.001	0.006	-0.002	0.006	-0.002	0.007	-0.000	0.008	-0.000	0.008	-0.001	0.007	-0.001	0.009	0.001
Head is female (1=yes)	-0.038	-0.052	-0.303**	-0.048	-0.302**	-0.047	-0.018	-0.022	-0.044	-0.057	-0.309**	-0.054	-0.309**	-0.053	-0.026	-0.026
Land characteristics and agricultural practices																
(log) Land under maize (ha)	-0.357***	-0.366***	-0.378***	-0.385***	-0.378***	-0.386***	-0.366***	-0.377***	-0.368***	-0.377***	-0.385***	-0.394***	-0.386***	-0.395***	-0.387***	-0.387***
Inorg. fert applied (1=yes)	0.282***	0.352***	0.284***	0.343***	0.289***	0.345***	0.261**	0.319***	0.371***	0.352***	0.348***	0.341***	0.353***	0.344***	0.344***	0.304***
Hybrid maize seeds (1=yes)	0.067	0.230***	0.076	0.234***	0.073	0.235***	0.067	0.239***	0.077	0.312***	0.078	0.314***	0.075	0.314***	0.098	0.336***
MSD on maize plots (1=yes)	0.128	0.198***	0.142*	0.204***	0.144*	0.203***	0.083	0.183***	0.341***	0.364***	0.362***	0.386***	0.363***	0.386***	0.295***	0.344***
Crop association (1=yes)	-0.032	-0.067	-0.024	-0.058	-0.024	-0.058	-0.040	-0.077	0.089	-0.037	0.085	-0.031	0.086	-0.030	0.091	-0.030
Crop res. cut&spread (1=yes)	0.186*	0.220**	0.192**	0.222**	0.192**	0.222**	0.182	0.217**	0.182	0.318***	0.182	0.307**	0.183	0.306**	0.173	0.310**
Trees/shrubs grown (1=yes)	0.045	-0.042	0.043	-0.030	0.042	-0.031	0.034	-0.048	-0.001	-0.134**	0.016	-0.118*	0.014	-0.121*	-0.025	-0.144**
Mech. erosion contr. (1=yes)	0.075	0.065	0.059	0.051	0.059	0.051	0.077	0.067	-0.009	0.037	-0.047	-0.007	-0.047	-0.008	-0.015	0.036
Agric. implements (1=yes)	0.100	0.085	0.110	0.078	0.111	0.081	0.094	0.098	0.085	0.082	0.096	0.075	0.097	0.077	0.077	0.095
Animal/mech. tillage (1=yes)	-0.020	0.060	0.020	0.075	0.017	0.075	-0.002	0.066	-0.012	0.060	0.029	0.074	0.026	0.074	0.007	0.067
Household wealth, market access and social capital																
Wealth index (normalized)	-0.239	-0.085	-0.555	-0.403	-0.544	-0.395	0.043	0.227	-0.232	0.009	-0.597	-0.326	-0.585	-0.319	0.060	0.312
Fertiliz. purchased (1=yes)	0.109*	0.074	0.127*	0.099	0.126*	0.098	0.106	0.071	0.093	0.064	0.110	0.086	0.109	0.085	0.088	0.059
Fertiliz. source FISP (1=yes)	0.061	0.069	0.054	0.074	0.053	0.071	0.065	0.073	0.048	0.063	0.041	0.067	0.039	0.064	0.051	0.065
Group members (% in SEA)	0.303	0.276**	0.320	0.267**	0.317	0.265**	0.384*	0.279**	0.365*	0.283**	0.385*	0.275*	0.382*	0.273**	0.454**	0.289**
Credit received (% in Ward)	-2.008*	-2.235*	-2.236*	-2.515**	-2.187*	-2.466**	-2.111*	-2.283*	-1.928*	-2.198*	-2.043*	-2.405*	-1.998*	-2.355*	-2.056*	-2.266*
Agricultural practices interactions with rainfall deviation																
MSD on maize plot*RainDev									-2.106***	-1.613***	-2.211***	-1.793***	-2.192***	-1.799***	-2.094***	-1.550***
Crop association *RainDev									-1.040	-0.194	-0.909	-0.133	-0.919	-0.139	-1.122*	-0.352
Crop residue*RainDev									0.168	-0.846	0.203	-0.750	0.193	-0.747	0.197	-0.793
Trees/shrubs*RainDev									0.486	0.952***	0.332	0.944***	0.332	0.956***	0.614	0.974***
Mech. Erosion cont*RainDev									0.871	0.340	1.100	0.662	1.100	0.666	0.934	0.377

Yield estimates on different samples

	Without interaction terms								With interaction terms							
	Whole sample (FE)	Whole sample (CRE)	psm2				MHD matched sample (FE)	MHD matched sample (CRE)	Whole sample (FE)	Whole sample (CRE)	psm2				MHD matched sample (FE)	MHD matched sample (CRE)
			NN matched sample (FE)	NN matched sample (CRE)	mahal matched sample (FE)	mahal matched sample (CRE)					NN matched sample (FE)	NN matched sample (CRE)	mahal matched sample (FE)	mahal matched sample (CRE)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(1-int)	(2-int)	(3-int)	(4-int)	(5-int)	(6-int)	(7-int)	(8-int)
Inorg. fert applied*RainDev									-0.723	0.004	-0.489	0.029	-0.487	0.023	-0.666	0.152
Hybrid maize*RainDev									-0.089	-0.770	-0.004	-0.757	-0.011	-0.751	-0.285	-0.908
Constant	7.677***	7.079***	8.434***	7.163***	8.443***	7.179***	7.678***	7.221***	7.309***	7.036***	8.107***	7.135***	8.120***	7.151***	7.317***	7.166***
Number of observations	2 469	2 469	2 363	2 363	2 367	2 367	2 364	2 364	2 469	2 469	2 363	2 363	2 367	2 367	2 364	2 364

Notes: * Rainfall deviation is calculated as the absolute value of the total rainfall deviation during the 2013-2014 and 2015-2016 cropping seasons from the long-term average.
** CoV of Oct-Apr rainfall between 1983 and 2016. *** Rotation and/or legume intercropping practiced on maize plots. *** p<0.01, ** p<0.05, * p<0.1.
Source: Authors' elaboration.

Annex 1. Determinants of income per capita on different samples

Household income estimates on different samples

	Without interaction terms		psm2						With interaction terms		psm2					
	Whole sample (FE)	Whole sample (CRE)	NN matched sample (FE)	NN matched sample (CRE)	mahal matched sample (FE)	mahal matched sample (CRE)	MHD matched sample (FE)	MHD matched sample (CRE)	Whole sample (FE)	Whole sample (CRE)	NN matched sample (FE)	NN matched sample (CRE)	mahal matched sample (FE)	mahal matched sample (CRE)	MHD matched sample (FE)	MHD matched sample (CRE)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(1-int)	(2-int)	(3-int)	(4-int)	(5-int)	(6-int)	(7-int)	(8-int)
Shock received (1=yes)	-0.239***	-0.241***	-0.248***	-0.245***	-0.245***	-0.243***	-0.227***	-0.228***	-0.301**	-0.389***	-0.277*	-0.372***	-0.290*	-0.379***	-0.261*	-0.372***
Climate variables																
Rainfall deviation*	0.567*	0.500*	0.607**	0.548*	0.596*	0.541*	0.514	0.473	0.680**	0.531*	0.754**	0.594**	0.742**	0.588**	0.626**	0.495*
CoV**	-	-0.087	-	-0.276	-	-0.292	-	0.093	-)	-0.219	-	-0.430	-	-0.451	-	-0.026
Diversification indexes																
Crops planted count index	0.092***	0.073***	0.097***	0.074***	0.098***	0.074***	0.102***	0.072***	0.110***	0.082***	0.113***	0.082***	0.114***	0.082***	0.122***	0.082***
Livestock diversity count index	0.040	0.019	0.040	0.024	0.042	0.025	0.038	0.020	0.025	0.006	0.027	0.013	0.028	0.013	0.021	0.006
Income sources count index	0.185***	0.212***	0.190***	0.215***	0.190***	0.215***	0.191***	0.214***	0.168***	0.195***	0.176***	0.201***	0.175***	0.199***	0.176***	0.197***
Household socio-demographic																
(log) Nr. of household members	0.080	-0.334***	0.048	-0.348***	0.043	-0.348***	0.060	-0.340***	0.099	-0.336***	0.071	-0.350***	0.068	-0.350***	0.078	-0.340***
(log) Age of household head (years)	-1.451***	-0.823***	-1.516***	-0.836***	-1.514***	-0.836***	-1.435***	-0.828***	-1.449***	-0.827***	-1.518***	-0.840***	-1.515***	-0.840***	-1.432***	-0.831***
(log) Edu of household head (years)	0.014	0.037***	0.014	0.037***	0.013	0.037***	0.009	0.037***	0.015	0.037***	0.014	0.038***	0.013	0.037***	0.010	0.038***
Head is female (1=yes)	-0.027	-0.038	-0.001	-0.044	-0.005	-0.044	-0.053	-0.055	-0.006	-0.035	0.020	-0.041	0.017	-0.041	-0.033	-0.054
Household wealth																
(log) Land owned (ha)	0.221***	0.201***	0.217***	0.206***	0.215***	0.205***	0.227***	0.213***	0.227***	0.203***	0.222***	0.207***	0.220***	0.207***	0.233***	0.215***
Wealth index (normalized)	1.844***	1.672***	2.068***	1.856***	2.040***	1.831***	1.973***	1.835***	1.725***	1.579***	1.951***	1.759***	1.923***	1.737***	1.853***	1.741***
Market access and social capital																
Maize sold to FRA (% in SEA)	0.911***	0.976***	0.987***	1.073***	0.968***	1.054***	1.029***	1.131***	0.918***	1.005***	0.979***	1.088***	0.963***	1.072***	1.044***	1.170***
Cash safety net (% in SEA)	0.645	0.515	0.362	0.292	0.326	0.256	0.628	0.550	1.061	0.853	0.959	0.742	0.957	0.726	1.035	0.868
Group members (% in SEA)	-0.154	-0.134	-0.152	-0.117	-0.140	-0.112	-0.133	-0.127	-0.139	-0.139	-0.130	-0.121	-0.120	-0.117	-0.119	-0.133
Credit received (% in Ward)	0.871	1.093	0.653	0.919	0.599	0.872	0.701	0.966	1.049	1.268	0.799	1.066	0.769	1.039	0.865	1.137
Interactions with shock																
Crops planted*Shock									-0.078**	-0.038	-0.071**	-0.034	-0.071**	-0.034	-0.083**	-0.039
Livestock diversity* Shock									0.060**	0.047*	0.059**	0.046*	0.060**	0.047*	0.061**	0.046*
Income sources*Shock									0.062*	0.060*	0.047	0.052*	0.052	0.054*	0.055	0.059*
Maize sold to FRA*Shock									0.742	1.509**	0.336	1.242	0.467	1.324*	0.804	1.709***
Cash safety net prog*Shock									-1.881	-1.159	-2.879**	-1.763	-2.933**	-1.778	-1.738	-0.909
Constant	6.173***	6.207***	6.376***	6.314***	6.390***	6.313***	6.177***	6.194***	6.096***	6.290***	6.278***	6.397***	6.291***	6.402***	6.089***	6.273***
Number of observations	2,491	2,491	2,383	2,383	2,387	2,387	2,393	2,393	2,491	2,491	2,383	2,383	2,387	2,387	2,393	2,393

Notes: * Rainfall deviation is calculated as the absolute value of the total rainfall deviation during the 2013-2014 and 2015-2016 cropping seasons from the long-term average.
** CoV of Oct-Apr rainfall between 1983 and 2016. *** Rotation and/or legume intercropping practiced on maize plots. *** p<0.01, ** p<0.05, * p<0.1.
Source: Authors' elaboration.

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