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Climate variability, adaptation strategies and food security in Malawi

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Abstract

This paper assesses farmers' incentives and conditioning factors that hinder or promote adaptation strategies and evaluates its impact on crop productivity by utilizing household level data collected in 2011 from nationally representative sample households in Malawi. We distinguish between (i) exposure to climatic disruptions, (ii) bio-physical sensitivity to such disruptions, (iii) household adaptive capacity in terms of farmers' ability to prepare and adjust to the resulting stress, and, finally, (iv) system-level adaptive capacity that serve as enabling factors for household-level adaptation. We employ a multivariate probit (MVP) and instrumental variable technique to model farming practice selection decisions and their yield impact estimates. We find that *exposure* to delayed onset of rainfall and greater climate variability as represented by the coefficient of variation of rainfall and temperature is positively associated with the choice of risk-reducing agricultural practices such as tree planting, legume intercropping, and soil and water conservation (SWC); however, it reduces the use of inputs (such as inorganic fertilizer) whose risk reduction benefits are uncertain. *Biophysical sensitivity* of plots increases the likelihood of choice of tree planting and SWC. In terms of *household adaptive capacity*, we find that wealthier households are more likely to adopt both modern and sustainable land management (SLM) inputs; and are more likely to adopt SLM inputs on plots under more secure tenure. In terms of system-level adaptive capacity, results show the key role of rural institutions, social capital and supply-side constraints in governing selection decisions for all practices considered, but particularly for tree planting and both organic and inorganic fertilizer. Finally for productivity, we find that on average use of both modern and SLM practices have positive and statistically significant impact on productivity of maize. For SLM practices that also respond to exposure and sensitivity, these results provide direct evidence of their potential to aide households in adapting to further climate change. Results presented have implications for understanding and overcoming barriers to selection for each practice, distinguishing structural aspects such as exposure and sensitivity from potential interventions at the household or systemic levels linked to adaptive capacity.

JEL codes: Q01, Q12, Q16, Q18
Key words: Climate change, adaptation, impact, Malawi

Contents

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1. Introduction

Malawi is ranked as one of the world's twelve most vulnerable countries to the adverse effects of climate change (World Bank 2010) and as a result subsistence farmers suffer from climate related stressors in a number of different ways. These impacts include increased exposure to extreme climate events such as droughts, dry spells and floods (Chinsinga, 2012). Given that agricultural production remains the main source of income for most rural communities, the increased risk of production failure associated with increased frequency of extreme events poses a major threat to food security and poverty reduction. Adaptation of the agricultural sector to the adverse effects of climate change is thus an important priority to protect and improve the livelihoods of the poor and to ensure food security (Bradshaw *et al*., 2004; Wang *et al*., 2009).

Adaptation to current or expected climate variability and changing climate conditions involves adjustment in natural or human systems in response to actual or expected climate stimuli or their effects, which moderates harm or exploits beneficial opportunities (IPCC 2001). Changing farming practices is one important means of adaptation. Examples include modifying planting times and changing to varieties resistant to heat and drought (Phiri and Saka, 2008); development and adoption of new cultivars (Eckhardt *et al*., 2009); changing the farm portfolio of crops and livestock (Howden *et al*., 2007); adopting improved soil and water management practices including conservation agriculture (Kurukulasuriya and Rosenthal, 2003; McCarthy *et al*., 2011); integrating the use of climate forecasts into cropping decisions (Howden *et al*., 2007); increasing use of irrigation (Howden *et al*., 2007); increasing regional farm diversity (Reidsma and Ewert, 2008); and shifting to non-farm livelihood sources (Morton, 2007). Which of these actually contributes to adaptation depends on the locally specific effects of climate change, as well as agro-ecological conditions and socio-economic factors such as market and institutional development. Adaptation also depends on farmer's capacity and incentives to respond to changes and undertake adjustments in farming practices, i.e. their adaptive capacity.

Despite growing policy interest in adaptation, and increasing resources dedicated to promoting a range of sustainable land management and productivity enhancing practices for agricultural development and sustainability in many regions including Malawi, the adoption rates are generally quite low sometimes leading to stagnant or worsening yields and land degradation (Wollni *et al*., 2010; Tenge *et al*., 2004). One question that arises is whether these practices are actually effective adaptation strategies in the specific circumstances of Malawian farmers; e.g. which practices or combination of practices can be considered "climate smart"[1] in the Malawian context. A second question is how household and system-level adaptive capacity, or lack thereof, affects the selection of farm practices. In this paper we seek to answer these two questions in the Malawian context through a careful analysis of farmers' incentives and conditioning factors that hinder or accelerate use of a set of practices with potential adaptation benefits.

Given our dataset, in this paper we focus on analysing the determinants of household farming practice selection and productivity impacts of four different potentially risk-reducing climate-smart agricultural practices (maize-legume intercropping, soil and water conservation (SWC), trees, and use of organic fertilizer) that are high priorities in the Malawi National Agricultural plan (GoM,

[1] Climate smart agricultural practices are defined as those practices that increase adaptive capacity and resilience of farm production in the face of climate shocks thereby improving food security, and which can also mitigate GHG emissions, mainly through increased carbon sequestration in soils (FAO, 2011)

2008). They are considered effective in terms of increasing resilience of agricultural systems and reducing vulnerability to climate shocks, and in this way contribute to adaptation. We also consider two practices that are aimed primarily at improving average yields, though with uncertain benefits in terms of adapting to climate change and/or reducing risk to current climate stresses, improved maize varieties and use of inorganic fertilizers.[2]

The question this paper aims to address contributes to the growing literature on agricultural adaptation measures, including, among others, Pender and Gebremedhin (2007); Lee (2005); Kassie *et al*. (2010); Tekleword *et al*. (2013); Di Falco *et al*. (2011); Deressa and Hassen (2010); McCarthy *et al*. (2011); Rosenzweig and Binswanger (1993); Heltberg and Tarp (2002) and Wollni *et al*. (2010). This paper also contributes to the literature on quantification of vulnerability and adaptive capacity (Adger *et al*., 2004; Smit and Wandel, 2006; Adger, 2006; Gallopin, 2006; Fussel, 2007 & 2009; Engle, 2009; Panda *et al*., 2013). Our contribution to the existing literature is threefold: firstly our analysis uses a comprehensive large, nationally representative plot-level survey with rich socio-economic information, merged with geo-referenced climatic and bio-physical information as well as higher-level institutional characteristics at the community and district level. This allows us to evaluate the role of climatic risk, agronomic, household and institutional variables in determining farmers' choice of farming practice and consequently their impact on crop productivity. We argue that climate variability as well as other shifts in recent climate patterns are major determinants of farm practice choice, extending the literature which examines the effects of weather shocks using the level of rainfall or deviation from its mean on productivity. While acknowledging the important role of weather shocks, we pay particular attention to long term climate variability as a proxy for expectations about future uncertainty.

Second, we explicitly account for the possibility of famers' choosing a mix of practices (Teklewold *et al*., 2013). In order to model simultaneous and correlated farming practice selection decisions we used a method that takes into account potential interdependence between different practices. Third, we estimate the causal impact of use of these practices on productivity using instrumental variables techniques (IV) improved using Lewbel's (2012) method as well as conditional recursive mixed process (CMP) estimators as proposed by Roodman (2011). This method takes into account both simultaneity and endogeneity issues, and produces consistent estimates for recursive systems in which all endogenous variables appear on the right-hand-side as observed. Our analysis also adds value to the existing literature by undertaking an in-depth investigation on the impacts of use of these technologies across different segments of the population, an issue scarcely addressed by existing literature.

The rest of the paper is organized as follows. Section two provides an overview of agriculture and climate change in Malawi and a selected literature review. Data sources, sample composition and descriptive results are presented in section three. The fourth section presents the analytical methods with emphasis on empirical models and hypothesized relationships. The main analytical results are presented and discussed in section five. Section six concludes by presenting the key findings and the policy implications.

[2] Conservation agriculture is also high in Malawi national agricultural priority plan and considered to have adaptation potential but we lack data on these practices and as a result those are not included in our analysis.

2. Background and overview of literature

2.1 Agricultural production and climate risk in Malawi

In Malawi, agriculture remains an important component of the economy; employing 85% of the labour force, accounting for about 39% of the Gross Domestic Product (GDP) and 83% of Malawi's foreign exchange earnings (Chirwa and Quinion, 2005). The agricultural sector is divided into subsectors; estates and smallholder farmers. The latter accounts for 78% of the cultivated land and generates about 75% of Malawi's total agricultural output, indicating the predominance of the smallholder agricultural sector (Chirwa and Quinion, 2005). The average farm size is about 1.12 hectare (ha), although more than 72% of the smallholders farm less than one hectare, a size too small to achieve food self-sufficiency at the household level with the current farming methods. Benin *et al*. (2008) found that Malawi is the third most densely populated country in sub-Saharan Africa (SSA) (at 2.3 rural people per hectare of agricultural land) after Rwanda (3.8 people per hectare) and Burundi (2.7 people per hectare). The use of irrigation is limited, with vast majority of farmers practicing rain fed agriculture only.

The principal crops grown in Malawi are maize, tea, sugarcane, groundnut, cotton, wheat, coffee, rice and pulses. A significant feature of Malawi's agriculture is the dominance of maize in farming systems. It is estimated that more than 70% of the arable land is allocated to maize production (GoM, 2006). According to Dorward *et al*. (2008), the share of farmers growing maize varies from 93% to 99% in the country's main regions. The paradox is that even though maize is the dominant crop among smallholder farmers in Malawi, over the last two decades maize productivity has been erratic. Only 10% of the maize growers are net sellers, with as high as 60% being net buyers. Thus, while agriculture and maize are critically important to the livelihoods of most Malawians, their overall productivity performance raises serious concerns about their long-term viability. The factors that are commonly cited as underlying low crop productivity include weather variability, declining soil fertility, limited use of improved agricultural technologies and sustainable land management practices, low/poor agricultural extension services, market failures, and underdevelopment and poorly maintained infrastructure (World Bank, 2010).

The predicted impacts of climate change in Malawi can be expected to impact mostly smallholders that depend on rainfall (Denning *et al.,* 2009). A synthesis of climate data by the World Bank indicated that in the period 1960 to 2006, mean annual temperature in Malawi increased by 0.9°C (World Bank, 2012). This increase in temperature has been concentrated in the rainy summer season (December – February), and is expected to increase further. Long term rainfall trends are difficult to characterize due to the highly varied inter-annual rainfall pattern in Malawi. It should be also noted that assessments of climate change impacts on Malawian agriculture are highly variable across agro-ecological zones (Boko *et al.,* 2007; Seo *et al*., 2009). The socio economic impact of such changes on smallholder farmers is a function of their adaptive and coping strategies (Morton, 2007).

The National Adaptation Programmes of Action (NAPA) remains the key climate change policy document in Malawi which was formulated in 2006 (GoM, 2006; Chinsinga, 2012). In the agricultural sector, the Ministry of Agriculture and Food security, has attempted to operationalize NAPA priorities through the Agriculture Sector Wide Approach (ASWAp). The ASWAp identifies several strategies which are meant to increase the resilience of communities in rural areas to the adverse effects of climate change. In particular, promotion of conservation agriculture[3] is given high priority, due to its expected productivity benefits as well as to mitigate the effects of weather variability and climate change (Chinsinga, 2012; GoM, 2008). The ASWAp is also seeking to harmonize the Malawian Farm Input Subsidy Program (FISP) with the Agricultural Development Program–Support Project (ADP-SP) and Green Belt Initiative to promote more sustainable and climate robust agricultural development in the country through improving input use efficiency. The Government of Malawi has increased its budget share for agriculture from 6.1% in the period 2000–2005 to 15.9% for 2006–2009 and is aiming to increase it further to 24% by 2015 with the implementation of the ASWAp. In 2012/13 this share was close to 20% of national budget with, the FISP accounting for nearly 65% of the total MoA annual budget (budget statement 2012). However, the high costs of the FISP associated with imported fertilized, have contributed to recent financial constraints in the country (Holden and Lunduka, 2012). The promotion of sustainable land management can be one way to ease the financial pressure of subsidizing fertilizer.

2.2 Literature review

We attempt here to link two important strands of literature that have developed separately but that are key in discussing adaptation in smallholder agricultural systems; namely that on risk and adoption of agricultural technologies based in the economic tradition, and that on vulnerability and adaptive capacity as presented from different disciplinary perspectives in the climate change literature. The results presented in the paper rely on techniques and theory of the former, and on the context and narrative of the latter. We link the two strands to provide new insights on practical aspects of adaptive capacity on the ground and how it links to farmers' decisions under climate risk.

Starting with the impact of risk on practice selection, there is a large body of literature on the theoretical and empirical impacts of production risk on farmers' *ex ante* production technology choices (e.g., Fafchamps, 1999, 1992; Chavas and Holt 1996; Just and Candler, 1985; Sadoulet and de Janvry, 1995; Kassie *et al*., 2008, 2013). This literature indicates that there are several barriers to technology adoption including lack of insurance, limited access to credit, and price risk, and mainly focuses on the impact of production risk on overall output. Pope and Kramer (1979) considered inputs that could be both risk-increasing and risk-decreasing. In general, the use of risk-decreasing inputs increases where producers are more risk-averse or in more risk-prone environments. This is important in the context of climate change. In particular, many sustainable land management (SLM) practices are risk-decreasing, so that increased frequency of extreme weather events should favour adoption of SLM.

There are few empirical studies that explicitly evaluate the impact of climate risk on the adoption of SLM practices or other input choices (e.g. Kassie *et al*., 2008; Arslan *et al*. (2013); Heltberg and Tarp, 2002; Deressa *et al*., 2011). Arslan *et al*. (2013) provides evidence of a positive correlation between rainfall variability and the selection of SLM type practices. Kassie *et al*. (2008) analyze the impact of production risk on the adoption of conservation agriculture, a form of SLM, as well as the use of inorganic fertilizer. They find that risk deters adoption of fertilizer, but has no effect on the conservation agriculture adoption decision. Heltberg and Tarp (2002) found that farmers

[3] Conservation agriculture (CA) is an approach that aims to sustainably improve farm productivity, profits and food security by combining three principles. These three principles are: minimum mechanical soil disturbance; permanent organic soil cover; and crop rotation (FAO, 2011).

located in regions with greater exposure to extreme climate events were less likely to engage in market transactions, implying a greater emphasis on meeting subsistence needs with own production.

Aside from risk, several other factors have also been identified as barriers to the adoption of SLM practices including high up-front costs but delayed benefits (Sylwester, 2004), credit and insurance market imperfections (Carter and Barrett, 2006), seasonal household labour constraints (Barrett, 2008). McCarthy *et al.* (2011) synthesized recent empirical literature on factors affecting the adoption of SLM practices, with a strong focus on sub-Saharan Africa. The authors found that delayed benefits, access to credit, access to information on new practices, availability of seedlings and other SLM inputs in local markets, tenure and community norms on land use, were important constraints identified in many empirical analyses. In addition, given that many SLM practices generate positive spillovers on neighbouring land, collective action can also be an important factor affecting decisions to adopt these practices.

Turning to the literature on adaptive capacity, the concepts of exposure and sensitivity, as well as scale of adaptive capacity are key. The above literature is clearly also very relevant to the ongoing work in the global climate change community in the area of adaptation to climate change, and specifically the debate on vulnerability, resilience, and adaptive capacity. In the vulnerability literature, Fussel (2007) nicely summarizes the different approaches to vulnerability in different fields, and presents a framework distinguishing between aspects of vulnerability that are internal and external to the system considered, and between socioeconomic and biophysical. Adaptive capacity expresses the ability of a system to prepare for stresses and changes in advance or adjust and respond to the effects caused by the stresses, thereby modulating the sensitivity so as to decrease vulnerability (Smit *et al.*, 2001).[4]

Engle (2011) makes an important distinction between characterizing adaptive capacity versus measuring it. He highlights how most studies have focused on characterizing adaptive capacity, intended as assessment based on predetermined system attributes that are assumed to increase adaptive capacity. The use of aggregated indices that assess adaptive capacity based on assumptions about its determinants fall in this category (e.g. Brooks *et al.*, 2005; Patt *et al*, 2010). The alternative is to directly assess the adaptive capacity in a system, so as to understand what factors determine this capacity. An example of the latter approach is provided by Panda *et al* (2013) where the propensity to adopt farming practices that maintain higher yields is analysed, highlighting the importance of risk-reducing options such as crop insurance in determining adaptive capacity.

It is not unusual in the adaptation literature to assume that engaging in agricultural practices or technologies that increase incomes, and more specifically yields, represents a measure of adaptive capacity. For example, Di Falco *et al.* (2011) tried to disentangle the productive implications of adaptation using a survey conducted in Ethiopia and found that there are significant and non-negligible differences in food productivity between the farm households that adapted and those

[4] In this paper we focus on the link between vulnerability and adaptive capacity; however, there is also a resilience to illustrate the characteristics of systems that achieve a desirable state in the face of change, being applied to social-ecological systems (Folke, 2006; Janssen *et al.*, 2006). Adaptive capacity in the resilience literature (or adaptability) is the capacity of actors in the system to manage and influence resilience (Walker *et al.* 2004). Hence, adaptive capacity is a concept shared by the resilience and vulnerability strands of literature (Engle, 2011); however, for empirical applications we find the vulnerability framework to be more informative.

that did not adapt. In their review of the existing literature, Knowler & Bradshaw (2007) noted that the adoption of conservation agricultural practices could be associated with better farm performance in terms of reduced cost, higher plot productivity and consequent higher farm income. Teklewold *et al*. (2013) also found significant, and positive impacts from the adoption of a combination of sustainable agricultural practices on maize income. Kassie *et al*. (2008) provide evidence of a positive and significant impact of stone bunds on agricultural productivity on Ethiopian highlands. Nonetheless the positive coefficient is not observed in high rainfall areas, suggesting that the effectiveness of the practice adopted is agro-ecology-specific rather than universally valid. Branca *et al.* (2011) undertook a comprehensive meta-analysis of SLM practices and found that improved agronomic practices such as cover crops, crop rotations (especially with legumes) and improved varieties have increased cereal productivity by 116% on average whereas agroforestry is associated with a 69% increase. Tillage management and agroforestry were found to be particularly beneficial in dry agricultural areas. Based on the above literature, in this paper we take a similar view on the yield impacts of farm practice selection, hypothesizing that the selection of practices associated with higher productivity is evidence of adaptive capacity.

3. Data and descriptive analysis

3.1 Data description

This paper merged diverse geo-referenced datasets so as to include the relevant climate, bio-physical, and socio-economic variables affecting vulnerability and adaptive capacity of farmers:

i. For exposure to climatic disruptions, rainfall data was obtained using Africa Rainfall Climatology version 2 (ARC2) from the National Oceanic and Atmospheric Administration (NOAA), and average minimum and maximum temperature were calculated using ECMWF ERA INTERIM reanalysis model data;[5]

ii. For bio-physical sensitivity to climate disruptions we use information on soil nutrient availability obtained from the Harmonized World Soil database;[6]

iii. Determinants of household adaptive capacity are based on data from the Third Integrated Household Survey (IHS3), which was conducted from March 2010 to March 2011 covering a period of twelve months implemented by the Central Statistical Authorities (CSA) in collaboration with the World Bank. The Survey collected information from 12,288 households statistically designed to be representative at both national, district, urban and rural levels. It was designed to provide information on the various aspects of household welfare in Malawi such as household composition and characteristics, health, wage employment, and income sources, as well as data on consumption, food security, nonfarm enterprises, and durable and agricultural asset ownership, among other topics.[7] For households that were involved in agricultural activities data was also collected on land

[5] See http://www.cpc.ncep.noaa.gov/products/fews/RFE2.0 desc.shtml for more information on RFE algorithms.

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

[7] The full sample consists of 16,372 plots, however in this study we focused on plots that have been cultivated with maize during the survey rainy season (11,208 plots) given the fact that maize is a staple crop which is produced and consumed by a large proportion of rural Malawians. Details about the sampling procedures can be found from the report produced by the CSA in Malawi (IHS, 2012).

tenure, labour and non-labour input use, and crop cultivation and production at the plot level. Location and land area of plots are available for use with geographic information system (GIS) databases

iv. Determinants of system-level adaptive capacity in terms of enabling factors for adaptation were based on the (a) IHS3 community level survey that captured issues related to collective action, access to information, and to infrastructure including market and roads among others was also administered, and (b) data from a number of government and non-government institutions that are relevant for understanding use of sustainable land management activities at the household level, focusing on information available at a centralized (district) level. This includes data on total fertilizer distributed by district, proportion of land covered by forest by district, number of agricultural extension and development officer by district, number of micro finance and donor agricultural projects operation by district, total wage paid out in 08/09 by Malawi Social Action Fund (MASAF[8]) and district household population. We also collected the Malawi 2009 election results to control for the effects of voting patterns on household participation in the Malawi farm input subsidy programme (FISP).[9] We then merged the IHS3 Enumeration area (EA) and districts with this information to control for supply side constraints in understanding farming practice selection decisions and yield effect.[10]

For the exposure data, the fact that the IHS3 survey data included geo-referenced household and EA level Latitude and Longitude coordinates allowed us to link socio-economic data to remote sensing time series indicators such as rainfall during the growing season, long-term mean rainfall and the coefficient of variation in rainfall, as well as mean and maximum temperature and the coefficient of variation of maximum temperature (1983-2011). Taking the annual measure of main cropping season rainfall at each EA level, we calculate the coefficient of variation for rainfall (CV), measured as the standard deviation divided by the mean for the respective periods: 1983-2011, which is scale invariant, thereby providing a comparable measure of variation for households that may have very different rainfall levels. Similarly, information on soil nutrient availability was merged to the household dataset to control for the effects of bio-physical characteristics. By merging the IHS3 data with historical data on rainfall and temperature at the community level, we create a unique data s*et al*lowing for microeconomic analysis of climate impacts in Malawi.

3.2. Descriptive statistics

We focus in this paper on four different potentially climate smart agricultural practices: maize-legume intercropping, soil and water conservation, trees, and use of organic fertilizer, as well as two other practices that are aimed primarily at improving average yields—improved maize varieties and use of inorganic fertilizers. Table 2 shows the proportion of households that implemented the aforementioned agricultural practices on their plots, disaggregated by province.

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[8] The Malawi Social Action Fund (MASAF) is a project designed to finance self-help community projects and transfer cash through safety net activities.

[9] Democratic Progressive Party (DPP) was the ruling party at the time and the main opposition party was the Malawi Congress Party (MCP). The variables created include vote counts in the constituencies that cover the IHS3 EAs, DPP votes as a share of total votes cast and the MCP votes as a share of total votes.

[10] We thank to Talip Kilic at the World Bank for providing us with this data.

Maize–legume intercropping can help increase crop productivity through nitrogen fixation and also contributes to maintain productivity in a changing climate (Delgado *et al*., 2011). Maize–legume intercropping is practiced on about 22.1% of the plots during the cropping season analyzed in this study, and it is particularly prevalent in the Southern Province (35.5%).

Planting selected perennials, trees and shrubs, is part of a sustainable agricultural system in Malawi, whereby perennials are planted either sequentially (during fallow) or contemporaneously (intercropped) with an annual food crop. This kind of farming system maintains soil cover, improves nutrient levels, increases soil organic matter, improves water filtration and avoids soil loss, in addition to providing shade for other crops and a secondary source of food, fodder, fiber and fuel (Garrity *et al.,* 2010; Ajayi *et al*., 2009; McCarthy *et al*., 2011; Mercer, 2004; Franzel and Scherr, 2002; Verchot *et al*., 2007). In addition to adaptation, the perennials agricultural system contributes also to mitigation by increasing carbon sequestered both above and below ground (Verchot *et al*., 2007). In our sample, perennials are planted by 39% of the sample households. It's important to highlight that unlike other farming practices (which are measured at plot level), this variable is measured at the household level and captures if household has any trees on any plot.

SWC structures provide multiple on-farm private benefits in the form of increased and more stable yields by reducing water erosion, improving water quality, and promoting the formation of natural terraces over time, in addition to off-farm private and public benefits including the reduction of downstream flooding and of waterways' sedimentation as well as the enhancement of biodiversity (Blanco and Lal, 2008; McCarthy *et al*., 2011). SWC structures considered here include contour bunds – built of either earth or stone, terraces, gabions/sandbags, vetiver grass, tree belts or drainage ditches. Our data shows that about 40% of the maize plots have been treated with SWC structures and this figure is highest in the Central Province (43%) followed by the Sothern Province (41%). As with trees, SWC structures often entail large up-front costs, with benefits accruing – sometimes slowly – over time (McCarthy *et al*., 2011).[11]

Use of organic fertilizer is another major component of a sustainable agricultural system and a commonly suggested method of improving soil fertility, while capturing economies of scope in crop-livestock systems. Our data shows that organic fertilizer (which is composed of animal manure, compost and green manure) is used on about 12.2% of the sample maize plots. The adoption seems to be larger in the Central region (16.8%) compared to the other two provinces (7.2% for the North and 10.8% for the Southern region).

The use of high yielding varieties can contribute to improving food security and income for the rural population by providing higher yields (e.g., Kijima *et al*., 2008; Mendola, 2007; Berceril and Abdulai, 2010; Asfaw *et al*., 2012b, 2012c; Amare *et al*., 2011 etc). Nevertheless, whether improved high yielding varieties perform better than local varieties under harsh climatic conditions is very much an empirical question. The proportion of plots planted with improved maize varieties is

[11] We are quick to point out that the use of seed or fertilizer, which changes from year to year, can be different from trees and SWC which are more like capital items. The presence of these items on the farm is often reflects past decisions much more than current decisions. However in the context of Malawi we approach the decision on trees/SWC as a decision to maintain trees and SWC, where population densities are high – and thus potentially significant opportunity costs to retaining trees, and even higher costs for maintaining SWC structures. So the existence of SWC/tree does capture the maintenance decision and retaining trees is a yearly decision given fuel wood opportunity costs as well as opportunity costs of land not cultivated in this densely populated context.

about 51% and this figure is larger in the Northern Province (56%); the high adoption figures are partly attributable to the farm input subsidy program.

Lastly, we consider the utilization of inorganic fertilizers whose average application rate on the maize plots of our sample is about 63 kg ⁄acre, which is below blanket recommendation of 150 kg/acre by MoA (Guide to Agric production in Malawi). About 74.8% of maize plots are treated with inorganic fertilizers, which is relatively high compared to other SSA countries, but about 40% or less of other crop plots receive fertilizers. As with the use of improved hybrid seeds, the relatively high inorganic fertilizer use can be largely attributed to the farm input subsidy program. Looking across the different provinces, there seems to be no significant differences in the use of inorganic fertilizers. In all three provinces, the proportion of plots treated with inorganic fertilizer is over 70%. Although the impact on productivity of using inorganic fertilizer is widely documented, it is important to note that it may also cause soil degradation in the long term due to the depletion of organic matter in the topsoil (Branca *et al.*, 2011; FAO, 2011; Tilman *et al*., 2002) and is often associated with more variable net agricultural income.

We see a different picture when we look at the use of multiple practices at the same time on the same plot. Of the 11,206 plots considered in the analysis, about 96% of the plots benefited from one or more farm management practices although all six of the practices were applied on only fourteen plots. Inorganic fertilizer is the most common practice used by the sample households. It is used as a single technology on 11.3% of plots, in combination with improved seed on 20.5% of plots and in combination with trees and improved seed on 13% of plots. Improved seed alone is adopted on 5.2% of plots, in combination with trees on 3.1% of plots. Of the plots, 2.4% received only the maize-legume intercropping practice while SWC measures only are adopted on 2.2% of the plots. The bottom line is that the proportions of use of a given practice in combination with other practices are relatively small (see Table 1) indicating that there are few dominant packages. Instead, this evidence suggests that individual households are choosing packages specific to the agro-ecological and socio-economic characteristics.

Table 1. Distribution of farm practice selection by Province (Percent of farmers reporting engaging in practice)

Variables	North province (N=1897)		Central province (N= 3697)		Southern province (N=5614)		Total (N=11208)	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Improved seed	0.565	0.496	0.536	0.499	0.476	0.499	0.511	0.500
Maize-legume intercropping	0.104	0.306	0.077	0.266	0.355	0.479	0.221	0.415
Trees	0.511	0.500	0.275	0.447	0.426	0.495	0.391	0.488
Organic fertilizer	0.072	0.259	0.168	0.374	0.108	0.311	0.122	0.327
Inorganic fertilizer	0.747	0.435	0.785	0.411	0.724	0.447	0.748	0.434
SWC measures	0.377	0.48	0.429	0.495	0.409	0.492	0.404	0.490
Improved seed only	0.031	0.174	0.053	0.225	0.058	0.233	0.052	0.222
Legume intercropping only	0.011	0.105	0.010	0.098	0.037	0.189	0.024	0.152
Trees only	0.072	0.259	0.018	0.131	0.029	0.167	0.032	0.177
Organic fertilizer only	0.004	0.065	0.017	0.129	0.004	0.061	0.008	0.090
Inorganic fertilizer only	0.105	0.307	0.179	0.383	0.072	0.258	0.113	0.316
SWC measures only	0.015	0.120	0.027	0.163	0.020	0.142	0.022	0.146
Seed and legume	0.001	0.023	0.000	0.000	0.003	0.052	0.001	0.038
Seed and trees	0.063	0.243	0.016	0.125	0.031	0.173	0.031	0.174
Seed and organic	0.006	0.079	0.013	0.112	0.009	0.093	0.010	0.098
Seed and inorganic	0.212	0.409	0.267	0.443	0.161	0.368	0.205	0.404
Legume and trees	0.006	0.079	0.003	0.057	0.028	0.164	0.016	0.125
Legume and organic	0.003	0.056	0.001	0.037	0.005	0.070	0.003	0.059
Legume and inorganic	0.042	0.200	0.027	0.163	0.107	0.310	0.070	0.255
Organic and inorganic	0.008	0.089	0.029	0.168	0.006	0.076	0.014	0.117
Seed, legume, trees	0.000	0.000	0.001	0.028	0.003	0.058	0.002	0.044
Seed, legume, organic	0.000	0.000	0.000	0.000	0.000	0.019	0.000	0.013
Seed, legume, inorganic	0.003	0.051	0.001	0.037	0.023	0.149	0.012	0.110
Seed, tree, organic	0.002	0.046	0.004	0.059	0.005	0.073	0.004	0.065
Seed, tree, inorganic	0.212	0.409	0.104	0.306	0.119	0.324	0.130	0.336
Seed, organic, inorganic	0.011	0.105	0.046	0.209	0.017	0.128	0.025	0.157
Legume, trees, organic	0.002	0.040	0.001	0.033	0.005	0.068	0.003	0.054
Legume, trees, inorganic	0.024	0.154	0.018	0.132	0.090	0.286	0.055	0.228
Legume, organic, inorganic	0.005	0.072	0.007	0.082	0.013	0.112	0.009	0.097
Trees, organic, inorganic	0.007	0.086	0.018	0.131	0.004	0.065	0.009	0.095
Seed, legume, trees, organic	0.001	0.032	0.001	0.028	0.021	0.145	0.011	0.105
Seed, legume, trees, inorganic	0.000	0.000	0.000	0.000	0.000	0.013	0.000	0.009
Seed, legume, organic, inorganic	0.000	0.000	0.001	0.023	0.005	0.070	0.003	0.052
Seed, trees, organic, inorganic	0.011	0.105	0.023	0.150	0.017	0.130	0.018	0.133
Legume, trees, organic, inorganic	0.006	0.079	0.005	0.068	0.012	0.108	0.008	0.092
All six	0.001	0.023	0.001	0.023	0.002	0.044	0.001	0.035
None	0.032	0.175	0.047	0.211	0.035	0.184	0.038	0.192

Note: The number of observation here refers to number of maize plots

Table 2 presents productivity of maize by each farming practice type disaggregated by province. The descriptive statistics show a productivity difference in maize yield between adopters and non-adopters of each distinguished practice. Adopters of inorganic fertilizer have about 83% higher yields compared to non-adopters while adopters of maize-legume intercropping produce about 26% more compared to non-adopters. The mean productivity difference for adoption of improved maize seed is about 39%. Results show that there are no statistically significant productivity difference between adopters and non-adopters for SWC and trees. It is however important to highlight that yield benefits of both trees and SWC structures often accrue slowly over time compared to the other agricultural practices and generate benefits external to the farm; additionally, there are important weather-resilience benefits to these practices not captured in mean yield figures. Overall the summary statistics in Table 2 suggest that adoption of some of the selected agricultural practices may have a positive role in affecting quantity of maize yield with significant differences depending on the type and range of practices taken into account. However, a simple comparison of means does not allow to disentangle the effects that other observable variables and factors might have on production, especially considering that the farming practice selection decision is endogenous. Thus, a rigorous analytical model is estimated to verify whether these differences in mean maize yields remain unchanged after controlling for all confounding factors. To measure the impact of use of farming practices, it is necessary to take into account the fact that households who used the practices might have achieved a higher yield even if they had not used.

Table 2. Maize productivity under varying farm practices (kg/acre)

Variables	North province (N=1897)		Central province (N= 3697)		Southern province (N=5614)		Total (N=11201)	
	Mean	Std. Err.	Mean	Std. Err.	Mean	Std. Err.	Mean	Std. Err.
Maize-legume intercrop								
No	849.2	27.2	1050.2	47.8	1051.9	78.3	1011.7	37.9
Yes	1680.2	162.2	1590.3	195.2	1184.9	67.4	1270.9	60.2
Difference (%)	97.8(8.1)***		51.4 (3.1)***		12.6 (1.1)		25.6 (3.3)***	
Trees								
No	962.4	48.4	1076.5	45.7	1126.3	87.0	1084.5	45.3
Yes	910.6	41.6	1131.3	119.5	1062.6	58.7	1044.9	43.4
Difference (%)	-5.4(0.8)		5.1(0.7)		-5.6(0.5)		-3.5(0.6)	
SWC measures								
No	944.7	42.9	1040.3	36.3	1150.3	89.7	1077.2	46.8
Yes	919.3	43.1	1159.7	97.4	1025.5	43.1	1057.0	40.9
Difference (%)	-2.7 (0.3)		11.5(1.3)		-10.8(1.1)		-1.9(0.3)	
Improved seed								
No	908.0	53.2	942.1	41.1	865.7	41.6	895.9	27.0
Yes	957.5	38.7	1220.6	79.3	1355.9	107.8	1234.5	57.8
Difference (%)	5.4 (0.7)		29.6 (2.9)***		56.6 (4.4)***		37.8 (5.2)***	
Inorganic fertilizer								
No	695.7	33.3	820.8	92.7	565.7	62.0	659.6	43.3
Yes	1017.3	40.8	1165.5	53.6	1302.8	73.2	1207.1	40.0
Difference (%)	46.2 (4.4)***		41.9(3.0)***		130.3 (5.9)***		83.0 (7.4)***	

Note: Number of observations refers to the number of maize plots. *** p<0.01, ** p<0.05, * p<0.1. t-stat in parenthesis.

4. Empirical strategies

4.1. Modelling farming practice selection decisions: decomposing the role of exposure to climate stress, sensitivity, and adaptive capacity

Based on the extensive literature on the choice of farming practice (including input use), we model the farming practice selection decision as the outcome of a constrained optimization problem by rational agents (Feder *et al.* 1985; Foster and Rosenzweig, 2000; Suri, 2011 and de Janvry *et al.* 2010). The most common constraints include those on the budget, access to information, credit and the availability of both the technology and other inputs. Thus, households are assumed to maximize their utility subject to these constraints, and adopt a given technology if and only if the technology is available and affordable, and at the same time the selection decision is expected to be beneficial (in terms of profits or otherwise) (de Janvry *et al.*, 2010).

We model utility as function of the income gained from each plot, so that the adoption decision of farmer i for the cropping season t can be expressed as follows:

$$A^j_{ik(t-1)} = \begin{cases} 1 & if\ \ E_{t-1}\left(\left(Y_{ikt}\middle|A^j_{ik(t-1)} = 1\right) - \left(Y_{ikt}\middle|A^j_{ik(t-1)} = 0\right)\right) > 0 \\ 0 & otherwise \end{cases} \tag{1}$$

Where $A^j_{ik(t-1)}$ is the farmer i's binary adoption decision for practice j on plot k at time t-1, which denotes the time when adoption decisions are taken, and Y_{ikt} is the vector of outputs considered in our model (productivity) from plot k at time t. In other words, equation 1 states that farmer i adopts practice j if at time (t-1) he/she expects that production at time t will be higher under adoption. More specifically the output of plot k at time t can be expressed as:

$$Y_{ikt} = \alpha' V_{ikt} + \beta' W_{ct} + \gamma^j A^j_{ik(t-1)} + \varepsilon_{ikt} \tag{2}$$

Where V_{ikt} is a vector of household, plot and community characteristics, W_{ct} is a bundle of climatic variables characterizing the cropping season at time t in community c, and ε_{ikt} is the error term. Therefore we can rewrite the adoption condition equation as follows:

$$E_{t-1}\left(Y_{ikt}|A^j_{ik(t-1)} = 1\right) - E_{t-1}\left(Y_{ikt}|A^j_{ik(t-1)} = 0\right) = \alpha' V_{ik(t-1)} + \beta' W_{c(t-1)} + E_{t-1}(\gamma^j) - \left(\alpha' V_{ik(t-1)} + \beta' W_{c(t-1)}\right) = E_{t-1}(\gamma^j) > 0 \tag{3}$$

Despite being quite obvious, this means that the farmer selects a given practice if and only if the expectations for its impact built at time (t-1); $E_{t-1}(\gamma^j)$ is positive. Given the fact that the impact of adoption is case specific, it is then reasonable to model the expected impact of adoption as a function of the observed variables that also affect production and unobservable characteristics (U_{ikt}).

$$E_{t-1}(\gamma^j) = f\left(V_{ik(t-1)}; W_{ct-1}; U_{ik(t-1)}\right) > 0 \tag{4}$$

Farmers are also more likely to adopt a mix of measures to deal with a multitude of agricultural production constraints than adopting a single practice. In this context, recent empirical studies of technology adoption decisions assume that farmers consider a set of possible technologies and choose the particular technology bundle that maximizes the expected utility accounting for interdependent and simultaneous adoption decisions (Dorfman, 1996; Teklewold *et al.*, 2013). In order to be able to account for this interdependency, we use a multivariate probit (MVP) technique applied to multiple plot observations to jointly analyze the factors that increase or hinder the probability of adopting each agricultural practice analyzed in this paper. This approach simultaneously models the influence of the set of explanatory variables on each of the practices, while allowing the unobserved and unmeasured factors (error terms) to be freely correlated. One source of correlation may be due to complementarity (positive correlation) or substitutability (negative correlation) between different practices.

The MVP model is characterized by a set of binary dependent variables ($A^j_{ik(t-1)}$) that equal 1 if farmer i adopts the practice j on plot k, and zero otherwise, such that:

$$A^j_{ik(t-1)} = \begin{cases} 1 & if\ A^*_{ijk} = \delta V_{ik(t-1)} + \theta W_{c(t-1)} + e_{jk(t-1)} > 0 \\ 0 & otherwise \end{cases}, \text{ for each } j=1,\ldots,j \quad (5)$$

In equation (5) the assumption is that a farmer i has a latent variable, A^*_{ijk}, which captures the observed and unobservable preferences or demand associated with the j^{th} practice. This latent variable is assumed to be a linear combination of observed characteristics ($V_{ik(t-1)}$and $W_{c(t-1)}$) that affect the adoption of the j^{th} practice, as well as unobserved characteristics captured by the error term ($U_{ik(t-1)}$).[12] If adoption of a particular practice is independent of whether or not a farmer adopts another practice (i.e., if the error terms are independently and identically distributed (iid) with a standard normal distribution), then equation (5) specifies a univariate probit model for each *j*, where information on farmers' adoption of one farming practice does not alter the prediction of the probability that they will adopt another practice. However, if adoption of several farming practices is possible on the same plot and adoption of various practices is correlated with each other, a more realistic specification is to assume that the error terms in equation (5) are correlated with each other. We assume that $e_{jk(t-1)}$ jointly follow a multivariate normal (MVN) distribution, with zero conditional mean and variance normalized to unity. Allowing for non-zero off-diagonal elements in the covariance matrix gives an MVP model that jointly represents decisions to adopt a particular farming practice.

Based on empirical work and economic theory, we have summarized variables hypothesized to explain the adoption decision and resulting yield increase under four major categories, (i) exposure to climatic stress, (ii) bio-physical sensitivity to such stress, (iii) household-level determinants of adaptive capacity in terms of farmers' ability to prepare and adjust to the resulting stress, and, finally, (iv) system-level determinants of adaptive capacity in terms of enabling factors for adaptation. The rationale of these sets of variables and their characteristics are described in more detail below. Summary statistics of explanatory variables disaggregated at provincial level are presented in Table 3.

The first set of variables used in the analyses is climate variables that characterize the exposure to climate-related stress. Our rainfall data comes from NOAA ARC2 and temperature data comes from ECMWF. We use long-term historical data on rainfall patterns and temperatures to capture farmer expectations about climate at the beginning of the season when they make input decisions.

[12] Note that the notations for observed variables (*V* and *W*) in this adoption specification is the same as those in the output model specification above. The specific variables in these vectors however may differ in econometric estimation, as explained below.

We include actual climate realizations to control for their effects on yields. The long-term historical variables include long-term average rainfall, the coefficient of variation of rainfall, the average delay in the onset of the rainy season[13], long-term maximum growing season temperature, and the coefficient of variation in maximum temperature. Lower mean rainfall and higher maximum temperatures are expected to increase the use of risk-reducing inputs such as SLM inputs, whereas higher mean rainfall and lower maximum temperatures should favour improved seeds and fertilizer use. Greater riskiness, reflected in the coefficients of variation, is expected to increase the use of SLM inputs, but decrease the use of improved seeds and fertilizer. Actual climate realisation variables include growing season rainfall, the maximum temperature observed in the growing season, and the total amount of dry spells observed during the rainy season. Dry spells are defined as the total number of dekads[14] with less than 20mm rain during germination and ripening (Tadross *et al*., 2009).

Figure 1 shows the geographic distribution of the coefficient of variation of rainfall and maximum temperature at EA level on a dekadal basis. As can be seen, there are significance differences in terms of rainfall and temperature variability across the three geographical regions in Malawi. Figure 2 shows the geographic distribution of current and long run average rainfall and we can observe that the Northern provinces experience relatively high level of rainfall compared to the South and Central. As for current and long run average temperature, Figure 3 clearly show that the areas in the Northern province experience low temperature followed by Central and Southern province. Finally, Figure 4 shows the geographic distribution of onset of rainy season.

We include several plot-specific characteristics, such as soil nutrient availability constraints, plot size and slope of the plot. Land size can be expected to affect adoption positively as farmers with larger land size may find it easier to experiment with a new technology on a part of their land.

A diverse set of potential household-level determinants of adaptive capacity are considered. Household wealth indicators include wealth index[15] based on durable goods ownership and housing condition, agricultural machinery index based on agricultural implements and machinery access, and livestock size (measured in tropical livestock unit (TLU)). Household size, age, gender and education level of the household head are also included. Family size in terms of adult equivalent units is a potential indicator of labour supply for production, and labour bottlenecks can also be a significant constraint to the use of some farm management practices. For instance

[13] We defined onset of the rainy season as a period where 2 dekads of rainfall is greater or equal to 50mm after December 1st (Tadross *et al*., 2009).

[14] Defined as a contiguous period of 10 days.

[15] The household wealth index is constructed using principal component analysis, which uses assets and other ownerships. In this specific case the following variables have been included: number of (per-capita) rooms in the dwelling, a set of dummy variables accounting for the ownership of dwelling, mortar, bed, table, chair, fan, radio, tape/CD player, TV/VCR, sewing machine, paraffin/ kerosene/ electric/ gas stove, refrigerator, bicycle, car/motorcycle/minibus/lorry, beer brewing drum, sofa, coffee table, cupboard, lantern, clock, iron, computer, fixed phone line, cell phone, satellite dish, air-conditioner, washing machine, generator, solar panel, desk, and a vector of dummy variables capturing access to improved outer walls, roof, floor, toilet, and water source. The household agricultural implement access index is also computed using principal components analysis and covers a range of dummy variables on the ownership of hand hoe, slasher, axe, sprayer, panga knife, sickle, treadle pump, watering can, ox cart, ox plough, tractor, tractor plough, ridger, cultivator, generator, motorized pump, grain mail, chicken house, livestock kraal, poultry kraal, storage house, granary, barn, and pig sty.

Figure 1. Coefficient of variation of rainfall and max temperature (1983-2011)

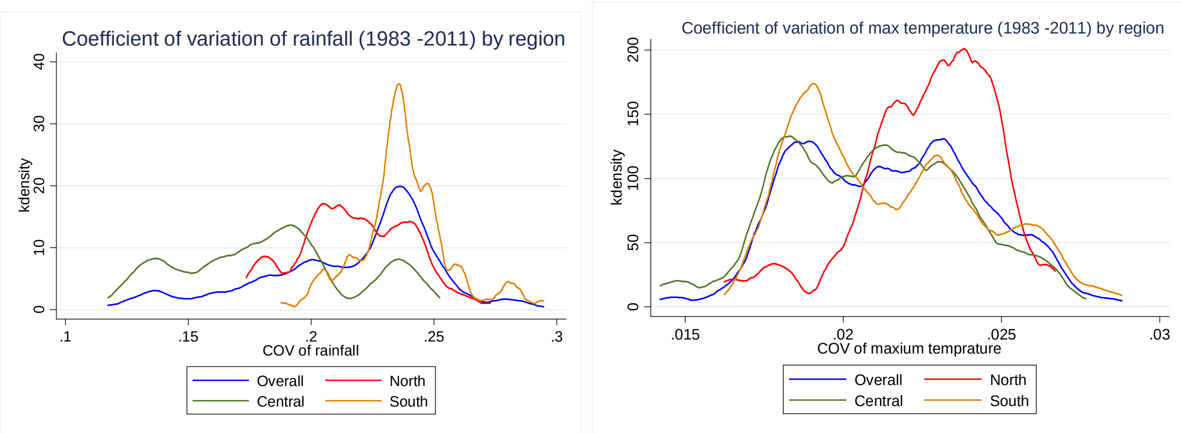


Figure 2. Total amount of rainfall during the rainy season (current and long run)

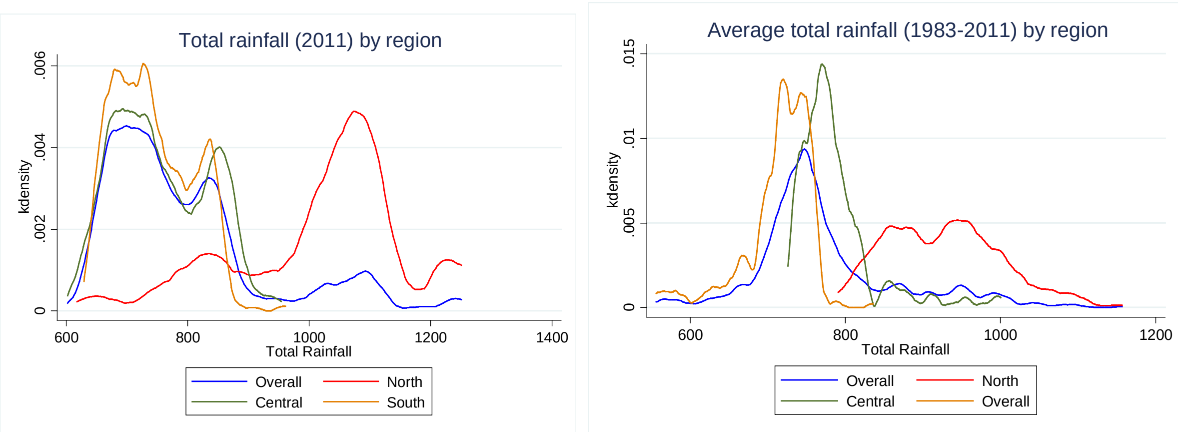
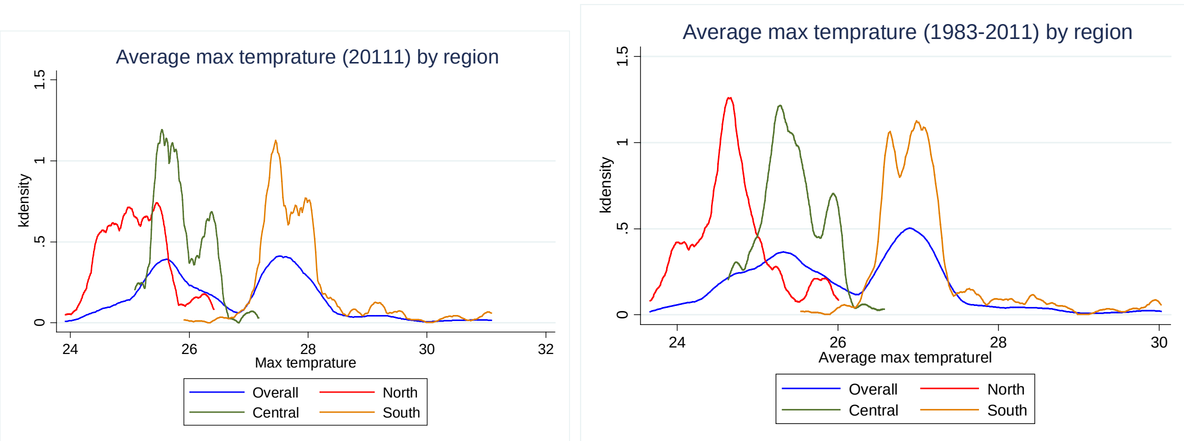


Figure 3. Average maximum temperature during rainy season (current and long run)



investments in, and maintenance of, SWC can be particularly labour demanding and may be too expensive to undertake in households with limited access to labour. Furthermore, land tenure status is taken into consideration since if tenure security increases the likelihood that farmers adopt strategies that will capture the returns from their investments in the long run (e.g. Kassie *et al.*, 2010; Denning *et al.*, 2009; Teklewold *et al.*, 2013).

When considering system-level determinants of adaptive capacity, access to institutions and transaction costs are among the main determinants governing adoption decisions. Transaction costs have been used as definitional characteristics of smallholder farmers and as the main factor responsible for market failure in developing countries (Sadoulet and de Janvry, 1995). However, they pose challenges related to measurement. Therefore, this study proxies transaction costs via observable factors that explain transaction costs or mitigate transactions costs, such as geographical areas, distance to district centres, road density and output price. Indicators for institutions include the number of village development committees in the community, the number of microfinance and saving institutions in the community, collective action index[16] and share of households who received extension advice on specific farm management practices in the community. By increasing travel time and transport costs, distance related variables are expected to have a negative influence on adoption decisions. By facilitating information flow or mitigating transactions costs access to institutions variables are expected to have a positive effect on the adoption decision. On the other hand the theory of impacts of collective action on adoption decision is not straightforward. With use of multiple practices, some of which generate purely private returns (e.g. improved seeds) and some of which generate public good spillovers (e.g. SWC measures), whether any one practice increases or decreases depends on whether the practices are complements or substitutes. If we posit that collective action reduces the costs of providing the input with public goods spillovers, then those farmers should increase depending on the relative complimentarity/substitutability amongst those inputs. The only thing we can say unambiguously is that the adoption of the practice with the greatest public goods spillovers should increase with this index. We also consider additional district level supply side constraints such as total fertilizer distributed by district, proportion of land covered by forest by district, number of agricultural extension and development officer by district, number of micro finance and donor agricultural projects operation by district, total wage paid out in 08/09 by Malawi Social Action Fund (MASAF) by district and district household population.

[16] The collective action index is constructed from community level indicators using principal component analysis and takes into account the number of activities where community members provided seed money to address the issue, number of activities where members gave money to actually undertake the activity, number of activities for which manual labor was provided, number of activities for which outside funding was sought, and a set of dummy variables accounting for member participation in school construction or maintenance, health clinic construction or maintenance, agricultural or forest or irrigation activities, and law enforcement activities.

Table 3. Descriptive summary of selected variables

Variables	Northern province (N= 1404)		Central province (N= 2871)		Southern province (N=3567)		Total (N=7842)	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Exposure to climatic stress								
Coefficient of variation of rainfall (1983-2011)	0.21	0.02	0.20	0.04	0.26	0.02	0.23	0.04
Long term mean rainfall (1983-2011) (mm)	926.73	74.17	785.37	48.38	713.92	44.14	773.51	92.08
Average delay in the onset of the rainy season (1983 -2011)	0.16	0.05	0.16	0.06	0.18	0.05	0.17	0.06
Rainfall in during the rainy season (mm)	1018.2	139.0	755.6	78.6	741.9	64.0	793.2	133.1
Total amount of dry spells during rainy season	0.01	0.10	0.43	0.67	2.47	0.68	1.38	1.26
Coefficient of variation of maximum temperature (1983 -2011)	0.02	0.00	0.02	0.00	0.02	0.00	0.02	0.00
Long-term maximum temperature (1989-2010)	24.68	0.50	25.43	0.38	27.13	0.72	26.15	1.17
Average maximum temperature during rainy season	25.10	0.53	25.83	0.41	27.88	0.80	26.73	1.34
Bio-physical sensitivity								
Slope of plot (0=flat, 1=steep)	0.14	0.35	0.10	0.31	0.10	0.30	0.11	0.31
GPS based land size (acre)	2.20	1.69	2.46	1.95	3.12	2.95	2.71	2.45
Nutrient availability constraint (1-4 scale, 5 = mainly non-soil)	1.95	0.76	1.57	0.80	1.21	0.52	1.45	0.72
Household level variables								
Age of household head (years)	44.51	15.91	42.83	16.14	42.98	16.86	43.20	16.44
Gender of household head (1=male)	0.79	0.41	0.78	0.42	0.71	0.45	0.75	0.43
Household size (AE)	4.10	2.00	4.01	1.86	3.63	1.73	3.85	1.84
Household head highest level of education (years)	6.58	3.81	4.93	3.79	4.58	4.01	5.06	3.96
Livestock ownership (tropical livestock unit (TLU))	1.12	2.91	0.54	2.36	0.46	2.59	0.61	2.58
Wealth index	0.15	1.83	-0.38	1.75	-0.45	1.64	-0.31	1.73
Agricultural implements access index	0.68	1.25	0.69	1.44	0.20	1.11	0.47	1.29
Land tenure (1= own, 0= rented)	0.91	0.29	0.86	0.34	0.92	0.27	0.90	0.30
System-level variables								
Distance to major district centre (Km)	180.11	108.57	120.18	52.63	91.88	84.39	118.04	85.82
Village development committees in the community (number)	1.69	1.95	2.42	3.11	2.06	3.28	2.12	3.03
Saving & credit organization in the community (number)	0.14	1.94	0.40	1.56	0.37	2.34	0.34	2.01
Proportion of households with access to extension advice in the community	59.72	29.12	50.38	28.56	45.40	25.35	49.79	27.73
Collective action index	-0.07	0.84	0.39	1.20	-0.12	0.80	0.07	1.00
DPP vote as a share of total vote cast	0.95	0.03	0.54	0.18	0.71	0.22	0.69	0.24
Seed and/or fertilizer vendor in EA (1=yes)	0.11	0.31	0.40	0.49	0.30	0.45	0.30	0.45
Fertilizers distributed in MT per household	1.57	0.61	1.45	0.45	1.06	0.31	1.28	0.48
Proportion of land covered by forest	0.13	0.15	0.18	0.17	0.09	0.13	0.13	0.15
Number of micro-finance and donor agri. projects operating in district	6.50	1.47	9.53	4.01	4.89	2.21	6.69	3.52
MASAF wages paid in 08/09 season (million MKW)	18.9	16.0	28.0	10.4	36.7	13.3	30.8	14.6

Number of observations refers to the number of maize producing households.

4.2 Modelling the links between practice selection and yields

Taking productivity impacts as a key indicator of adaptive capacity, we move to an analysis of the relationship between farm practice selection and yields. In this respect, the relevant estimating equation for the yield model is given by equation 2. The impact of adoption of the j^{th} practice on the outcome variables is measured by the estimates of the parameter γ^j. Estimating yield equation as in this equation, however, might generate biased estimates because it assumes that agricultural practice selection (or input use) (*A*) is exogenously determined, while it is likely endogenous, as discussed above. As a matter of fact the decision to adopt or not is not random but rather based on individual self-selection. To make this more explicit we can plug equation 4 into equation 2 as follows.

$$Y_{ikt} = \alpha' V_{ikt} + \beta' W_{ct} + \gamma^j A^j_{ik(t-1)}\left(V_{ik(t-1)}; W_{ct-1}; U_{ik(t-1)}\right) + \varepsilon_{ikt} \qquad (6)$$

Given that time *t* immediately follows *t-1* from a chronological perspective, it is quite intuitive that variables like household, community and soil characteristics are expected to change only marginally between the two time periods; which implies that equation 6 can be rewritten as follows.

$$Y_{ikt} = \alpha' V_{ikt} + \beta' W_{ct} + \gamma^j A^j_{ik(t-1)}\left(V_{ikt}; W_{ct-1}; U_{ik(t-1)}\right) + \varepsilon_{ikt} \qquad (7)$$

It is clear from equation 7 that A^j_{ikt-1} is endogenous: farmers who select certain practice may have systematically different characteristics from the farmers who do not. Moreover, unobservable characteristics of farmers and their farms may affect both the selection decision and the expected outcome variables, resulting in inconsistent and biased estimates of the effect of agricultural practice selection on productivity.

Therefore, to explicitly account for multiple endogeneity problems in our structural model, we employ the conditional recursive mixed-process estimator (CMP) as proposed by Roodman (2011). Unlike previous studies which estimate the productivity (welfare) effect of adopting a single agricultural practice (e.g. Kassie *et al*., 2010; Amare *et al*., 2012, Asfaw *et al*., 2012c), we estimate a simultaneous equations model of productivity using CMP estimators to examine the effect of adoption of different practices on maize productivity. This approach is suitable for a large family of multi-equation systems where the dependent variable of each equation may have a different format (for example, binary, categorical, and bounded and unbounded continuous). It also takes into account both simultaneity and endogeneity, and produces consistent estimates for recursive systems in which all endogenous variable appear on the right-hand-side as observed. Since our model is a recursive process (imposed by the instrumentation strategy), consisting of one structural equation ('productivity' equation) and reduced-form adoption equations, the analysis is essentially a limited information maximum likelihood (LIML) estimator. The advantage with this approach, as opposed to two-stage least squares and related linear methods, is the gain in efficiency as it takes into account the covariance of the errors and uses the information about the limited nature of the reduced-form dependent variable (Roodman, 2011).

The major limitation of implementing this approach is the feasibility in terms of computational burden and achieving convergence especially for a large family of multi-equations. Therefore we restricted ourselves to a maximum of three equations at a time for this paper. Looking at the MVP results, we categorized the six adoption variables into two groups based on their similarities in terms of factors affecting them and the nature of the technologies. Hence in modelling the impacts of adoption using CMP, we analyse the adoption of modern inputs (improved seed or inorganic fertilizer) (A^1_{ikt-1}), and sustainable land management practices (trees or soil and water conservation or organic fertilizer or legume intercropping) (A^2_{ikt-1}) [17] resulting in the estimating equation for productivity as follows:

$$Y_{ikt} = \alpha' V_{ikt} + \beta' W_{ct} + \gamma^1 A^1_{ik(t-1)} + \gamma^2 A^2_{ik(t-1)} + \varepsilon_{ikt} \tag{8}$$

$$A^j_{ikt-1} = \delta V_{ikt} + \theta W_{c(t-1)} + e_{jk(t-1)}\, , for\ j = 1, 2 \tag{9}$$

The consistency of this method depends on the validity of instruments to identify the adoption equations, which in turn, relies on two conditions. First, the instruments must be correlated with the endogenous variables (adoption of agricultural practices), and second, they must not be correlated with the unobserved factors that may affect the maize yield (i.e. the error term of the yield model). We use long-term (1983-2011) historical variables that capture rainfall patterns and temperatures, as potential instruments for household decisions to adopt agricultural practices during the current year to capture expected climate at the beginning of the season ($W_{c(t-1)}$). We use the coefficient of variation (COV) of rainfall, the coefficient of variation of maximum temperature and delay in the onset date of the rainy season. As farmers form expectations about the climatic conditions of their area based on their experiences, we expect that they plant crops and use farm practices that are suited to their expectation. Variation in rainfall and temperature across space and time should generate corresponding variation in household response or behaviour in terms of change in farming practices that will in turn create variation in agricultural output and thus household income. The impacts of long term climatic variables on productivity are realized mainly through their impact on input choices. For this reason, we posit that the variables capturing long term rainfall and temperature variability are reasonably valid instruments for the CMP framework to be consistent.

5. Empirical results

5.1. Determinants of practice selection– MVP results

Our first objective in this study is to examine farmers' incentives and conditioning factors that hinder or accelerate adaptation strategies in terms of farming practices selections, and secondly to evaluate the causal impact of this selection on maize productivity. The first objective gives insights into the driving forces behind farmers' practice selection decisions where the dependent variable takes the value of 1 if the farmer adopts specific practices on a given plot and 0 otherwise. The model fits the data reasonably well – the Wald test of the hypothesis that all regression coefficients in each equation are jointly equal to zero is rejected. The likelihood ratio test of the null hypothesis that the error terms across equations are not correlated is also rejected as reported in Table 4.

We find that the estimated correlation coefficients are statistically significant and different from zero in eleven of the fifteen pair cases, where two coefficients are negative and the remaining nine are positive, suggesting the propensity of adopting a practice is conditioned by whether another

[17] Another caveat of our impact estimation procedure is that we can't estimate the impact of adoption of various combinations of these practices on outcome variables. This is mainly because the adoption of multiple practices on the same plot is very limited as reported in Table 1 which makes it very difficult to implement IV/CMP estimator for adoption of various combinations of these inputs.

practice in the subset has been adopted or not. Besides justifying the use of MVP in comparison to the restrictive single equation approach, the sign of the coefficients support the notion of interdependency between practice selections. This finding may be attributed to complementarity or substitutability between the practices; for example the use of improved seed is complementary to the use of inorganic fertilizer but substitutable with maize-legume intercropping. The positive correlation coefficient between two yield enhancing technologies (inorganic fertilizer and improved seed) is the highest among all (22%) which is not surprising given the fact that productivity potential of high yielding varieties highly depends on the use of inorganic fertilizer. This is one of the reasons why poor farmers may refrain from switching to high yielding varieties if they do not have capital to purchase inorganic fertilizer as well. The high correlation is also expected given the fact that both inputs are part of the input subsidy support program. Inorganic fertilizer on the other hand is substitutable with the use of organic fertilizer, but complementary with the rest of the practices. Adoption of organic fertilizer is also significantly complementary with trees, maize-legume intercropping and the SWC measures. The positive correlation between adoption of maize-legume intercropping and use of organic fertilizer indicates that, given the very low soil fertility of most farmland in Malawi currently, low cost fertility-improving inputs are still complements and not yet substitutes. The use of multiple fertility-enhancing inputs also indicates that for many households, different constraints are binding on the different fertility-enhancing inputs, e.g. access to inorganic fertilizer subsidy coupons, or number of animals owned given very thin manure markets.

Table 4. Estimated covariance matrix of the regression equations between the adaptation measures using the MVP joint estimation model

	Improved Seed	Inorganic Fertilizer	Maize-legume intercropping	Trees	SWC measures
Inorganic fertilizer	0.219***				
Maize-legume intercropping	-0.957***	0.044**			
Trees	0.019	0.038**	-0.002		
SWC measures	-0.007	0.039**	0.067***	0.064***	
Organic fertilizer	0.022	-0.105***	0.071***	0.044**	0.056***

Likelihood ratio test of rho21 = rho31 = rho41 = rho51 = rho61 = rho32 = rho42 = rho52 = rho62 = rho43 = rho53 = rho63 = rho54 = rho64 = rho65 = 0: chi2(15) = 2025.71 Prob > chi2 = 0.0000

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Standard errors in parenthesis.

The MVP results reported in Table 5 show that the adoption decisions of different farm management practices are quite distinct and to a larger extent the factors governing the adoption decision of each of them are also different suggesting the heterogeneity in adoption of farm management practices.

Results show the importance of climatic variables, i.e. exposure, in explaining the probability of farm households' decision to adopt different agricultural practices. We find that greater variability in rainfall and maximum temperature during the growing season increase adoption of risk-reducing practices but reduce the use of inputs with uncertain benefits in terms reducing risk to current climate stresses. For instance, in areas with greater variability in rainfall and temperature, more legume intercropping, trees and SWC measures are used whereas the probability of adopting inorganic and organic fertilizer is low. The only exception is improved seed, which is positively associated with greater variability.

In communities where the average delay in onset of rainy season is high, farmers are more likely to adopt more of improved seeds, trees and SWC measures whereas, the probability to adopt inorganic fertilizer is negatively correlated with delay in onset of rainy season. We also find that higher mean rainfall and lower maximum temperatures increase the use of inorganic fertilizer, whereas higher mean rainfall and higher maximum temperatures favour improved seeds and trees. Our results are consistent with the findings of Kassie *et al*. (2010) and Teklewold *et al*. (2013), who found that yield enhancing technologies like improved seeds and inorganic fertilizer provide a higher crop return in wetter areas than in drier areas. Overall our findings suggest that farmers are responding to climate patterns in terms of their adaptation strategies and that information on changes in climatic variability should be an integral part of extension activities.

Biophysical plot characteristics are also found to be important determinants of adoption for most of the practices. Plot size has a positive effect on adoption of legume intercropping, trees and SWC measures, however, it is negatively correlated with the adoption of improved seeds. As expected, plot slope is negatively correlated with the use of improved seed and inorganic fertilizer but positively correlated with adoption of legume intercropping, trees, and SWC measures. We also find that farm households with less fertile soils or high nutrient availability constraints are more likely to implement some of these farm management practices especially trees, legume intercropping and SWC measures.

As expected, the household wealth index and agricultural implements index are positively associated with adoption of risk-reducing inputs as well as risk increasing inputs. The only exception is the use of legume intercropping. Household demographics to some extent also played significant role in explaining household adoption decisions. Education status of the household plays a positive role in most cases, which is consistent with other studies (e.g. Teklewold *et al*., 2013). The effect of age and gender of the household head seems to be heterogeneous (see Table 5 for detail). We find that farm households who own their land are less likely to adopt improved seed and inorganic fertilizer compared to farmers who rented. On the other hand the decision to adopt organic fertilizer, trees, maize-legume intercropping and SWC is positively and strongly correlated with owning the land. Our results are consistent with a number of studies that have demonstrated that the security of land ownership has substantial effect on the agricultural performance of farmers (e.g. Kassie *et al*.,, 2008; Denning *et al*., 2009; Teklewold *et al*., 2013). To the extent that ownership is associated with greater tenure security than rental agreements, particularly in the longer term, better tenure security increases the likelihood that farmers adopt strategies that will capture the returns from their investments in the long run. On the other hand farmers with less tenure security tend to demand more inputs with short term benefits like inorganic fertilizer and improved seed. Kassie *et al*. (2008) also found that in areas of Ethiopia where land is scarce and search costs are high, farmers are likely to apply more inputs with short term returns on rented plots than owned plots; as noted above Malawi also has high rural population densities.

At the system-level, results show the key role of rural institutions, social capital and supply-side constraints in governing adoption decisions of farm households. Availability of seed and/or fertilizer vendor in the community is positively correlated with the use of inorganic fertilizer and maize legume intercropping but in communities where their availability is limited, farmers tend to use more organic fertilizer and trees. As expected distance to district centres and road density significantly affect the use of inputs. Distance to district centers, as expected, negatively affects adoption decisions; indicating that distance to major markets and the political center constitutes a time constraint on the ability of farmers to access information and inputs. The coefficients associated with the local road density (measured as the metres of roads in a 10 km radius from the centroid of the community) are generally positive and significant consistent with reduced local marketing and transactions costs. Access to government extension services also plays a significant role though the effect is heterogeneous – positive for improved seed and trees but negative for legume intercropping and organic fertilizer. The presence of village development committees in the community is positively correlated with use of all the inputs though the coefficients are statistically significant for improved seed and organic fertilizer. The coefficient of collective action index is positive and significant for three of the practices - organic fertilizer, legume intercropping and trees. These results are not surprising given the fact that the public goods spillover impacts are greatest for these practices compared to the improved seeds and inorganic fertilizer. Overall with scarce information sources and high transaction costs, such informal institutions and collective action facilitate the exchange of information and mitigate transaction costs to enable farmers to access inputs which are consistent with the findings of Pender and Gebremedhin (2007) and Wollin *et al*. (2010).

Participation in FISP plays a crucial role in the use of improved seed and inorganic fertilizer but input coupon receipt is endogenous to the adoption decision, and hence, we need a proxy for receipt of input subsidy. We do so using total level of fertilizers distributed by district per household. As expected, we find that the total fertilizer distributed at district level affects the probability of adoption of inorganic fertilizer positively. This coefficient is also positive for the rest of the practices although it is negatively correlated with adoption of legume intercropping. We also used a variable that captures the major party (DPP) votes as a share of total votes cast as a proxy to control for political influence in the targeting of government program like the FISP. We find that it is positive correlated with the use of improved seeds but with no significant effect on the use inorganic fertilizers.

Table 5. Results of the multivariate probit model – determinants of farming practice selection: climate risk exposure, sensitivity and adaptive capacity

	Improved seed		Inorganic fertilizer		Maize-legume intercropping		Trees		SWC		Organic fertilizer	
	Coef.	p-value	Coef.	p-value	Coef.	p-value	Coef.	p-value	Coef.	p-value	Coef.	p-value
Exposure to climate stress												
Coefficient of variation of rainfall (1983 -2011)	2.315***	0.00	-1.311**	0.03	4.750***	0.00	5.053***	0.00	0.919*	0.09	-0.518	0.44
Long-term mean rainfall (1983-2011)	0.002***	0.00	0.002***	0.00	0.001*	0.09	0.002***	0.00	0.001	0.11	-0.000	0.50
Average delay in the onset of the rainy season (1983 -2011)	0.861***	0.00	-1.387***	0.00	-1.010***	0.00	2.027***	0.00	2.164***	0.00	-0.245	0.50
Coefficient of variation of maximum temperature (1983 -2011)	17.049**	0.02	10.926	0.18	25.999***	0.00	82.419***	0.00	71.597***	0.00	-34.463***	0.00
Long-term maximum temperature (1989-2010)	0.069**	0.03	-0.081**	0.02	0.010	0.80	0.364***	0.00	0.003	0.92	-0.107**	0.01
Bio-physical sensitivity												
log (land size (acre))	-0.059***	0.00	0.043**	0.04	0.375***	0.00	0.260***	0.00	0.088***	0.00	0.038	0.15
Slope of plot (0=flat, 1=steep)	-0.076*	0.06	-0.034	0.45	0.121**	0.01	0.330***	0.00	0.723***	0.00	-0.022	0.69
Nutrient availability constraint (1-5 scale)	-0.001	0.96	0.024	0.30	0.055*	0.05	0.194***	0.00	0.131***	0.00	0.022	0.43
Household level variables												
Wealth Index	0.090***	0.00	0.176***	0.00	-0.073***	0.00	-0.003	0.78	-0.002	0.85	0.029**	0.01
Index on Agricultural implements	0.024**	0.03	0.044***	0.00	-0.032**	0.02	0.129***	0.00	0.046***	0.00	0.075***	0.00
Land tenure (1=own, 0=rented)	-0.244***	0.00	-0.194***	0.00	0.161***	0.01	0.381***	0.00	0.107**	0.02	0.256***	0.00
Livestock (TLU)	0.009	0.41	0.002	0.89	-0.002	0.88	-0.027***	0.01	0.011	0.29	0.054***	0.00
Average education per AE	-0.000	0.97	0.023**	0.02	-0.004	0.71	-0.009	0.34	-0.002	0.84	-0.006	0.59
Head can read/write Chichewa	0.170***	0.00	0.121***	0.00	-0.032	0.37	0.049	0.13	0.200***	0.00	0.004	0.91
Age of head (years)	-0.229***	0.00	0.116***	0.00	-0.073*	0.09	0.356***	0.00	-0.032	0.39	0.008	0.86
Gender of household head (1=male)	0.103***	0.00	-0.014	0.69	-0.166***	0.00	-0.062*	0.07	0.050	0.13	-0.008	0.85
Household size (AE per land)	0.002	0.48	-0.003	0.28	-0.043***	0.00	0.007**	0.02	-0.007	0.12	-0.003	0.55

System-level variables												
Seed and/or fertilizer vendor in EA (1=yes)	0.040	0.20	0.074**	0.03	0.073**	0.05	-0.326***	0.00	-0.025	0.42	-0.127***	0.00
Percentage of plots received extension advice at EA	0.004***	0.00	0.000	0.78	-0.002***	0.00	0.007***	0.00	-0.001	0.10	-0.002***	0.00
log (distance to district centre (km))	-0.053***	0.01	-0.102***	0.00	-0.045*	0.06	-0.069***	0.00	-0.209***	0.00	-0.060**	0.03
log (road density in m in 10 km radius)	0.022***	0.00	0.026***	0.00	-0.008	0.17	-0.021***	0.00	0.012**	0.02	0.005	0.44
Number of village development committees in the community	0.007*	0.09	0.003	0.49	0.003	0.56	0.005	0.22	0.005	0.22	0.014***	0.00
Number of credit and saving organization in the community	0.007	0.23	0.001	0.91	0.007	0.29	0.025***	0.00	0.000	0.99	0.004	0.54
Collective action index	0.001	0.92	-0.008	0.62	0.061***	0.00	0.030*	0.06	0.008	0.60	0.087***	0.00
DPP votes as a share of total votes cast	0.151*	0.08	-0.064	0.54								
Price of maize (MKW/kg)	0.007	0.12	-0.008	0.12	-0.020***	0.00	0.011**	0.03	0.000	0.97	0.001	0.92
Fertilizers distributed in MT per hh	0.108**	0.01	0.556***	0.00	-0.141***	0.01	0.257***	0.00	0.083*	0.06	0.161***	0.01
Proportion of land covered by forest	0.013	0.91	-0.026	0.84	0.221	0.11	0.383***	0.00	0.531***	0.00	0.134	0.36
District agricultural extension and development officers per hh	0.289	0.73	-1.237	0.19	-1.198	0.22	2.991***	0.00	-4.657***	0.00	2.002*	0.09
Number of micro-finance and donor agri. projects operating in district	0.020***	0.00	-0.068***	0.00	-0.085***	0.00	-0.146***	0.00	-0.011*	0.08	-0.011	0.20
log (MAFAP wage paid per hh in 08/09)	-0.281***	0.00	0.291***	0.00	0.503***	0.00	-0.669***	0.00	0.204***	0.00	0.038	0.65
Log (district household population)	-0.099*	0.09	0.224***	0.00	0.288***	0.00	0.519***	0.00	-0.120**	0.04	0.240***	0.00
Region fixed effect (reference: Southern Province)												
northern province	-0.425***	0.00	-0.754***	0.00	0.015	0.91	0.711***	0.00	-0.025	0.82	-0.410***	0.00
central province	-0.009	0.90	-0.043	0.58	-0.351***	0.00	0.156**	0.03	0.400***	0.00	-0.016	0.86
Constant	-1.123	0.37	-3.027**	0.03	-8.192***	0.00	-12.205***	0.00	-2.803**	0.03	0.091	0.96
Log-Likelihood	-31675.59											
LR test of rho=0 : Chi2 (182)	0.000											
Number of observations (plot)	10521											

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at EA level.

5.2. Average yield effects of adoption

We estimate the impacts of adoption on maize yields using 3 different specifications to check for robustness of the results (Table 6): OLS, CMP estimators and instrumental variables (IV) estimation using heteroskedasticity-based instruments (with additional instruments constructed using Lewbel, 2012 method).[18] The first and second columns present the estimation by OLS of the maize productivity function without controlling for any potential endogeneity of adoption indicators, which is the simplest approach to investigate the effect of adoption of agricultural practices on productivity. The third and fourth columns present the estimated coefficients of CMP and IV estimators. As discussed in the previous section the CMP approach has a caveat in terms of computational burden and achieving convergence for a large family of multi-equations. Our model with all six endogenous variables does not converge, therefore the CMP column presents the results using the two groups of practices as explained above (modern inputs and SLM)

The OLS results would lead us to conclude that there are significant differences in maize productivity by households that adopted the practices compared to the productivity of households that did not adopt. The coefficients of the adoption variables are all positive and statistically significant for all practices with the exception of SWC, which is not significant. This approach, however, is subject to potential bias and inconsistency as it assumes that the adoptions of these agricultural practices are exogenously determined in the production function while they are potentially endogenous. The impact estimates using the CMP technique accounts for this problem, and the IV technique boosted by Lewbel (2012) method further corrects for potential weak instruments and heteroskedasticity problems.[19]

We can observe that results for the impact on maize yields are qualitatively quite consistent among all three specifications. After controlling for the multiple endogeneity problems simultaneously, the analyses reveal that, on average the adoption of modern inputs and SLM practices have positive and statistically significant impacts on maize productivity. Climatic variables play a significant role in explaining the variations in maize productivity. As expected, average precipitation during the rainy season is positively and significantly associated with maize productivity whereas it's inversely related with average temperature during the growing season. Total amount of dry spells experienced during the rainy season is also negatively related to maize productivity. We also find an inverse relationship between plot size and productivity of maize which is consistent with many other findings in the literature.[20] As expected, plot quality is positively related with maize productivity – the higher the nutrient availability constraint, the lower the productivity of maize. Maize productivity is also higher for rented plot compared to own plots.

Maize productivity is negatively correlated with the age of household head but positively correlated with family size. We do not find significant differences in productivity on plots managed by men and those managed by women. As expected household wealth proxied by wealth index and

[18] All estimates are reported accounting for cluster heteroskedasticity at the EA level.
[19] The IV models are estimated using Stata's ivreg2h command:
http://ideas.repec.org/c/boc/bocode/s457555.html
[20] One explanation of inverse farm size productivity is related to errors in land measurements, however, contrary to earlier conjectures, Carletto *et al*. (2013) find that the empirical validity of the inverse relationship hypothesis is strengthened, not weakened, by the availability of better measures of land size collected using GPS devices in Uganda. Given that we also used plot measurements collected using GPS devices, our findings are consistent with Carletto *et al*. (2013).

agricultural implements index is positively correlated with maize productivity. Distance to district centres and road density variables have both their expected signs. We also find a positive contribution of safety net program such as MASAF on maize productivity which is robust across all specifications. We also find heterogeneous impact across the three regions. Farmers in the Northern and Central Provinces tend to suffer from lower maize productivity compared to farmers in the Southern Province.

5.3 Differentiated impacts of adoption

All of the estimators presented above assume that the impact of adoption of specific practice is constant, irrespective of who adopts it. The average impact of a given farm management practice based on this assumption is a concise and convenient way of evaluating impacts. Heckman *et al*. (1997) justify this approach if researchers and policy makers believe that (a) total output increases total welfare, and (b) detrimental effects of the technology on certain parts of the population are not important or are offset by either through an overarching social welfare function or from family members or social networks.

However, within the context of adoption of farm practices, a number of dimensions of heterogeneity may be relevant. Even if the mean effect is significant, whether adoption of a given practice has a significant beneficial or detrimental effect might vary across the subgroups of adopters. Production decisions may vary by the availability of household labour, gender of the household head, geographic location, and/or by access to key assets, such as land. There are a number of ways to present the heterogeneous impacts of adoption of a given practice. For example, one could divide the sample of households into different demographic groups (e.g., by gender or age cohort) and perform separate analysis on each group, and test to see if estimated impacts are different. Another way to present distributional impacts of technology adoption is by using a quintile regression approach, or interacting the adoption variable with different household socioeconomic characteristics. One could assess, for example, whether poorer or better-off households experienced larger gains from adopting a given technology. For this paper, we employed the first option in understanding the distributional impact of adoption by dividing households based on gender of the household head, median farm size and geographic regions.

Table 7 presents the distributional impacts of adoption by gender, region and land size. We find that the positive impact of adoption of modern input and SLM remains robust for both male and female headed households, but the impact of modern input is not significant for female headed households. Surprisingly for SLM inputs, the magnitude of the impact is higher for female headed households (i.e. 24% for SLM compared to 16% for modern inputs). Overall the positive impact of adoption of modern inputs is more pronounced in male headed households compared to female headed households whereas the opposite is the case for sustainable land management practices perhaps suggesting the gender differentiated role of adoption of SLM practices. Looking across the three provinces, the positive impact of modern input and SLM practices seems to be driven by the Southern province.

Table 6. Impact of adoption of adaptation practices on maize productivity (log kg/acre)

	OLS				CMP		IVreg2h	
	(1)		(2)		(3)		(4)	
	Coef	p-value	coef	p-value	Coef.	p-value	coef	p-value
Improved seed (1=yes)	0.334***	0.000						
Inorganic fertilizer (1=yes)	0.655***	0.000						
Maize-legume intercropping (1=yes)	0.623***	0.000						
Trees (1=yes)	0.443***	0.000						
SWC (1=yes)	-0.003	0.956						
Organic fertilizer (1=yes)	0.155***	0.002						
Modern inputs (1=yes)			0.730***	0.000	0.913***	0.000	0.543***	0.000
SLM (1=yes)			0.374***	0.000	2.314***	0.000	0.150*	0.085
Rainfall during the rainy season (mm)	0.160**	0.015	0.173**	0.012	0.194***	0.000	0.020	0.453
Average maximum temperature during rainy season	-1.051***	0.000	-1.086***	0.000	-1.173***	0.000	-0.760***	0.000
Total amount of dry spells during rainy season	0.097	0.255	0.120	0.178	-0.049	0.165	-0.101***	0.001
log(land size (acre))	-0.207***	0.000	-0.139***	0.000	-0.271***	0.000	-0.089***	0.000
Land tenure (1=own, 0=rented)	-0.241***	0.001	-0.227***	0.002	-0.408***	0.000	-0.187***	0.001
Slope of plot (0=flat, 1=steep)	0.031	0.656	0.020	0.778	-0.299***	0.000	-0.014	0.784
Nutrient availability constraint (1-5 scale)	-0.154***	0.002	-0.139***	0.005	-0.135***	0.000	-0.070***	0.000
Wealth Index	0.079***	0.000	0.089***	0.000	0.087***	0.000	0.087***	0.000
Index of Agricultural implements access	0.037**	0.024	0.039**	0.026	-0.021	0.196	0.045***	0.000
Average education per AE	0.001	0.912	0.004	0.769	0.005	0.723	0.012	0.263
Head can read/write Chichewa (1=yes)	0.077	0.103	0.092*	0.059	0.059	0.188	0.104***	0.009
Age of head (years)	-0.146**	0.011	-0.115**	0.047	-0.205***	0.000	-0.111**	0.018
Gender of household head (1=male)	0.000	0.993	-0.032	0.534	-0.027	0.563	-0.039	0.308
Household size (AE per land)	0.014***	0.000	0.016***	0.000	0.017***	0.000	0.019***	0.000

log (distance to district centre (km))	-0.191***	0.005	-0.207***	0.003	-0.138***	0.000	-0.238***	0.000
log (road density in m in 10 km radius)	0.017	0.425	0.015	0.486	0.016**	0.031	0.013*	0.088
Number of village development committees in the community	0.007	0.310	0.007	0.411	-0.012*	0.052	0.008**	0.048
Number of credit and saving organizations in the community	0.005	0.423	0.010	0.127	0.011	0.212	0.016***	0.000
Number of micro-finance & donor agri. projects in district	-0.056***	0.004	-0.074***	0.000	-0.030***	0.001	-0.080***	0.000
log (MAFAP wage paid per hh in 08/09)	0.665**	0.012	0.681**	0.011	0.747***	0.000	0.077	0.352
log(district household population)	0.456***	0.000	0.509***	0.000	0.400***	0.000	0.358***	0.000
northern province	-1.668***	0.000	-1.743***	0.000	-2.250***	0.000	-1.107***	0.000
central province	-0.598***	0.008	-0.698***	0.003	-0.971***	0.000	-0.496***	0.000
Constant	24.982***	0.000	25.351***	0.000	26.744***	0.000	24.350***	0.000
Number of observations	10,647		10,647		10,647		10,647	
LR chi2(107), Prob > chi2					4169.8(0.00)			
Adjusted R2	0.306		0.283				0.251	
Log-Likelihood	-20,713.55		-20,890.03		-31212.7		-21,125.93	

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at EA level.

Table 7. Heterogeneous impact of adoption on maize productivity by gender, region and land size – Ivreg2h estimator

	Modern input		Sustainable land management	
	Coef.	p-value	Coef,	p-value
Gender				
Male	0.737***	0.000	0.163*	0.089
Female	0.191	0.201	0.236*	0.091
Land size				
Small	0.367***	0.002	0.064	0.671
Large	0.550***	0.000	0.078	0.513

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The figures in the brackets are standard errors.

6. Conclusions and policy implications

This study utilizes farm household level data collected in 2011 from a nationally representative sample of 7842 households (11208 plots). We employ a multivariate probit (MVP) technique to model simultaneous and interdependent farm practice selection decisions by farm households. The causal impact of selecting various practices is estimated by utilizing conditional recursive mixed process and instrumental variables estimators.

The analysis generates three important findings relevant for the emerging body of literature on CSA: 1) climate change related effects are an important determinant of the practices farmers select, but these effect are quite heterogeneous across agro-ecologies and thus the distribution of practices selected, 2) farm practice selection is an important means of adaptation that farmers are already practicing as demonstrated by positive yield effects across a range of practices, exposure and sensitivity to climate change and 3) both household and community level factors are important determinants of adaptive capacity, and there are substantial barriers to adaptation via farm practice selection.

The first finding is based on the analysis of various climate related effects over time and space for Malawi which indicated highly heterogeneous distribution of effects even within a relatively small country such as Malawi. These climate effects have important impacts on which practices are selected and ultimately on their yield benefits. Our results show that farmers in areas of higher mean rainfall and lower maximum temperatures tend to use more inorganic fertilizer, while those in areas of delayed onset of rainfall and higher maximum temperatures were more likely to have SLM practices. Climate risk clearly plays an important role in determining the practices selected. We find that greater climate variability as represented by the coefficient of variation of rainfall and temperature increases adoption of risk-reducing inputs such as SLM measures, but reduce the use of inputs (such as inorganic fertilizer) with riskier benefits under these conditions.

Our second major set of findings relates to the yield impacts of the practice selection across varying conditions. Results indicate that both modern inputs and the risk reducing SLM practices have a positive, statistically significant effect on maize yields. However, the effectiveness of practices varies by exposure to climatic risk with greater benefits from the SLM practices in areas of higher exposure and sensitivity; whereas improved seed and fertilizer perform better in areas of lower risk. Such results indicate the importance of farm practice selection as an adaptation strategy. The impact observed however tends to be heterogeneous across gender and land size. For instance the positive productivity impact of adoption of modern inputs is more pronounced in male headed households compared to female headed households whereas the opposite is the case for sustainable land management practices. This implies that a differentiated approach might be needed in promoting adoption of these practices to different segments of the rural population.

The analysis of climate impacts on yields further indicate that climate risk is a serious threat to production, as the average maximum temperature over the season is consistently and strongly related to lower maize yields. This indicates that if climate change occurs as predicted, there will be a need to identify viable heat tolerant maize varieties or shift to new crops.

The third major area of findings from this paper relate to the nature of adaptive capacity. Variables associated with household and community level adaptive capacity, such as access to rural institutions, social capital and household characteristics are also found to be key in determining which practices are selected – although which institutions are important for adaptive capacity depends on the practice. At household level, wealth, gender and education are key determinants of practice selection. Wealth and education are important predictors of fertilizer and improved seed use. At community level we find that institutional barriers to adaptive capacity vary by the type of practice – e.g. extension advice has positive impacts on seeds and fertilizer use, but negative effects on intercrops and organic fertilizer.

Our findings on substitutes/complements may also have implications for understanding household level adaptive capacity as we find that barriers to one input that is highly complementary to another (e.g. fertilizer seeds) implies need to address barriers to both. Besides justifying the use of MVP in comparison to the restrictive single equation approach, these results support the notion of interdependency between adoption decision of different farm management practices which may be attributed to complimentarity or substitutability between the practices.

It is important to point out that we have not yet estimated the impact of adoption of these practices on reducing yield variability in the face of variable climate conditions. Increasing yields is just one of the reasons to adopt these technologies but reducing downside loss can be the other reason. Therefore the results should be interpreted with the caveat in mind. Future research will try to assess the role of adoption of SLM practices on yield variability under variable climate regime by making use of panel data when possible. Finally we also can't estimate the impact of adoption of various combinations of these practices on outcome variables in this paper. However this knowledge is relevant to the debate on whether farmers should adopt technologies piecemeal or in a package and for designing effective extension policies by identifying a combination of technologies that deliver the highest payoff. Therefore, we recommend further research to also look at modeling impact analysis in a multiple technology choice framework to capture useful economic information contained in interdependent and simultaneous adoption decisions.

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