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Food Security Impact of Agricultural Technology Adoption under Climate Change: Micro-evidence from Niger

Solomon Asfaw[1], Federica Di Battista[2] and Leslie Lipper[1]

Abstract

We assess farmers' incentives and the conditioning factors that hinder or promote adoption of agricultural technologies under climate risk and evaluate its impact on food security in Niger. 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 multivariate probit and instrumental variable techniques to model the selection decisions and its impact. The results clearly indicate that while the use of modern inputs and organic fertilizers significantly improves crop productivity, results are unclear for the impact of crop residues. Moreover, factors driving modern input use are different than those of crop residues and organic fertilizer which can be characterized at low investment capital requirements, higher labour requirements and longer time for results versus modern inputs which can be characterized as higher investment capital requirements, less labour requirement and shorter time for returns. Exposure to climatic stress and bio-physical factors are identified as key factors that hinder or accelerate adoption. Results also show that greater climate variability as represented by the coefficient of variation of rainfall and temperature and recent climate shocks as represented by average rainfall shortfall increases use of risk-reducing inputs such as crop residue, but reduce the use of modern inputs. In addition, the key role of system-level adaptive capacity in governing input use decision. 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 system levels linked to adaptive capacity.

Keywords: Climate change, adaptation, food security, multivariate probit, instrumental variable, Niger, Africa

JEL Classification: Q01, Q12, Q16, Q18

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1. Introduction

Climate change and land degradation hinder agricultural productivity and the ability of the agricultural sector to feed the world's increasing population. This issue is particularly felt in Niger, where the agriculture sector is characterised by land scarcity and unstable rainfall. A recent mapping of vulnerability and poverty in Africa listed Niger as one of the countries that are both most vulnerable to climate change and with the least capacity to respond (Orindi et al., 2006; Stige et al., 2006). Given that agricultural production remains the main source of income for most rural communities in Niger, the increased risk of crop failure associated with increased frequency of extreme events poses a major threat to food security and poverty reduction. In view of this impending climate change threat upon the poor, it is critical to have a deeper understanding of the household adaptation strategies and targeted measures that could protect and improve the livelihoods of the poor and ensure food security (Bradshaw et al., 2004).

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). These may include both on and off farm activities. At the farm level, there are a wide range of strategies that may contribute to adaptation which 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); improved soil and water management practices including conservation agriculture (Kurukulasuriya and Rosenthal, 2003; McCarthy et al., 2011); increasing regional farm diversity (Reidsma and Ewert, 2008) and shifting to non-farm livelihood sources (Morton, 2007). Which of these actually contribute to adaptation depends on the locally specific effects climate change has and will have, as well as agro-ecological conditions and socio-economic factors such as market development. Adaptation also depends on the farmer's capacity and incentives to undertake adjustments in farming practices, e.g. 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 in many regions, the level of use of these practices in Niger is generally quite low, perhaps leading to stagnant or worsening yields and continuing land degradation. One question that arises is whether these practices are actually effective adaptation strategies in the specific circumstances of Nigerien farmers – e.g. their adaptation effectiveness. A second question is how household and system-level adaptive capacity, or lack thereof, affects the selection of farm practices with adaptation benefit.

Given the scarce evidence available for Niger and the Sahel area in general, this paper generates empirical evidence on farmers' incentives and the conditioning factors that hinder or accelerate the use of a set of potentially risk-reducing climate-smart agricultural practices (organic fertilizers, crop residues, legume intercropping, soil and water conservation practices (SWC)) that are high priorities in the Nigerien National Agricultural Plan. They are considered effective in terms of increasing resilience of agricultural systems and reducing exposure 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 in reducing risk to current climate stresses (improved varieties and use of inorganic fertilizers).[3] And a second objective is to understand which practices have the potential to boost agricultural productivity and increase incomes under varying climate conditions.

The question this paper aims to address contributes to the growing literature on adaptation measures (e.g., Pender and Gebremedhin, 2007; Kassie et al., 2010, 2013; Tekleword et al., 2013; Di Falco et al., 2011; Di Falco and Veronesi, 2012; Deressa and Hassen, 2010) and 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 fourfold: firstly our analysis uses a comprehensive large national representative plot-level survey with rich socio-economic information, merged with geo-referenced climatic information. This allows us to evaluate the role of bio-physical and climatic variables in determining farmers' input use decisions, and consequently, the impact on crop productivity and profitability.

We argue that climate variability and other shifts in recent climate patterns are major determinants of farm practice choices, 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 farmers' 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 the 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 the Lewbel (2012) method, as well as conditional recursive mixed process (CMP) estimators as proposed by Roodman (2011), which take into account both simultaneity and endogeneity risks, and produce consistent estimates for recursive systems in which all endogenous variables appear on the right-hand-side as observed. Finally, given the absence of evidence on the use and impact of climate-smart farming practices from the Sahel area at large and from Niger in particular, which is largely attributed to the lack of reliable data from this country, our study itself adds great value in filling this gap in the existing literature.[4]

The paper is structured as follows. In section 2 we provide a detailed review of the existing literature with a specific focus on the existing evidence for Sub-Saharan Africa, whereas in section 3 we describe the data used and provide some descriptive results. In section 4 we describe the empirical methodology used. Section 5 presents the empirical results, and in section 6 we draw conclusions and provide policy implications.

[3] The choice of the set of agricultural practices considered in this paper is mainly driven by the availability of data - the use of organic and inorganic fertilizer, crop residue, improved seed as well as anti-erosion measures are very well documented in the survey. The survey questionnaire also provides a rich section on tree plantation, but unfortunately the response rate in this section was very low, which made this set of information not usable.

[4] The only studies coming from Niger or from the Sahel area that we are aware of are Baidun-Forson (1994) and Baidun-Forson (1999).

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, as well as on the supply and demand side constraints 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; Di Falco et al., 2011; Di Falco et al., 2014). This literature indicates that there are several barriers to technology use, ranging from lack of insurance and limited credit access to 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 are in more risk-prone environments, which is important in the context of climate change. In particular, many sustainable land management (SLM) practices are risk-decreasing, so that the 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; Di Falco and Veronesi, 2012; Di Falco et al., 2014; Deschenes and Greenstone, 2007; Seo and Mendelsohn, 2008; Kurukulasuriya and Mendelsohn, 2008; Seo and Mendelsohn, 2008; Wang et al., 2010). Arslan et al. (2013) provided evidence of a positive correlation between rainfall variability and the selection of of SLM type practices. Kassie et al. (2008) found that production risk deters adoption of fertilizer, but has no effect on the conservation agriculture adoption decision. Heltberg and Tarp (2002) found that farmers 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 supply and demand side constraints have also been identified to account for the use of SLM practices, including high up-front costs but delayed benefits (Sylwester, 2004), credit and insurance market imperfections (Carter and Barrett, 2006), tenure insecurity (Pender and Gebremedhin, 2007), household endowments of physical and human capital (Pender and Fafchamps, 2005), agricultural extension and market access (Holden and Shiferaw, 2004; Teklewold et al., 2013b; Arslan et al., 2013) and limited off-farm opportunities (Pender and Gebremedhin, 2007). McCarthy et al. (2011) synthesized recent empirical literature on factors affecting the use of SLM practices, with a strong focus on sub-Saharan Africa.
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 also very relevant to the ongoing work in the global climate change community in the area of adaptation to climate

change, and specifically to 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, such as that between the socio-economic and the bio-physical. 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 of the system so as to decrease vulnerability (Smit et al., 2001).[5]

Engle (2011) makes an important distinction between characterizing adaptive capacity and measuring it. He highlights how most studies have focused on characterizing adaptive capacity, intended as assessments 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 into 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 (e.g., Di Falco et al., 2011; Kassie et al., 2008; Branca et al. 2011). 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 indication of adaptive capacity.

[5] In this paper we focus on the link between vulnerability and adaptive capacity; however, there is also a focus on resilience to illustrate the characteristics of systems that achieve a desirable state in the face of change, being applied to socio-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.

3. Data description and descriptive statistics

3.1 Data

We use two main sources of data in our analysis: socio-economic data from the Niger National Survey of Household Living Conditions and Agriculture (ECVMA) and historical data on rainfall and temperature from the National Oceanic and Atmospheric Administration (NOAA) and the European Centre for Medium Range Weather Forecasts (ECVMA), respectively.

The primary source of our socio-economic data is the Niger ECVMA survey which was conducted from July to December 2011 and implemented by the Niger Institut National de la Statistique (INS) in collaboration with the World Bank. The data is representative at the national, (major) regional, and urban/rural-level. The household sample is drawn from all 8 regions of the country with the exception of certain strata in Arlit (Agadez Region) because of difficulties in reaching the location. The sample was chosen through a random two stages process, at the end of which 270 enumeration areas (EA) and 4074 households were drawn. It was designed to provide information on various aspects of household welfare in Niger 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.[6] For households that were involved in agricultural activities, data was also collected on land tenure, labour and non-labour input use, and crop cultivation and production at the plot level. Data was also collected at community level to capture determinants of system-level adaptive capacity in terms of enabling factors for adaptation, which include issues related to collective action, access to information, and to infrastructure including market and roads, among others.

The ECVMA survey data also recorded geo-referenced household and EA level Latitude and Longitude coordinates using handheld global positioning system (GPS) devices, which creates the possibility of linking household level data with geo-referenced climate and soil data. We extracted time series indicators such as historical rainfall and temperature at the highest resolution and longest time period publicly available at the time of writing. Rainfall data are extracted from the Africa Rainfall Climatology version 2 (ARC2) of the National Oceanic and Atmospheric Administration's Climate Prediction Center (NOAA-CPC) for each dekad (i.e. 10 day intervals) covering the period of 1983-2012. ARC2 data are based on the latest estimation techniques on a daily basis and have a spatial resolution of 0.1 degrees (~10km).[7] Temperature data are surface temperature measurements at each

[6] We restricted the sample to rural households involved in farming activities during the rainy season. At the end of the cleaning process our sample was composed 5340 plots with 1938 households (see table 1)

[7] Average of a 10 km radius buffer of decadal sum of daily values per each enumeration area centroid. For more details on ARC2 algorithms see: http://www.cpc.ncep.noaa.gov/products/fews/AFR_CLIM/AMS_ARC2a.pdf

dekad for the period of 1989-2010 obtained from the European Centre for Medium-Range Weather Forecasts (ECMWF) at a spatial resolution of 0.25 degrees.[8]

These data are then merged with the ECVMA data at the EA level (270 EAs in ECVMA) to create a set of exposure to climate variables to represent the short and long term variations both within- and across-years in rainfall and temperature that are hypothesized to affect adoption of agricultural practices and agricultural productivity based on the agronomy, climate and economics literature. Some of the exposure variables created include 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.

Table 1: Description of the sample households by land use type

	Land use types			
	Agricultural	Agro-pastoral	Pastoral	Total
Number of plots	2487	2393	460	5340
Number of households	845	836	257	1938

We also extracted EA level information on soil nutrient availability from the Harmonized World Soil database (HWSD) to control for the effects of bio-physical characteristics. The HWSD has a resolution of 30 arc-seconds and combines existing regional and national updates of soil information worldwide.[9] The HWSD is based on a spatial layer with Soil Mapping Units (SMU) linked to a Microsoft Access .mdb file storing the various parameters for the SMUs. Each SMU is a combination of different subunits, without spatial attributes but showing a different area share. By merging the ECVMA data with historical data on rainfall and temperature at the community level, we create a unique data set allowing for microeconomic analysis of climate impacts in Niger. To the best of our knowledge, there are no other studies that bring together such data from various sources to understand the linkages between climate variability and adoption of farming practices that have adaptation potential.

[8] Point extraction per each enumeration area centre point of values of average of a 50 km radius buffer of decadal values.

[9] For more information see: http://webarchive.iiasa.ac.at/Research/LUC/External-World-soil-database/HTML/

3.2 Description of climate variability in Niger

We provide a detailed description of the climate variables available (both objective and subjective) and a preliminary view of how they may influence their adaptation strategies. Data from NOAA presented in Figure 1 show the time pattern of average rainfalls and temperature during the rainy season in Niger by land use type.

Figure 1: Average rainfalls and temperature in rainy season by land use type

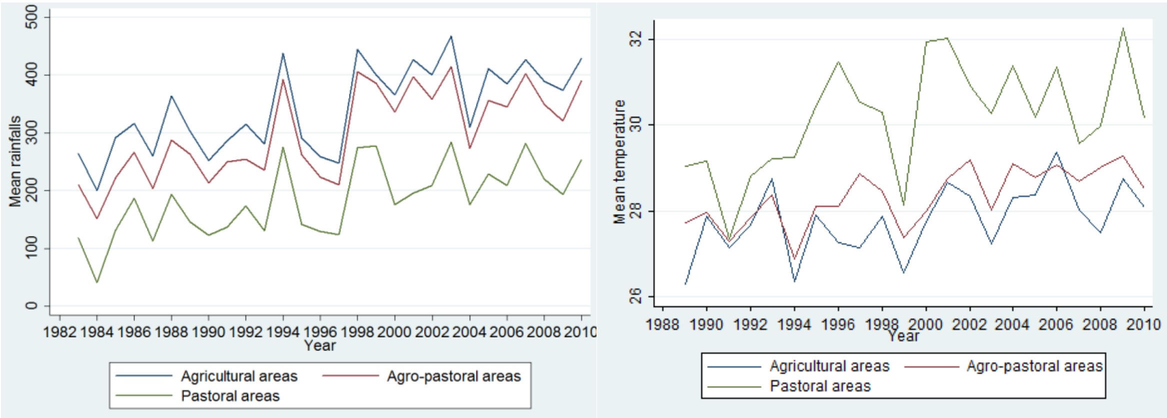


Figure 1 clearly shows that the amount of rainfall is increasing over time with minor differences among land use types. This trend is confirmed by forecasts from NECSD (2006) which predicted rainfalls to increase in the Sahel region due to climate change. We can observe in Figure 1 very high oscillations in the rainfall pattern. This is also evident from Figure 2 which shows the distribution of the coefficient of variation of rainfall across time. We can observe that the pastoral areas experience relatively low levels of rainfall and high variability compared to the agricultural and agro-pastoral areas. Figure 3 also shows the distribution of current and long run average rainfall and we can observe significant differences across the different land use types. Such high temporal and spatial rainfall variability makes Nigerien farmers vulnerable, hindering the ability of national agricultural production to satisfy the increasing population's demand for food.

Figure 2. Coefficient of variation of rainfall and max temperature (1983-2011)

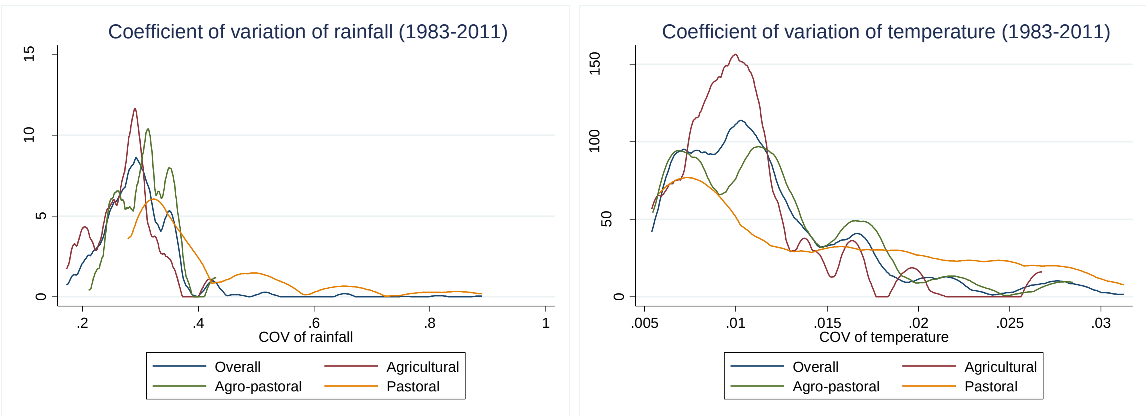
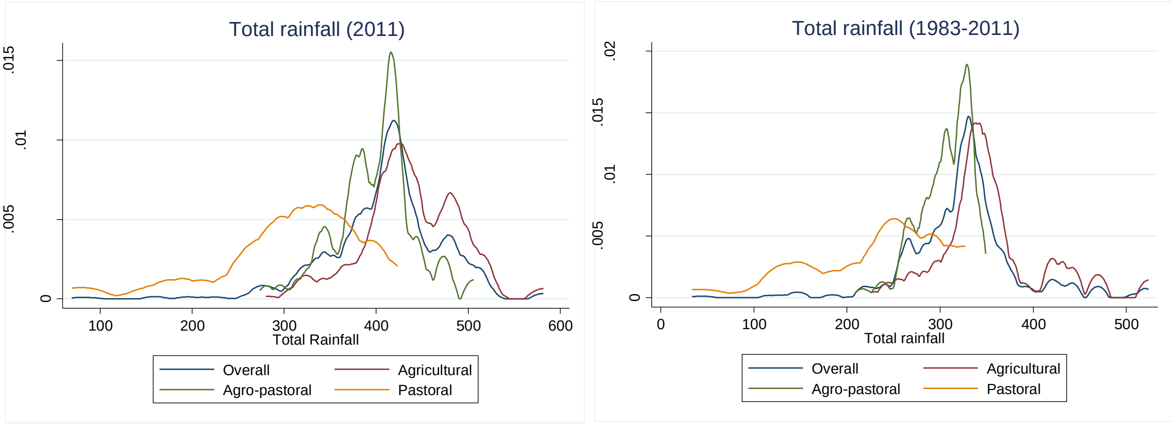
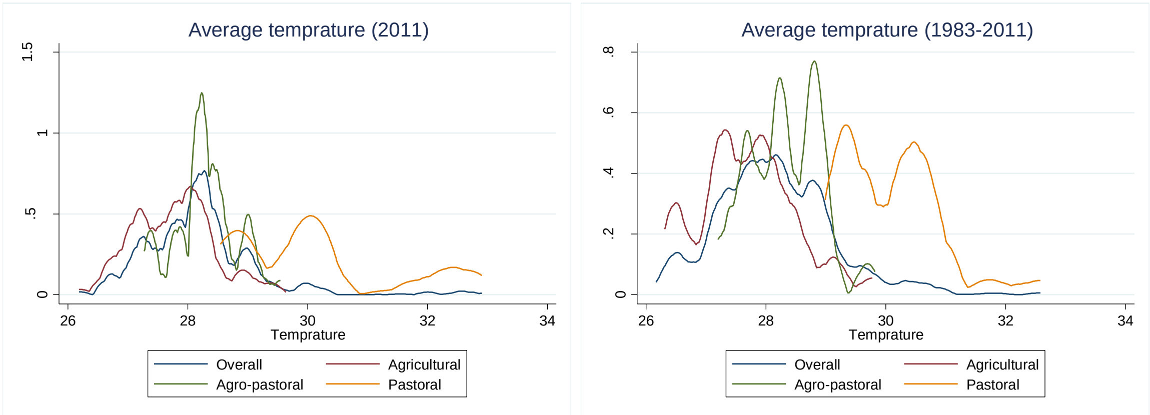


Figure 3. Total amount of rainfall during the rainy season (current and long run)



Average and maximum temperature trends over time also provide a good picture of the problems from climate change in Niger. As shown in Figure 1 average temperatures in the rainy season are clearly increasing over time. Figure 4 also shows the spatial distribution of the current and long run average temperature which indicate temporal and spatial differences and variability. Although Nigerien farmers are specialized in the cultivation of crops that are particularly resistant to high temperatures (for example, millet and sorghum), the increase in the temperature level will eventually change farming environments in the three land use types. In particular, one of the most plausible scenarios is the expansion of the desert areas (Kandji et al., 2006); as only less than 15% of the land is arable (IFAD, 2009), a further expansion of the Sahara would further constrain the production of the country's agricultural sector.

Figure 4. Average temperature during rainy season (current and long run)



To complement the objective climate data presented above, we also present more subjective data from the agriculture section module of the ECVM/A. They provide information on how households involved in agriculture activities perceive climate change, as well as the strategies used to adapt to and mitigate the effect of climate changes.

Most of the households interviewed reported changes in rainfall and temperature patterns in the 5 years preceding the interview (see Table 2). Despite what we observed in Figure 1, in all land use types the most relevant phenomena are the reduction in the amount of rainfall (this is probably a consequence of the 2009 drought) and the change in the distribution of rain. The general tendency for the sample households is to report less rainfall (81%), worse rain distribution (77%) and more frequent droughts (84%); this is particularly true for pastoral areas. Although agricultural areas share the same overall patterns, 38% of households report more frequent floods compared to 19% for both agro-pastoral and pastoral areas. About 72% and 82% of the sample households reported respectively more of a delayed start and an early finish of the rainy season in the 5 years before the interview. Changes in temperatures also affected 65% of Nigerien households, who reported longer heat periods.

Table 2: Perception of climate changes reported for the last 5 years by land use types – in proportion

	Land use types			
	Agricultural (N=906)	Agro-pastoral (N=892)	Pastoral (N=632)	Total (N=2430)
Less rainfalls	0.78	0.77	0.89	0.81
	[0.01]	[0.01]	[0.01]	[0.01]
More rainfalls	0.15	0.15	0.07	0.13
	[0.01]	[0.01]	[0.01]	[0.01]
Worst distribution rainfalls	0.79	0.74	0.78	0.77
	[0.01]	[0.01]	[0.02]	[0.01]
Shorter heat period	0.16	0.14	0.1	0.14
	[0.01]	[0.01]	[0.01]	[0.01]
Longer heat period	0.63	0.65	0.68	0.65
	[0.02]	[0.02]	[0.02]	[0.01]
More frequent drought	0.77	0.83	0.95	0.84
	[0.01]	[0.01]	[0.01]	[0.01]
More frequent floods	0.38	0.19	0.19	0.26
	[0.02]	[0.01]	[0.02]	[0.01]
Delay in the start of the rainy season	0.71	0.66	0.82	0.72
	[0.02]	[0.02]	[0.02]	[0.01]
Rainy season comes earlier	0.74	0.84	0.92	0.82
	[0.01]	[0.01]	[0.01]	[0.01]

Note: The numbers in brackets are standard errors. The household sample here is larger, given that we use the entire sample available for this section and not the sample composed by households involved in farming activities only and interviewed in both waves.

Since the 3 or 4 months-long Nigerien rainy season feeds the population for 12 months, changes in its timing, duration or intensity have strong implications in terms of agricultural production and food security for the country. Table 3 provides a picture of the most common strategies households used to adapt to the effects of climate change. The most commonly used strategies across all land use types is to diversify income sources (48%) especially in pastoral areas and where climate change manifests through a change in rainfall patterns. Migration is also a common strategy used mostly in the agricultural zones of the country. Change in seeds varieties, use of anti-erosion methods and switches from livestock raising to crop production are also quite common strategies used, particularly in agricultural and agro-pastoral areas. Households in pastoral zones tend to engage more in dry-season agriculture and to raise fewer sheep and switch to goats when facing changes in temperatures and in rainfall patterns.

Table 3: Strategies to adapt to and mitigate climate change effects by land use types – in proportion

	Change in temperature				**Change in rainfall patterns**			
	Agricultural (N=906)	Agro-pastoral (N=892)	Pastoral (N=632)	Total (N=2430)	Agricultural (N=906)	Agro-pastoral (N=892)	Pastoral (N=632)	Total (N=2430)
Change seed varieties	0.24	0.26	0.24	0.25	0.32	0.36	0.19	0.3
	[0.02]	[0.02]	[0.03]	[0.01]	[0.02]	[0.02]	[0.02]	[0.01]
Use methods to protect against erosion	0.24	0.28	0.18	0.24	0.27	0.31	0.17	0.26
	[0.02]	[0.02]	[0.02]	[0.01]	[0.02]	[0.02]	[0.02]	[0.01]
Engage in dry season agriculture	0.21	0.16	0.39	0.24	0.21	0.16	0.31	0.22
	[0.02]	[0.02]	[0.03]	[0.01]	[0.02]	[0.02]	[0.03]	[0.01]
Plant trees	0.16	0.14	0.18	0.16	0.15	0.12	0.15	0.14
	[0.02]	[0.02]	[0.02]	[0.01]	[0.02]	[0.01]	[0.02]	[0.01]
Irrigate more intensively	0.08	0.12	0.17	0.11	0.09	0.09	0.14	0.1
	[0.01]	[0.02]	[0.02]	[0.01]	[0.01]	[0.01]	[0.02]	[0.01]
Raise less livestock and increase crop production	0.21	0.26	0.26	0.24	0.25	0.26	0.21	0.24
	[0.02]	[0.02]	[0.03]	[0.01]	[0.02]	[0.02]	[0.02]	[0.01]
Raise fewer small ruminants and switch to cattle	0.17	0.17	0.11	0.15	0.17	0.14	0.08	0.14
	[0.02]	[0.02]	[0.02]	[0.01]	[0.02]	[0.02]	[0.01]	[0.01]
Raise fewer cattle and switch to camels	0.07	0.09	0.1	0.08	0.07	0.06	0.12	0.08
	[0.01]	[0.01]	[0.02]	[0.01]	[0.01]	[0.01]	[0.02]	[0.01]
Adopt techniques to regenerate grass cover favoured by livestock	0.13	0.14	0.14	0.14	0.15	0.13	0.12	0.13
	[0.02]	[0.02]	[0.02]	[0.01]	[0.02]	[0.02]	[0.02]	[0.01]
Raise fewer sheep and switch to goats	0.16	0.18	0.32	0.21	0.19	0.18	0.34	0.22
	[0.02]	[0.02]	[0.03]	[0.01]	[0.02]	[0.02]	[0.03]	[0.01]
Migration	0.39	0.27	0.25	0.31	0.37	0.24	0.22	0.28
	[0.02]	[0.02]	[0.03]	[0.01]	[0.02]	[0.02]	[0.02]	[0.01]
Diversify sources of revenue	0.47	0.48	0.49	0.48	0.44	0.47	0.54	0.48
	[0.02]	[0.02]	[0.03]	[0.01]	[0.02]	[0.02]	[0.03]	[0.01]

Note: The numbers in brackets are standard errors.

3.3 Description of farming practices (inputs) and socio-economic variables

Given our dataset, we focus on four different potentially climate-smart agricultural practices (use of crop residue, legume intercropping, soil and water conservation (SWC), and use of organic fertilizer) and consider two practices that are aimed primarily at improving average yields (improved varieties and use of inorganic fertilizers). Table 4 shows the proportion of households that implement the aforementioned agricultural practices on their plots, disaggregated by land use type.

Unlike legume intercropping, the use of crop residue[10] is more widespread in the rural areas of the country and particularly in Maradi's, Zinder's and Diffa's agro-pastoral zones. Crop residue is practiced on about 40% of the plots during the cropping season analysed, whereas legume intercropping is practiced in only 6% of the plots.

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 providing off-farm private and public benefits (Blanco and Lal, 2008; McCarthy et al., 2011). SWC structures considered here include sand bags, half moons, zai, tree belts, and wall and stone perimeters. Erosion problems[11] are reported on more than 15% of the plots in the sample. The problem is particularly acute in the pastoral areas, reporting 27% of the plots affected by erosion. Despite the high rate of erosion, we can observe from Table 4 that the use of an anti-erosion measure is very low in all the land use types. Only 3% (4% in pastoral areas) of the plots have been treated using techniques aiming to off-set the effects of soil degradation.

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 show that organic fertilizer (which is composed of animal manure, compost and green manure) is used on about 33% of the sample plots. The uptake seems to also be heterogeneous across the different land use types.

The use of high yielding varieties could contribute to improving food security and income for the rural population by providing higher yields (e.g., Kijima et al., 2008; Mendola, 2007; Asfaw et al., 2012a, 2012b; Amare et al., 2011 etc). Nevertheless, whether improved high

[10] It is however important to point out that for farmers in Niger crop residues are highly valuable as they are used as feed for livestock, as fuel for cooking, and as thatching/craft material.

[11] The ECVM/A dedicates a section of the agriculture questionnaire to erosion problems affecting land owned by the household. Even if not based on a scientific measurement of the level of degradation of the soil, the section provides a good picture of farmers' perception of the problem. According to the literature discussed above (Knowler & Bradshaw, 2007) the perceived severity, more than the actual magnitude, of the erosion issue is a key determinant for farmers' use of sustainable land management practices; thus this information is of paramount importance for our analysis.

yielding varieties perform better than local varieties under harsh climatic conditions is very much an empirical question. Despite the potential productivity benefit, the proportion of plots planted with improved varieties in Niger is only about 2%. We also consider the utilization of inorganic fertilizers and our data show that about 11% of sample plots are treated with inorganic fertilizer, which is relatively high compared to the use of improved seeds. Looking across the different land use types, there seems to be significant differences in the use of inorganic fertilizers. Although the impact on productivity of using inorganic fertilizer and improved seed is widely documented, the benefits in terms of adapting to climate change and/or reducing risk to current climate stresses is uncertain.

Given the very low uptake of some of the practices (e.g. legume intercropping, improved varieties and SWC measures), in the subsequent section we mainly focus and organize our descriptive and empirical analysis on three major inputs/techniques widely used by Nigerien farmers: organic fertilizers (O), modern inputs (use of inorganic fertilizer or improved seed)[12] (F), and crop residues (R).

[12] We have grouped both the use of inorganic fertilizer and improved seed into one category since the level of use for improved seeds is very low.

Table 4: Descriptive summary of farming practices and other input use – in proportion

	Land use types			
	Agricultural (N=2487)	Agro-pastoral (N=2393)	Pastoral (N=460)	Total (N=5340)
Organic fertilizers	0.37	0.25	0.12	0.33
	[0.48]	[0.44]	[0.33]	[0.47]
Modern inputs:	0.13	0.11	0.06	0.12
	[0.34]	[0.31]	[0.24]	[0.33]
Inorganic fertilizers	0.12	0.09	0.03	0.11
	[0.32]	[0.29]	[0.16]	[0.31]
Improved seeds	0.02	0.02	0.03	0.02
	[0.13]	[0.13]	[0.18]	[0.14]
Conservation practices:	0.46	0.50	0.31	0.47
	[0.50]	[0.50]	[0.46]	[0.50]
Crop residues	0.39	0.45	0.27	0.40
	[0.49]	[0.50]	[0.44]	[0.49]
Legume intercropping	0.06	0.05	0.03	0.06
	[0.24]	[0.21]	[0.17]	[0.23]
Anti-erosion measures:	0.03	0.03	0.04	0.03
	[0.18]	[0.16]	[0.19]	[0.17]
Sand bag	0.01	0.00	0.02	0.00
	[0.07]	[0.03]	[0.13]	[0.07]
Half moon	0.00	0.00	0.00	0.00
	[0.06]	[0.05]	[0.07]	[0.05]
Zai	0.00	0.00	0.00	0.00
	[0.03]	[0.06]	[0.00]	[0.04]
Tree belts	0.02	0.02	0.02	0.02
	[0.13]	[0.12]	[0.15]	[0.13]
Wall	0.00	0.00	0.00	0.00
	[0.02]	[0.03]	[0.00]	[0.02]
Stone perimeter	0.01	0.01	0.00	0.01
	[0.09]	[0.08]	[0.05]	[0.08]

Note: The numbers in brackets are standard errors.

Table 5 reports the use of combined practices on the same plot to understand whether farmers in Niger use a mix of measures to deal with a multitude of production constraints rather than use a single practice. Of the 5350 plots considered in the analysis, about 61% of the plots benefited from one or more farm management practices, although all three of the practices were applied on only 3% of the plots. Table 5 reveals that although the use of crop residues and organic fertilizers are used in most of the cases as a standalone practice, it is not uncommon to find them combined together, especially in agricultural and agro-pastoral areas. On the other hand, the use of modern inputs in combination with other inputs is quite low. The bottom line is that the proportions of use of a given practice in combination with other practices are relatively small, 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 5: Percentage of use of practices' in combinations by land use types

	Land use types			
	Agricultural (N=2487)	Agro-pastoral (N=2393)	Pastoral (N=460)	Total (N=5340)
Residue, Organic & modern inputs (ROF)	0.04	0.03	0.02	0.03
	[0.19]	[0.16]	[0.12]	[0.18]
Residue and organic(RO)	0.13	0.10	0.04	0.12
	[0.33]	[0.30]	[0.19]	[0.32]
Residue and modern inputs(RF)	0.03	0.03	0.01	0.03
	[0.16]	[0.17]	[0.11]	[0.16]
Organic and modern inputs (OF)	0.03	0.02	0.01	0.03
	[0.18]	[0.14]	[0.12]	[0.17]
Residues (R)	0.36	0.41	0.27	0.38
	[0.48]	[0.49]	[0.44]	[0.48]
Modern inputs(F)	0.13	0.13	0.10	0.13
	[0.34]	[0.34]	[0.43]	[0.34]
Organic (O)	0.37	0.24	0.16	0.31
	[0.44]	[0.31]	[0.37]	[0.48]
NONE	0.14	0.22	0.47	0.18
	[0.48]	[0.49]	[0.48]	[0.49]

Note: The numbers in brackets are standard errors.

In Table 6 we analyze if users and non-users of these three inputs/techniques are distinguishable in terms of crop productivity.[13] Results show that users of modern inputs are statistically distinguishable in terms of crop productivity. Plots with modern inputs perform better than plots without modern inputs in terms of value of harvest in all land use types. On the other hand, users of crop residues tend to have lower crop productivity compared to non-users. It is important however to point that the results presented above are all indicative of the potential impact of use of these practices on crop productivity. Thus, in the subsequent sections we will carry out a rigorous empirical analysis to verify whether these differences in productivity remain unchanged after controlling for all confounding factors.

[13] We have considered all major crops cultivated during the rainy season for the analysis, which include millet, rice, sorghum, peanuts, sorrel, rice, maize, sesame, cassava, okra, onion, potatoes and other crops. Productivity is measured in terms of value (CFAC per acre) instead of quantities (kg per acre) because of the difficulty of aggregation of different kinds of crops, grown on the same plot, having different productivity levels and economic values, which might lead to misleading results. To compute the value of the harvest, each crop has been evaluated using average market price for the community computed from the consumption section of the questionnaire.

Table 6: Productivity differentials under varying farm practices and land use types

	Total		Agricultural		Agro-pastoral		Pastoral	
			Land use types					
	Non-users	Users	Non-users	Users	Non-users	Users	Non-users	Users
Use of organic fertilizers								
Plot area (acres)	4.30	4.68**	3.34	3.89***	4.66	5.75***	6.56	6.19
	[0.08]	[0.13]	[0.09]	[0.13]	[0.13]	[0.26]	[0.36]	[0.87]
Value of harvest- (‘000 CFAF/acre)	24.46	27.91	24.19	28.19	17.16	21.68	59.9	70.7
	[1.71]	[2.87]	[2.38]	[2.59]	[1.69]	[6.28]	[10.9]	[16.01]
N	3786	1554	1578	909	1821	572	387	73
Use of modern inputs								
Plot area (acres)	4.4	4.52	3.49*	3.89*	4.87	5.26	6.80	3.97***
	[0.07]	[0.19]	[0.08]	[0.23]	[0.12]	[0.30]	[0.35]	[0.97]
Value of harvest- (‘000 CFAF/acre)	22.70	43.60***	22.92	43.50***	16.11	32.02***	54.64	12.15**
	[1.28]	[7.35]	[1.38]	[9.91]	[1.45]	[1.14]	[10.01]	[2.99]
N	4642	698	2157	330	2073	320	412	48
Use of crop residues								
Plot area (acres)	4.5	4.32	3.54	3.54	5.11	4.72*	6.27	6.99
	[0.09]	[0.11]	[0.09]	[0.13]	[0.16]	[0.16]	[0.39]	[0.60]
Value of harvest- (‘000 CFAF/acre)	29.21	19.18***	29.05	19.72**	20.49	15.03	66.54	48.29
	[2.19]	[1.47]	[2.52]	[2.15]	[3.16]	[1.64]	[12.24]	[12.22]
N	3326	2014	1363	1124	1221	1172	313	147

Note: *** p<0.01, ** p<0.05, * p<0.1. The numbers in brackets are standard errors. 1 US$ = 470 CFAF

4. Empirical strategies

4.1. Modelling the adoption decision

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 technology and other inputs. 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 a 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:

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

Where $A^j_{ik(t-1)}$ is 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 productivity/profit 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 characterising 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 farmers select 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 production constraints than to adopt 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 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 decrease 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 characterised 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:

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

In equation (5) the assumption is that the rational i^{th} farmer has a latent variable, G^*_{ijk}, which captures the observed and unobserved preferences or demand associated with the j^{th} practice. This latent variable is assumed to be a linear combination of farmer, household, plot, climatic and community characteristics (V_{kt-1} and $W_{ct1,}$) that affect the use of the j^{th} practice, as well as unobserved characteristics (U_{kt-1}) captured by the error term u_{kt-1}. 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 (see table 7).

The first variables used in the analyses are climate variables that characterise exposure to climate-related stress. For input decisions, we use long-term historical data on rainfall patterns and temperatures to capture expected climate at the beginning of the season. For productivity, we include actual climate realizations. For input decisions, we use the coefficient of variation in rainfall (1983-2011), average rainfall shortfall (1983-2011)[14], the coefficient of variation temperature and number of dekads in which the maximum temperature was greater than 35 degrees. Greater riskiness, reflected in the coefficients of variation and average shortfall, is expected to increase use of risk-reducing inputs, but decrease use of modern inputs. Higher maximum temperatures are also expected to increase risk-reducing inputs such as crop residue and organic fertilizer, whereas lower maximum temperatures should favour improved seeds and chemical fertilizer use. For productivity, we use growing season rainfall and self-reported delay in onset of rainfall

[14] The shortfall variable has been computed as the average distance between the yearly precipitations during rainy season and their long-term mean. Those years reporting a level of rainfall higher than the long-run average have not been considered for the computation of the variable.

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

When considering system-level determinants of adaptive capacity, access to institutions and transaction costs are among the main determinants governing input choice decisions. This study proxies transaction costs and access to institutions via observable factors that explain transaction costs or mitigate transactions costs, such as geographical areas, distance-related variables and road density. By increasing travel time and transport costs, distance-related variables are expected to have a negative influence on input use decisions. By facilitating information flow or mitigating transactions costs, access to institutions variables are expected to have a positive effect on the input use decision. A diverse set of potential household level determinants of adaptive capacity are considered. Household wealth indicators include a wealth index[15] based on durable goods ownership and housing condition, an agricultural machinery index based on agricultural implements and machinery access, and livestock size (measured in tropical livestock units (TLU)). Household size, age, gender, sex ratio 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. Furthermore, land tenure status is taken into consideration since 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).

[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.

Table 7: Descriptive summary of selected variables by land use types

Variables	Agricultural		Agro-pastoral		Pastoral		Overall	
	Mean	Std. Err.	Mean	Std. Err.	Mean	Std. Err.	Mean	Std. Err.
Exposure to climatic stress								
Coefficient of variation of rainfall (1983-2011)	0.25	0.06	0.29	0.05	0.39	0.13	0.28	0.07
Average rainfall shortfall (1983 - 2011)	2.46	3.74	1.73	4.43	4.27	3.23	2.65	4.42
Long-term mean rainfall (1983-2011)	407.84	67.36	350.66	34.08	269.63	89.48	373.42	70.54
# dekades growing season max temp was over 35 oC (1989-2011)	38.83	23.26	64.09	19.40	143.94	50.09	57.96	37.29
Coefficient of variation of maximum temperature (1989-2011)	0.02	0.00	0.02	0.00	0.02	0.00	0.02	0.00
Long-term mean max temp (1983-2011)	33.62	0.80	34.38	0.52	36.27	1.18	34.16	1.03
Bio-physical sensitivity								
Types of soil in the plot								
Silty soil	0.05	0.23	0.04	0.20	0.04	0.19	0.05	0.21
Clay soil	0.10	0.30	0.09	0.28	0.33	0.47	0.12	0.33
Rocky soil	0.07	0.26	0.13	0.34	0.05	0.23	0.09	0.29
Topography of plots								
Plot is located on hill	0.06	0.25	0.05	0.22	0.03	0.18	0.06	0.23
Plot is located on gentle slope	0.08	0.28	0.16	0.37	0.19	0.39	0.12	0.33
Plot is located on steep slope	0.04	0.20	0.06	0.23	0.09	0.29	0.05	0.22
Plot is located in a valley	0.08	0.27	0.13	0.33	0.28	0.45	0.12	0.32
Nutrient availability constraint- (1-4 scale, 5 = mainly non-soil)	2.25	0.68	2.41	0.65	1.86	0.65	2.31	0.68
Log (total land area per hh) (ha)	2.40	0.73	2.63	0.76	2.39	0.99	2.44	0.82
Number of plot owned by the hh	3.96	2.15	3.93	2.04	2.53	1.65	3.72	2.11
Plot cultivated during dry season (1=yes)	0.14	0.35	0.07	0.25	0.14	0.35	0.12	0.32
Household level variables								
Female farm (1=yes)	0.12	0.33	0.18	0.38	0.07	0.26	0.14	0.35
Log (age of the user)	3.77	0.32	3.77	0.33	3.81	0.31	3.78	0.32
Log (household size)	2.01	0.43	2.01	0.47	2.03	0.41	2.01	0.45
Sex ratio	1.26	0.96	1.18	0.90	1.51	1.18	1.24	0.95
Dependency ratio	1.46	0.94	1.47	0.96	1.50	1.07	1.45	0.96
Log (highest education in the hh)	0.89	1.16	0.91	1.17	0.77	1.10	0.96	1.18
The hh owns the plot	0.81	0.39	0.85	0.35	0.83	0.37	0.81	0.39
Wealth Index	-0.11	0.12	-0.12	0.11	-0.09	0.16	-0.10	0.16
Index on Agricultural implements	0.82	1.20	0.99	1.31	0.12	0.82	0.80	1.25
Livestock size - in TLU	0.71	0.59	0.79	0.65	0.77	0.73	0.73	0.63
System-level variables								
At least one cooperative exist in the community (1=yes)	0.17	0.37	0.13	0.34	0.12	0.33	0.16	0.37
Distance from the nearest market	2.31	1.80	2.82	1.89	2.45	1.53	2.38	1.85
Distance from the Agric. Extension Office (km)	2.05	1.58	1.83	1.67	2.90	1.78	1.93	1.66
Distance to dowelling (km)	1.27	0.67	1.15	0.70	1.31	0.80	1.28	0.75
Log (road density: length in m in a 10 km radius)	9.92	2.01	9.78	2.54	8.27	4.32	9.83	2.47

4.2 Modelling the impact of adoption on crop outcomes

Taking productivity impacts as a key indicator of adaptive capacity, we move to an analysis of the relationship between farm practice selection and crop outcomes. 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 estimate of the parameter γ^j. Estimating crop outcome 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. To make this more explicit we can insert equation 4 into equation 2 as follows:

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

Given that time *t* immediately follows *t-1* from a chronological perspective, it is quite intuitive that variables involving 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:

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

It is clear from equation 7 that A^j_{ikt-1} is endogenous; farmers who select a certain practice may have systematically different characteristics from the farmers who do not. 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). This approach is suitable for a large family of multi-equation systems where the dependent variable of each equation may have a different format. It also takes into account both simultaneity and endogeneity, and produces consistent estimates for recursive systems in which all endogenous variables appear on the right-hand-side as observed. The major limitations of implementing this approach is computational burden and on achieving convergence especially for a large family of multi-equations. Therefore we restricted ourselves to a maximum of four equations which are seen below:

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

$$A^j_{ikt-1} = \delta V_{ikt} + \theta W_{c(t-1)} + e_{jk(t-1)}, for \text{ j=1, 2, 3} \quad (9)$$

The consistency of this method depends on the validity of instruments to identify the adoption equations, which in turn, rely on two conditions. First, the instruments must be correlated with the endogenous variables (use of agricultural practices). Second, they must not be correlated with the unobserved factors that may affect the plot's productivity (i.e. ε_{kt}). We consider using the coefficient of variation of rainfall (1983-2010), average shortfall of rainfall (2006-2010) and number of dekades the average temperatures is greater than 35º C (1983-2010) as potential instruments for the household decision to use agricultural practices during the current year. If farmers form expectations about the climatic conditions of their area, we might expect that they plant crops and use farm practices that are suited to their expectations. The formation of these expectations is key for production. Thus for households in rural areas, climate variation across space and time should generate corresponding variation in household response or behaviour in term of change in farm practices that will in turn create variation in agricultural output and thus household income.

Its impact on expected utility maximization is realized mainly through production technology choices. For this reason, we focus on climate variability which, we argue, generates uncertainty about expected climatic conditions.

5. Results and discussion

5.1 Determinants of adoption

The maximum likelihood estimates of the MVP model of use of farm management practices are presented in Table 8. It provides the driving forces behind farmers' decisions to use farm management strategies where the dependent variable takes the value of 1 if the farmer uses specific practices or inputs 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. Also the likelihood ratio test of the null hypothesis that the error terms across equations are not correlated is also rejected as reported in Table 8.

Table 8: Multivariate probit estimates – determinants of farming practice selection: climate risk exposure, sensitivity and adaptive capacity

	Crop residues		Organic fertilizer		Modern inputs	
	coef	Se	coef	se	coef	se
Exposure to climatic stress						
Average rainfall shortfall (1983 - 2011)	-0.003	0.002	-0.004**	0.002	-0.004*	0.002
Log (coefficient of variation of rainfall for rainy season (1983-2011))	0.478***	0.136	-0.164	0.137	-0.307**	0.155
Log (coefficient of variation of temperature (1989-2010))	1.809***	0.255	-2.913***	0.257	-3.337***	0.335
# years growing season average maximum temperature was over long term max temp	0.165***	0.026	-0.046*	0.025	0.009	0.032
Bio-physical sensitivity						
Silty soil (reference: sand)	0.227***	0.087	-0.081	0.087	0.058	0.098
Clay soil	-0.108*	0.064	-0.418***	0.066	-0.041	0.074
Rocky soil	0.036	0.064	-0.115*	0.064	0.040	0.075
Topography – hill (reference: flat)	-0.236***	0.083	0.061	0.080	-0.071	0.100
Topography – gentle slope	0.001	0.058	-0.068	0.060	-0.145*	0.077
Topography – steep slope	0.098	0.086	-0.187**	0.092	-0.254**	0.122
Topography – valley	0.172***	0.062	0.083	0.062	0.150**	0.072
Nutrient availability constraint- (1-4 scale, 5 = mainly non-soil)	0.140***	0.036	0.105***	0.036	0.051	0.043
Log (total land area)	-0.008	0.029	-0.067**	0.029	-0.015	0.034
Number of plot owned	0.000	0.012	-0.082***	0.012	-0.027*	0.014
Plot cultivated during dry season	-0.092	0.064	0.143**	0.060	0.377***	0.067
System-level variables						
At least one cooperative exist in the community	-0.236***	0.055	0.156***	0.053	-0.044	0.065
Distance from the nearest market	0.005	0.012	0.053***	0.012	-0.032**	0.015
Distance from the Agric. Extension Office	0.015	0.013	0.027**	0.013	-0.062***	0.015

Distance to dowelling	-0.053**	0.026	-0.314***	0.026	-0.068**	0.030
Log (road density: length in m in a 10 km radius)	-0.027***	0.010	0.055***	0.011	0.019*	0.011
Household level variables						
Wealth Index	-0.188	0.144	0.556***	0.136	1.112***	0.149
Index on Agricultural implements	-0.038*	0.020	0.097***	0.019	0.057**	0.022
Livestock size - in TLU	-0.052	0.035	0.068*	0.035	-0.047	0.043
Female farm	0.093*	0.053	-0.088	0.055	-0.056	0.067
Log (age of the user)	0.096	0.061	0.070	0.061	0.018	0.074
Log (household size)	0.021	0.057	0.036	0.057	-0.125*	0.068
Sex ratio	0.048**	0.019	-0.012	0.020	-0.038	0.024
Dependency ratio	-0.003	0.023	0.001	0.023	0.085***	0.027
Log (highest education in the hh)	-0.007	0.017	0.050***	0.017	0.051***	0.020
Household owns the plot	0.299***	0.049	0.279***	0.050	-0.019	0.055
Region fixed effect (reference: Niamey)						
Agadez	-0.135	0.313	2.116***	0.317	2.038***	0.372
Diffa	1.807***	0.233	1.405***	0.226	1.173***	0.280
Dosso	-0.200	0.175	-0.162	0.161	-0.161	0.172
Maradi	1.211***	0.182	1.083***	0.170	0.673***	0.189
Tahoua	-0.224	0.178	0.775***	0.161	-0.069	0.177
Tilliberi	-0.049	0.172	-0.522***	0.160	-0.725***	0.171
Zinder	1.483***	0.199	1.522***	0.188	1.286***	0.218
Constant	-9.994***	1.153	-12.975***	1.168	-14.214***	1.498
/atrho21	0.094***	0.024				
/atrho31	0.099***	0.029				
/atrho32	0.239***	0.029				
Likelihood ratio test of rho21 = rho31 = rho32 = 0: chi2(3) = 95.4929 Prob > chi2 = 0.0000						
Number of observation	5340					
Log-Likelihood	-8613.0604					
Wald chi2(114)	2025.66					

Note: *** p<0.01, ** p<0.05, * p<0.1

We find that the estimated correlation coefficients are statistically significantly different from zero and positive in all the three pair cases, suggesting the propensity of using a practice is conditioned by whether another practice in the subset has been used or not. Besides justifying the use of MVP in comparison to the restrictive single equation approach, the sign of the coefficients supports the notion of interdependency among the input use decision of different farm management practices which may be attributed to complementarity or substitutability among the practices. We find that the use of crop residue, organic fertilizer and modern inputs are all complementary to each other.

The positive correlation coefficient between modern inputs (inorganic fertilizer and improved seed) and organic fertilizer is the highest among all (23.9%). The positive correlation between modern inputs and use of organic fertilizer indicates that, given the very low soil fertility of most farmland in Niger 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.

The MVP results reported in Table 8 also show that decisions to use different farm management practices are quite distinct and, to a larger extent, the factors governing the decision of each of them are also different, suggesting the heterogeneity in use of farm management practices.

Results show the importance of climatic variables, i.e., exposure, in explaining the probability of farm households' decision to use different agricultural practices. We find that greater variability in rainfall and maximum temperature during the growing season increase the use of risk-reducing practices. For instance, in regions with greater variability in rainfall and temperature, more crop residue measures are used. On the other hand, the probability of using modern inputs and organic fertilizer is negatively correlated with variability in rainfall and temperature. Climatic shocks as represented by average shortfall of rainfall negatively affect the propensity to use crop residue and organic fertilizer though for crop residues this result is not statistically significant. We also find that in communities where temperature is higher (i.e. the number of dekades the average maximum temperature was over 35 degrees Celsius), farm households are more likely to use crop residues but less of organic fertilizers[16]. Our results are consistent with the findings of Kassie et al. (2010) and Teklewold et al. (2013a), who found that yield enhancing technologies like improved seeds and inorganic fertilizer provide a higher crop return in wetter areas than in drier areas. Our findings are also consistent with Arslan et al. (2013), who found a positive relationship between the use of conservation agriculture and climate variability. Overall our findings suggest that farmers are responding to climate patterns in terms of their adaptation strategies but the responses are heterogeneous depending on the practices and the type of climatic variable considered and that climatic variability should be an integral part of promotion activities.

Bio-physical plot characteristics are also found to be important determinants of most of the practices. Total land holdings and number of plots owned are negatively correlated with the use of organic fertilizer and modern inputs. As expected, the topography of the plots and the types of soils in the plots also play a crucial role in explaining the input use decision. Soil characteristics mainly influence the use of crop residues and organic fertilizers, but most of the coefficients are not significant for modern inputs use. The use of crop residues is more pronounced on silty soil and less on clay soil whereas organic fertilizers are less often used in clay and rocky soil compared to sand soil. The propensity of using crop residue is also higher in plots located in valley (in an area of cultivable land between the slopes of a hill) and less on plots located on a hill compared to plots located on flat land. Use of modern inputs is also lower on gentle and steep slopes but higher in valleys in reference to flat slope land types. We also find that farm households with less fertile soils or high nutrient availability constraints are more likely to implement crop residue and organic fertilizer. Overall, our results about the role of soil quality are in line with findings of Teklewold et al. (2013a).

[16] We have not included long run mean rainfall and temperature due to collinearity problems.

At the system level, results show the key roles played by rural institutions and transaction costs, largely confirming the existing literature (for example Asfaw et al., 2014; Arslan et al., 2013 and Knowler and Bradshaw, 2007). The greater the distance to the nearest agricultural extension officer (AEO), the higher the incentive to use practices requiring less initial capital and less skills (i.e. crop residues and organic fertilizers); the opposite holds true for the use of modern inputs. In this case the assistance provided by the AEO in terms of training and information dissemination is crucial for the use of improved seeds and/or inorganic fertilizers. The distance between the dwelling and the plot is also a common element negatively influencing the input choice i.e. the longer the distance, the higher the transportation costs, the lower the incentive to adopt a technology, which is consitent with other findings (e.g Teklewold et al. 2013a). Availability of road infrastructure as proxied by length of road density in a 10 km radius is positively correlated with use of organic fertlizer and modern inputs but negatively correlated with the use of crop residues. Farm housholds residing at far distances from the nearest periodic or permanent market tend to use more organic fertlizer but those who reside nearby markets tend to use more of modern inputs.

Results for wealth indicies such as the wealth index, the agricultural implement index and livestock ownership, are also in line with expectations and with the existing literature. Wealthier households use practices that require more initial capital both in terms of general and specific agricultural assets. As expected, livestock ownership is positively correlated with the use of organic fertilizers. The level of household wealth measured by the wealth index and index of agricultural inputs is negatively associated with the use of crop residues, confirming the idea that this practice, requiring a minimal initial investment, is carried out mostly by less wealthy households. On the other hand, the level of household wealth measured by the wealth index and index of agricultural inputs is positively correlated with the use of organic fertlizer and modern inputs. We find that farm households who own the land are more likely to use crop residue and organic fertilizer while the effect is not significant for modern inputs. 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. Denning et al., 2009; Teklewold et al., 2013a; Asfaw et al., 2014). To the extent that ownership is associated with greater tenure security than with rental agreements, particularly in the longer term, better tenure security increases the likelihood that farmers use strategies that will capture the returns from their investments in the long run.

Household demographics to some extent also play a significant role in explaining the household input use decision. The positive coefficient associated with education for the use of organic and modern inputs confirm its key role already pointed out in much of the literature (e.g. Teklewold et al., 2013a). Moreover, smaller-sized households (or with limited access to labour) and a higher dependency ratio find the use of modern inputs as labour-saving techniques particularly attractive. Crop residue is also more often used by females compared to male plot users (see Table 8 for details).

5.2 Impact of adoption on crop productivity

Table 9 reports results for OLS, conditional recursive mixed process (CMP) estimators and instrumental variables estimation using heteroskedasticity-based instruments (with additional instruments constructed using Lewbel, 2012 method) for the impact of input use on crop productivity (all estimates are reported accounting for cluster heteroskedasticity standard error at the household level). The simplest approach to investigate the effect of input use consists of estimating an OLS model of productivity estimate without controlling for any potential endogeneity problems and with a dummy variable equal to 1 if the farmer decided to use the practices on a given plot, 0 if otherwise (as in column (1 and 2) of Table 9). The OLS results would lead us to conclude that there are significant observable differences in terms of agricultural outputs between users and non-users. The value of crop harvest is significantly greater for users of modern inputs and organic fertilizers compared to the non-users (coefficient for crop residues is also positive but not significant). This approach, however, assumes that the uses of these agricultural practices are exogenously determined in the production function while the endogeneity test[17] determines the three dummies to be endogenous. Therefore the estimation via OLS would yield biased and inconsistent estimates. The impact estimates presented further on use conditional recursive mixed process (CMP) techniques to account for this problem and instrumental variables techniques boosted by the Lewbel (2012) method (ivreg2h) to correct for weak instruments and heteroskedasticity problems.

Before turning to the causal effects of adoption on crop productivity, we briefly discuss the quality of the selection instruments used. To probe the validity of our selection instruments, we looked at two major tests: the weak identification test and over identification tests. The test results support the choice of the instruments, as do the F-test values for all of the specifications (bottom of Table 9). The F-statistic of joint significance of the excluded instruments is greater than 10, thus passing the test for weak instruments. The null hypothesis in the case of the over identification test is that the selection instruments are not correlated with the yield error term and we fail to reject the null in all the cases.

As we can see from Table 9, results for the impact on plot productivity are quite consistent across different estimation strategies. As expected, results show that, on average, use of modern inputs has a positive and statistically significant impact on crop productivity. The use of organic fertilizers also significantly increases the value of the harvest per acre and this result is consistent for both estimation strategies. However the use of crop residues does not seem to increase crop productivity – the coefficient is not statistically significant in the case of OLS estimator, but Ivreg2h and CMP estimators report negative and significant effect of crop residue use on crop productivity. One possible explanation for the negative

[17] "The endogeneity test implemented […] is defined as the difference of two Sargan-Hansen statistics: one for the equation with the smaller set of instruments, where the suspect regressor(s) are treated as endogenous, and one for the equation with the larger set of instruments, where the suspect regressors are treated as exogenous" (Baum, et al., 2007)

effect of crop residue is that the yield benefit of use of sustainable land management practices such as crop residues often accrues slowly over time compared to other agricultural practices, such as modern inputs, which tend to have short term returns. The evidence is just one piece of the puzzle, and the finding would have to be confirmed through other types of studies. We have also not estimated the impact on reducing yield variability in the face of variable climate conditions, so the results should be interpreted with the caveats in mind. Our data also didn't fully capture when crop residue incorporation was started and the frequency that it was used so perhaps this can also provide an important lesson for design of future survey.

Table 9: Impact on productivity - Log value of harvest- ('000 CFAF/acre)

	OLS		CMP		IVREG2H	
	Coef.	se	Coef.	Se	Coef.	se
Modern inputs	0.381***	0.133	0.143***	0.066	0.103***	0.027
Organic fertilizer	0.718***	0.101	0.458***	0.160	0.446***	0.108
Crop residues	0.119	0.108	-0.456**	0.242	-0.314*	0.185
Rainfall during the growing season (mm)	0.635***	0.393	0.837**	0.387	1.579***	0.397
Household reports delayed onset of the rainy season in 2011	-0.474***	0.109	-0.421***	0.102	-0.506***	0.111
Female farm	-0.730***	0.160	-0.462**	0.226	-0.672***	0.163
Log (age)	-0.388**	0.180	-0.296	0.239	-0.421**	0.182
Log (household size)	-0.239	0.179	-0.211	0.230	-0.212	0.180
Sex ratio	-0.012	0.052	0.083	0.075	0.002	0.053
Dependency ratio	-0.017	0.064	-0.044	0.089	-0.033	0.065
Log (highest education in the hh)	0.027	0.048	-0.039	0.065	0.003	0.049
Silty soil (reference: sand soil)	0.060	0.224	0.499*	0.301	0.079	0.228
Clay soil	-0.288	0.187	-0.195	0.219	-0.205	0.188
Rocky soil	-0.646***	0.176	-0.530**	0.225	-0.604***	0.180
Topography – hill (reference: flat)	0.526**	0.223	0.067	0.291	0.504**	0.227
Topography – gentle slope	-0.213	0.150	-0.045	0.202	-0.151	0.155
Topography – steep slope	-0.424*	0.244	-0.025	0.310	-0.349	0.245
Topography – valley	-0.019	0.159	0.257	0.215	-0.035	0.159
Nutrient availability constraint- (1-4 scale, 5 = mainly non-soil)	-0.238**	0.103	-0.454***	0.139	-0.232**	0.105
The hh owns the plot	0.687***	0.157	1.043***	0.191	0.654***	0.162
Log (total land area per hh)	-0.810***	0.088	-0.733***	0.115	-0.773***	0.090
Number of plot owned by the hh	-0.060	0.048	-0.019	0.056	-0.044	0.047
Plot cultivated during the dry season	0.143	0.179	-0.107	0.234	0.042	0.185
At least one cooperative exist in the community	0.318**	0.147	-0.152	0.194	0.294*	0.150
Distance from the nearest permanent or periodic market	0.096***	0.034	0.056	0.049	0.086**	0.034
Distance from the nearest Agric Extension Office	-0.007	0.037	0.017	0.048	-0.004	0.037
Distance to dwelling	-0.203***	0.075	-0.131	0.098	-0.128	0.082
Log (road density- length in m in a 10 km radius)	0.052*	0.028	0.098***	0.037	0.064**	0.029

Wealth Index	0.320	0.435	-0.563	0.587	-0.088	0.455
Index on Agricultural implements	0.173**	0.078	0.048	0.092	0.140*	0.078
Livestock size - in TLU	0.298***	0.101	0.228*	0.136	0.288***	0.102
Regional fixed effect	YES		YES		YES	
Constant	0.642	2.536	4.327*	2.590	0.657	2.555
N	5340		5340		5340	
R2	0.153				0.137	
Log-Likelihood	-15,041.40		-23,537.85		-15,094.78	
Hansen J statistic ꟸ			1.091		1.195	
Underidentification test ꟸ			22.440**		294.574***	
Weak identification test ꟸ			10.495**		13.770***	

Note: *** p<0.01, ** p<0.05, * p<0.1

ꟸ Test for instruments validity for the CMP have been obtained by ivreg2

As described in the earlier section, agriculture in Niger is largely rain-fed. Thus, crop productivity in Nigerien households is strongly correlated with climate variables. This is perfectly reflected in our results: the amount of rainfall during the growing season, as expected, positively influences productivity of the plot. Furthermore, a late onset of the rainy season negatively and significantly affects value of production, consistent with findings of Verdin et al. (1999).

Soil characteristics, as expected, also explain plot productivity. Results for the availability of soil nutrients are also as expected, having a positive impact on productivity. Being an essential factor of production, access to land (both in terms of tenure's stability and in terms of number of plots owned) is a key factor in explaining the differentials in productivity. Land tenure status also explains variation in plot productivity. Secure land tenure implies better plot management in Niger, which in turn positively influences agricultural productivity, confirming the results from Clay et al. (1998). Results also show an inverse relation between land size and crop productivity which is consistent with many other findings in the literature. The coefficient of land size is negative and highly significant in all the specifications. 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).

Gender is a significant variable explaining productivity differences. Crop productivity from plots managed by women tends to be significantly lower than their male-managed counterparts. Our findings are consistent with many studies that show that productivity on plots managed by women are lower than those managed by men, which is often attributed to differences in access to productive resources (e.g., Quisumbing et al., 2001; Peterman et al., 2011). Moreover, crop productivity tends to decrease with the age of the farmer, which is in line with the findings from Tauer (1995) who provides evidence of the lower productivity of older farmers. Households with a larger stock of farming-related assets (both tools and livestock, the latter measured in Tropical Livestock Units) are significantly more productive (see Table 9 for detailed results).

6. Conclusions and policy recommendations

With this study we aimed not only to understand farmers' incentives and conditioning factors that hinder or accelerate use of farming practices with adaptation benefits, but also to provide rigorous evidence of its impact on crop productivity and crop net income. This study utilizes farm household level data collected in 2011 from a nationally representative sample of 4074 households in Niger. We employ a multivariate probit (MVP) technique to model simultaneous and interdependent farm practice selection decisions and utilize conditional recursive mixed process (CMP) and instrumental variables estimators for the casual impact estimation.

Results clearly indicate that while the use of modern inputs and organic fertilizers significantly improves crop outcomes, the yield impact of using crop residues is not statistically significant, which might be a consequence of the fact that the yield benefits of some SLM practices such as crop residues often accrue slowly over time compared to other agricultural practices, like modern inputs, which in turn tend to have short term returns. It is however important to note that we have not addressed in this paper the impact of the use of these practices on reducing yield (or income) variability in the face of variable climate conditions. Increasing productivity is just one of the reasons to use these technologies, but reducing downside loss can be another reason. Therefore the results should be interpreted with this caveat in mind.

In order to understand why adoption rates of practices that are effective adaptation strategies are low, we performed a multivariate probit analysis. What emerges clearly from the analysis is that farmers' decision to adopt practices that could provide them with adaptation benefits varies with climatic stress and agro-ecological conditions, bio-physical sensitivity to such disruptions, and the nature of the adaptive capacity required. Determinants of adaptive capacity that limit farmers' options occur at both the household and the community level. For instance we find that use of crop residue is higher in areas of greater climate variability, as represented by the coefficient of variation of rainfall and temperature as well as rainfall shocks measured by average rainfall shortfall increases. These practices have low investments but higher labour requirements, and involve longer periods to realize benefits. In contrast, modern input use is higher in areas of lower climatic variability, and its adoption is affected by proximity to extension services and markets. It's however important to point out that many of the determinants of adoption of crop residues and organic fertilizer have different signs e.g. climate variability. This defies the notion that organic fertilizer and crop residue as similar technologies (risk reducing inputs) that contrary with use of modern inputs.

Overall these analyses generate three important findings relevant for the emerging body of literature: 1) climate change related effects are important determinants of the practices farmers select, but these effects 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 the 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.

Some key lessons emerge from this study for policy makers and institutions. First of all, measures to guarantee access to land and stable land tenure are particularly needed for the use of long-term strategies to restore soil fertility. Given the strong role of extension in adaptive capacity found in this study, the support provided by AEO should be strengthened and improved where already in place and expanded to include a larger share of farmers. As some of the practices analyzed require high up-front costs which often constitute a severe constraint, access to credit should be guaranteed in order to make climate-smart farming practices affordable for even the poorest of farmers. Most importantly, the results in this paper provide very strong arguments for better targeting agricultural practices to respond to climate risk exposure and sensitivity, and then building adaptive capacity to support different interventions. Overall this paper argues for much greater awareness of heterogeneity in the exposure to climate risk and sensitivity and the implications for which agricultural practices will lead to improved productivity, as well as the types of interventions and who they should be targeted to in order to improve adaptive capacity.

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Economics and Policy Innovations for Climate-Smart Agriculture (EPIC)
EPIC is a programme hosted by the Agricultural Development Economics Division (ESA) of the Food and Agriculture Organization of the United Nations (FAO). It supports countries in their transition to Climate-Smart Agriculture through sound socio-economic research and policy analysis on the interactions between agriculture, climate change and food security.

This paper has not been peer reviewed and has been produced to stimulate exchange of ideas and critical debate. It synthetizes EPIC's ongoing research on the synergies and tradeoffs among adaptation, mitigation and food security and the initial findings on the impacts, effects, costs and benefits as well as incentives and barriers to the adoption of climate-smart agricultural practices.

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