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‘Clearing the air’: common drivers of climate-smart smallholder food production in Eastern and Southern Africa

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ABSTRACT

African smallholders should adopt climate-smart agriculture to make a sustainable transition towards cleaner, circular and more productive food systems. Farmers must play a key role in that process. However, the adoption and diffusion of climate-smart technologies have been slow. Here, a cross-sectional econometric analysis using primary data on sustainable farming practices in the cereal-legume farming systems of Ethiopia, Malawi, South Africa and Tanzania is applied to analyse the drivers and intensity of innovation adoption. Socio-economic barriers reduce adoption intensity among marginalised farmers, and proper incentives are needed to overcome them. Business links between technology-ready smallholders and small-to-medium enterprises must be created to enable the uptake and scaling-up of innovations and the development of industrial application models. Such results can support the design of evidence-based strategies for the sustainable transformation of production systems. While national climate policies already include climate-smart agriculture as an adaptation blueprint, policy makers need empirical evidence to support large-scale adoption. This research is an innovative contribution to that effort. It uses a unique household dataset where data is scarce; it considers the impact of smallholders' conditioning factors on technology climate-smartness level; and it estimates the correlations among a wide range of practices, agro-ecologies and geographical contexts.

1. Introduction

The global food production system faces many challenges. Due to increases in world population, food demand is projected to double over the next fifty years (Alexandratos and Bruinsma, 2012). Climate change is expected to affect food production and stress the natural resource base upon which agriculture depends (IPCC, 2014). This is particularly true in Sub-Saharan Africa, where a fast-growing population and diffuse food insecurity are coupled with environmental degradation, resource depletion and smallholder vulnerability (Li et al., 2019).

African agriculture systems require transformation to respond to such challenges. They must expand their production capacity while minimizing their environmental impact. As with other sustainability transitions, technological innovation plays a critical role in the development policy agenda for Africa (Mwalupaso et al., 2019). Climate-smart agriculture (CSA) can help by increasing productivity and food security while enhancing farming systems' resilience, reducing greenhouse gas emissions and sequestering carbon (FAO, 2013; Asfaw and Branca, 2018).

CSA has been widely promoted as an integrated cleaner production approach encompassing resource extraction minimization through increased use efficiency and reduced waste, residue valorisation and recycling, diminished air emissions and soil fertility losses and energy savings (Athira et al., 2019; Hens et al., 2018; Mwalupaso et al., 2019). For example, mulching and use of cover crops guarantee permanent soil cover, reduce resource losses caused by evapotranspiration and soil erosion and improve residue re-use by reducing emissions from burning; rotating or intercropping cereals with legumes increases production thanks to nitrogen fixation and reduced incidence of pests and diseases; organic fertilisation enhances systems circularity and waste recycling; minimum soil disturbance increases organic carbon and moisture, reducing yields' vulnerability to rainfall variability and declining soil fertility. Such technological, environmental and economic benefits have been widely reported (Adegbeye et al., 2019; Branca et al., 2013; Godfray et al., 2010; McIntyre et al., 2009).

Farmers face multiple climate-related risks (e.g., rainfall variability, declining groundwater tables, heat stress and droughts) and

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adopt CSA packages (e.g., crop diversification, stress-tolerant seed varieties, minimum tillage) to simultaneously tackle such risks and exploit all possible adaptation benefits. For example, conservation agriculture (combined crop rotation, mulching and minimum tillage) has been widely promoted in Africa (Hobbs et al., 2008). Empirical studies have found that the adoption of multiple CSA technologies, as a method of portfolio diversification, enables increased yields, income and poverty reduction (Khonje et al., 2018; Maguza-Tembo et al., 2017; Wainaina et al., 2017). Others have identified a link between the number of practices combined into a technology package and that package's climate-smartness level, measuring CSA adoption intensity as proxied by the number of practices adopted simultaneously (Aryal et al., 2018; Teklewold et al., 2013).

As users of such eco-friendly innovation packages and controllers of production processes, farmers play an important role in the agriculture sector's required transition towards sustainable development and circular economy. Small and medium-sized enterprises (SMEs), such as farmer cooperatives or individual service providers, can act as change agents encouraging the uptake of CSA technologies in cases where their business models offer scaling-up and industrial application mechanisms (Groot et al., 2019). However, the adoption and diffusion of CSA technology in Africa has been slow. Farmers are constrained by technological, socio-economic and institutional barriers, ineffective policies and the absence of proper incentives (Arslan et al., 2015; Long et al., 2016, 2019; Partey et al., 2018; Senyolo et al., 2018).

This work investigates the drivers of adoption of cleaner agriculture production at the smallholder level. It answers the following questions: do interrelationships between single CSA practices in technology packages exist; what socio-economic, physical and environmental factors can drive farmers' adoption of cleaner production technologies; and what is their impact on the adoption intensity of the technology packages selected?

We consider cereal-legume smallholders' production, which is key to food security in sub-Saharan Africa. We choose Ethiopia, Malawi, South Africa[1] and Tanzania as case studies because in these countries: (i) the agriculture sector makes similar contributions to national economic wealth; (ii) smallholders' production systems perform poorly and require investments to promote sustainable changes; (iii) climate-smart agriculture has been introduced but requires appropriate policy measures for scaling-up and industrial application.

Our results provide an important contribution to the existing body of literature, especially in terms of applied research and implications for enterprises and policymakers. They support the design of evidence-based strategies for the sustainable transformation of African smallholders' farming systems through the diffusion of cleaner climate-smart production technologies. Novel features of the analysis are described in what follows. We use a large and unique collection of household survey data that refers to a set of nine production practices adopted within a sample of 2,218 households. Given the scarcity of data about on-farm cleaner agriculture production practices in the study areas, this adds value to the research. It also allows us to provide more robust evidence for policymakers and expanded information about the options for scaling-up and industrial applications. Following Aryal et al. (2018), Makate et al. (2019) and Teklewold et al. (2013), we measure CSA adoption intensity, acknowledging the link between the number of practices combined into a technology package and its climate-smartness level. However: (i) we use a fractional regression econometric model (instead of a multinomial logistic one, as in previous studies) where the dependent variable is continuous (rather than categorical), allowing us to better capture the heterogeneity of farmers' choices regarding practices[2]; (ii) we conduct a cross-sectional analysis comparing four countries and different agro-ecologies, and estimate the correlation among a wider range of cleaner production practices and geographical contexts than has previously been considered in the literature; (iii) we thoroughly factor the effect of local context on farmers' choices into the analysis through interaction terms that combine the country-group categorical variable with economic, human and social explanatory variables, under the hypothesis that the relationship between such regressors and the climate-smartness of technology packages depends on the national context (instead of simply using explanatory variables indicating the geographical location); and (iv) we do not factor technology packages into the model as exogenous aspects, but rather identify them empirically through pair-wise correlation coefficients among single practices at household level.

The paper is structured as follows. A description of the research approach and study areas, including information about the cleaner farm production practices considered in the analysis, is presented in section 2. Data and methodology are presented in sections 3 and 4, respectively. Results are illustrated and discussed in section 5. Conclusions are reported in section 6.

2. Research approach and study areas

2.1. Research approach

This work looks at climate-smart agriculture practices adopted in the maize/millet-legume cropping systems in semi-arid and sub-humid agro-ecological zones and various climates: warm desert (Ethiopia), tropical savannah (Tanzania), humid sub-tropical (Malawi) and temperate (South Africa). The list of practices is summarised in Table 1 and described in what follows.

Improved agronomy includes practices such as the use of cover crops, the adoption of improved seed varieties, and the introduction of legumes as rotational (or intercropped) crops with maize and other cereals. Cover crops lead to higher yields due to decreased on-farm erosion and nutrient leaching, and reduced grain losses due to pest attack. Improved varieties increase yields because of their tolerance to heat and pests. Crop rotations and intercropping enhance soil fertility, reduce incidence of pests and diseases, and enrich nutrient supply to subsequent crops, leading to increased crop yields (Branca et al., 2013). *Integrated nutrient management* includes practices that promote the use of fertilizers, organic inputs and biological resources, reduce nutrient mining and maximize nutrient efficiency (Vanlauwe et al., 2010). *Tillage management* relies on minimum soil disturbance practices such as zero tillage, which are expected to reduce soil erosion, organic substance oxidation and fertility loss (Rusu et al., 2009). *Residue management* is implemented through the retention of crop residues on the soil surface (mulching). It enhances water infiltration and protects soils from sealing and crusting caused by rainfalls. Tillage and residue management-based systems are rich in soil organic carbon, and are

[1] In South Africa, the sample includes the poorest quintiles of the population, which are more reliant on the agricultural sector and are characterised by socio-economic factors comparable with those affecting smallholder farmers in other countries.

[2] In particular, Makate et al. (2019) estimate a multinomial logistic regression model to identify the determinants underlying specific CSA packages, and consider a categorical variable as a scalar response. On the contrary, we estimate a fractional regression model to verify how the selected socio-economic and environmental factors influence the CSA adoption intensity. We consider the rate of simultaneous adoption of CSA practices a dependent variable.

Table 1
Frequency of adoption of the climate-smart practices used in the cereal-mixed farming systems of the study areas, by country (number of households).

Management category	CSA practices	Ethiopia	Malawi	South Africa	Tanzania
Improved agronomy	Cover crops	52	96	111	19
	Crop rotations with legumes	493	351	292	136
	Legume intercropping	501	461	265	257
	Drought tolerant varieties	292	187	252	47
Integrated nutrient management	Organic fertilisation	420	265	176	6
Tillage and residue management	Mulching	59	78	165	25
	Minimum/Zero tillage	139	63	173	126
Enhanced water management	Tied ridging	181	59	231	4
	Planting pits	81	78	141	23

Source: own elaboration.

characterised by overall soil fertility higher than that of conventional systems (Scopel et al., 2004). *Enhanced water management* can help farmers make more water available to crops and use it more efficiently (Vohland and Barry, 2009). Tied ridging and planting pits involve creating a series of micro-catchment basins in a field which can retain surface runoff, reduce water and soil erosion, and harvest and store rainwater (Wiyo et al., 2000).

2.2. Study areas

Smallholders' agriculture is a key sector in the countries studied. It accounts for 31% of GDP in Ethiopia, 29% in Tanzania, and 26% in Malawi; and employs 66% of national work force in Ethiopia, 68% in Tanzania, and 72% in Malawi (World Bank, 2018). In South Africa, despite agriculture's limited contribution to GDP (less than 5%) and employment (about 6%), smallholders play an important role in food production and livelihood creation, as about 13% of agricultural land is managed by approximately 2.6 million small family farm units (Pienaar and Traub, 2015).

Common aspects of smallholders' farming in the study areas include limited adoption of climate-smart cleaner production practices compared to traditional, low-productivity agricultural techniques; and high susceptibility of farm production to weather-related events. In Ethiopia, minimum tillage has been introduced to address soil erosion, improve soil fertility and enhance sustainable crop production, but adoption is still minimal (Mesfin et al., 2011). In Tanzania, the adoption of zero-tillage and mulching is low, because these are perceived as risky new approaches (Kassie et al., 2013). In Malawi, conservation agriculture is implemented on less than 2% of cultivated land (CIAT and World Bank, 2018). In South Africa, the adoption of conservation practices is prevalent on commercial farms, but limited among smallholders. Smallholder farming in these countries is characterised by inadequate soil conservation practices, with consequent soil erosion and fertility depletion; shortened fallow periods; removal of plant residues from crop fields for animal fodder; low access to agricultural inputs and extension services support; and diminishing crop yields (Calzadilla et al., 2014; Liebenberg, 2015). This exposes smallholders to climate change impacts. In Ethiopia, crop production shortfalls are mostly attributed to climate erratic rainfalls and increased frequency of drought periods, e.g. the El Nino-induced droughts in 2015 and 2016 (Asrat and Simane, 2017). In Tanzania, farmers are experiencing the adverse impacts of climate change, including poor crop yields, reduced water availability, and increased occurrence of crop and livestock pests and diseases (Rwehumbiza, 2014). In Malawi, increased frequency of droughts and floods, along with high temperatures, are already posing further challenges to low-productivity smallholder farming and heightening the risk of seasonal food insecurity (Asfaw et al., 2014). In South Africa, droughts followed by high rainfall have led to widespread disease outbreaks (Thornton et al., 2014).

3. Data

This study uses data collected through a field survey conducted during January-February 2018 at seven sites in Ethiopia, Tanzania, Malawi and South Africa. Information about the following has been collected: smallholders' socio-demographic and economic profiles; improved agriculture practices and seed systems adopted; climate change-related aspects (perception, adaptation and coping strategies); membership in agricultural associations and access to extension and advisory services; and access to agricultural inputs and credit.

A total of 2,218 households were surveyed (615 in Ethiopia, 653 in Malawi, 348 in Tanzania and 602 in South Africa). The sample size was defined using the following Cochran's sample formula:

$$n_0 = Z^2{}_{pq/e^2} \qquad [1]$$

where: Z represents the standard deviation of the 95% confidence interval characterizing a normal distribution; p is the estimated proportion of households adopting maize-legume/millet-legume cropping systems; q is equal to $(1 - p)$; and e denotes the desired level of precision, which is represented by the margin of error. A multi-stage sampling procedure was used to obtain efficient and consistent estimates of the target population: first, the relevant population of farmers adopting target sustainable agriculture practices in each country was identified[3]; second, clusters representing lower administrative units (districts and wards) were selected[4]; third, households were randomly selected for interviews. Farmers interviewed showed different adoption levels depending on the specific practice considered and the country-case (see Fig. 1)[5].

[3] For each country-case study, the relevant population of farmers has been identified using the areas where maize-legume and millet-legume cropping systems are predominant, based on experts' opinion and secondary data available from local censuses.

[4] The lowest administrative units are 'districts' in Malawi, Tanzania and South Africa, 'wards' in Ethiopia.

[5] It would be interesting to analyse the drivers of adoption and the specific technology contribution with reference to the three pillars of climate-smart agriculture (food security, adaptation and mitigation) separately. However, data limitations exist. We will explore this topic in the future if additional data becomes available.

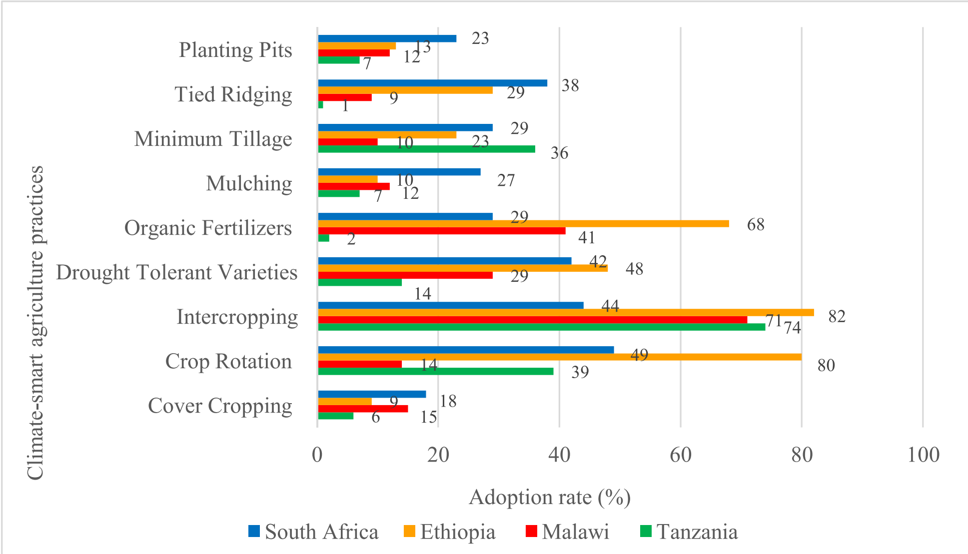

Fig. 1. Adoption of climate-smart farming practices, by country[6] (% of adopting households over total sampled households).
Source: own elaboration.

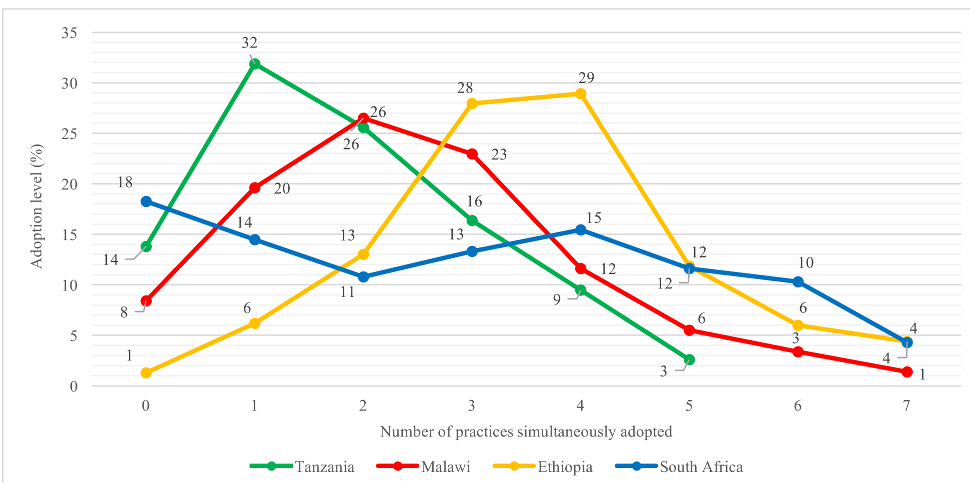

Fig. 2. Intensity of adoption of climate-smart farming practices, by country (% of households simultaneously adopting CSA practices over total sampled households).

4. Methodology

4.1. Fractional regression model

We apply a fractional regression model to estimate the effect of socio-economic and environmental independent variables on CSA adoption intensity (dependent variable; see section 4.2). Farmers' decisions to adopt single or multiple CSA practices are discrete and should be analysed using qualitative choice models. Univariate logit or probit econometric models defined for each practice might generate biased estimates, since they assume independence of the error terms related to different practices, whereas farmers may choose to implement a combination of technologies, and their decisions to adopt a specific practice could depend on the adoption of other techniques (Aryal et al., 2018). Furthermore, separate econometric models do not emphasize the interrelationships among different CSA practices, and do not consider common drivers of simultaneous adoption. Use of censored normal regression (e.g. Tobit model) was also excluded, because its application is not appropriate when data are defined only in the unit interval (in our case, the dependent variable ranges between 0 and 1): observations at the boundaries of a fractional variable are natural consequence of individual choices, and not of any type of censoring (Calabrese, 2012). We therefore opted for a fractional response model, which is used when the outcome of interest is a variable that takes on all possible values in a unit interval (Mullahy, 2015; Royston and Sauerbrei, 2008).

The fractional regression is a model of the mean of the dependent variable y, which ranges in the interval $0 \le y_i \le 1$ and is explained by a vector $1*K$ of explanatory variables $x \equiv (x_1, x_2, \ldots, x_k)$. The population model is:

[6] For each country, the cumulative adoption rate of all the CSA technologies is more than 100, because each household can implement multiple crop management practices.

Table 2
Correlation among CSA practices through pair-wise correlation coefficients.

	Cover cropping	Crop rotation	Intercropping	Drought tolerant varieties	Organic fertilizers	Mulching	Minimum tillage	Tied ridging	Planting pits
Cover cropping	1								
Crop rotation	0,1337***	1							
Intercropping	0.0637***	0.3350***	1						
Drought tolerant varieties	0.0185	0.1888***	0.0732***	1					
Organic fertilizers	0.1544***	0.2331***	0.1432***	0.0385*	1				
Mulching	0.2728***	0.2223***	0.1303***	0.1127***	0.0682***	1			
Minimum tillage	0.2709***	0.1824***	0.1256***	- 0.0062	0.1064***	0.2376***	1		
Tied ridging	0.1775***	0.1658***	0.0378*	- 0.0452**	0.1494***	0.1084***	0.0571***	1	
Planting pits	0.1718***	0.1415***	0.0730***	0.0501**	0.1146***	0.1780***	0.1591***	0.2830***	1

Source: own elaboration.
*significant at 10%, ** significant at 5%, *** significant at 1%.

Table 3
Independent variables: names, description and measurement units.

Variable category and name	Variable description and measurement units
Households' demographics	
Household head, gender (Dummy)	1 if male, 0 if female
Household head, age (Continuous)	Age of household head (years)
Household head, education level (Dummy)	1 if household head attended at least primary school, 0 otherwise
Households' physical assets	
Cropland area (Continuous)	Area of plots (hectare)
Livestock (Continuous)	Livestock owned (Tropical Livestock Units, TLU)
Chemicals (Dummy)	1 if household uses chemicals, 0 otherwise
Asset index (Continuous)	Index ranges between 0 (low use of agricultural assets) and 1 (high use of agricultural assets)
Households' economic assets	
Income (Continuous)	Household income (USD)
Credit (Dummy)	1 if household has access to credit, 0 otherwise
Input subsidy (Dummy)	1 if household receives subsidies, 0 otherwise
Households' human and social assets	
Household members (Continuous)	Number of household members
Group participation (Dummy)	1 if household is member of farmers' associations, 0 otherwise
Extension and advisory services (EAS) access (Dummy)	1 if household has access to extension and advisory services, 0 otherwise
Environmental context	
Agro-ecological zone, AEZ (Dummy)	1 if household is in semi-arid AEZ, 0 if in sub-humid AEZ
Climate change perception (Dummy)	1 if household perceived climate change, 0 otherwise

Source: own elaboration.

$$E(y_i \,/\, x_i) = G(\times_i \beta) \tag{2}$$

where G (.) is a known function satisfying $0 \leq G(z) \leq 1$ for all $z \in \mathbb{R}$.

In equation (2), β can be consistently estimated by non-linear least squares (NLS). Heteroscedasticity is likely to be present in this model, since Var $(y_i \,|\, x_i)$ is unlikely to be constant when $0 \leq y_i \leq 1$ (Papke and Wooldrige, 1996). NLS estimates, heteroscedasticity-robust standard errors and test statistics are obtained using STATA software and a quasi-likelihood estimation procedure.

The log-likelihood function is given by:

$$\ln L = \sum_{j=1}^{N} w_j y_j \ln\{G(\times_j \beta)\} + w_j (1 - y_i) \ln\{1 - G(\times_j \beta)\} \tag{3}$$

where: lnL is maximized; N is the sample size; y_i is the dependent variable; and w_j denotes the optimal weights. The functional form of G (.) considered in the present study refers to a probit model and is equal to:

$$\varphi(\times_j \beta) \tag{4}$$

where x_j are the covariates for individual *j*, and Φ is the standard normal cumulative density function.

4.2. Dependent variable: CSA adoption intensity

CSA adoption intensity, i.e. the rate of simultaneous adoption of practices, is the dependent variable of the econometric model. It is bounded between 0 (no adoption of CSA practices) and 1 (simultaneous adoption of all CSA options considered here). Many farmers adopt several climate-smart practices simultaneously (Fig. 2), confirming the existence of complementarity among single practices.

The existence and type of such associations have been verified through pair-wise correlation coefficients that measure the level of correlation among different practices. The correlation can be weak (coefficient range is 0.1–0.3), moderate (0.3–0.5) or strong (above 0.5). As shown in Table 2, out of 36 pairs of CSA practices, 34 pair-wise correlation coefficients results are statistically significant, confirming that different CSA technology options are often used as

Table 4
Independent variables: descriptive statistics by category group and country.

Variables	Mean *(St.Dev.)*			
	Tanzania	Malawi	Ethiopia	South Africa
Households' demographics				
Household head, gender	**0,845**	**0.735**	**0.924**	**0.502**
	(0.363)	*(0.442)*	*(0.266)*	*(0.500)*
Household head, age	**49.425**	**44.779**	**39.252**	**56.865**
	(15.163)	*(15.400)*	*(11.072)*	*(14.347)*
Household head, education level	**0.586**	**0.855**	**0.533**	**0.711**
	(0.493)	*(0.353)*	*(0.499)*	*(0.454)*
Households' physical assets				
Cropland area	**3.033**	**0.967**	**0.416**	**40.093**
	(2.917)	*(0.704)*	*(0.313)*	*(123.438)*
Livestock	**0.216**	**0.038**	**0.120**	**0.041**
	(0.395)	*(0.102)*	*(0.181)*	*(0.458)*
Chemicals	**0.560**	**0.245**	**0.159**	**0.008**
	(0.497)	*(0.430)*	*(0.366)*	*(0.091)*
Asset index	**0.823**	**0.728**	**0.313**	**0.256**
	(0.124)	*(0.137)*	*(0.135)*	*(0.113)*
Households' economic assets				
Income	**195.195**	**31.2082**	**49.481**	**147.145**
	(356.593)	*(47.480)*	*(55.130)*	*(252.420)*
Credit	**0.086**	**0.283**	**0.345**	**0.009**
	(0.281)	*(0.451)*	*(0.476)*	*(0.099)*
Input subsidy	**0.661**	**0.208**	**0.028**	**0.018**
	(0.474)	*(0.406)*	*(0.164)*	*(0.134)*
Households' human and social assets				
Household members	**3.155**	**3.657**	**4.533**	**2.206**
	(1.668)	*(1.800)*	*(1.943)*	*(1.400)*
Group participation	**0.201**	**0.268**	**0.122**	**0.012**
	(0.401)	*(0.443)*	*(0.327)*	*(0.107)*
Extension and advisory services (EAS) access	**0.069**	**0.326**	**0.389**	**0 .103**
	(0.254)	*(0.469)*	*(0.488)*	*(0.304)*
Environmental context				
Agro-ecological zone	–	0.4793	0.1854	–
	-	*(0.500)*	*(0.389)*	-
Climate change perception	**0.782**	**0.867**	**0.974**	**0.784**
	(0.414)	*(0.340)*	*(0.159)*	*(0.412)*

Source: own elaboration.

complements rather than substitutes. Farmers adopt CSA packages to enhance synergic factors affecting crop productivity (soil fertility, water availability and climate variability).

4.3. Independent variables and descriptive statistics

The independent variables used in the econometric model, together with their measurement units, are described in Table 3. The descriptive statistics are shown in Table 4.

Households' demographics provide information about the gender, age and education level of household heads. Descriptive statistics indicate that sampled farmers are mostly male, middle-aged (39–57 years) and have a primary education. Ethiopia shows the highest percentage of male household heads (92.4%), followed by Tanzania (84.5%), Malawi (73.5%) and South Africa (50.2%). Malawian and South African farmers are more educated than those in Ethiopia and Tanzania. In general, male and educated household heads are more willing to adopt new technologies (De Janvry et al., 1991; Holden et al., 2001).

The second group of variables includes households' physical assets: size of cropland used; ownership of livestock (measured using Tropical Livestock Units[7]); use of chemicals; and other assets, combined in an index built through a Multiple Correspondence Analysis[8]. The effect of households' physical assets on technology innovation adoption is expected to be positive, due to households' improved management capacity (Mwangi and Kariuki, 2015). Farmers use less than 5 ha of cropland in all country-cases except South Africa, where they use 40 ha on average. Tanzania has the highest asset index level, followed by Malawi, Ethiopia and South Africa. Tanzanian farmers are more engaged in livestock production.

The third group of variables includes households' economic assets, namely income, credit availability and subsidy access. The effect of households' economic assets on technology innovation adoption is expected to be positive, because economic resources allow for investments in innovative agriculture techniques.

[7] Tropical Livestock Units (TLU) are computed by converting to common units the number of livestock heads of different animal species. Conversion factors used are: cattle = 0.7; sheep= 0.1; pig=0.2; chicken=0.01 (FAO, 2009).

[8] The items considered in the asset index are the radio, telephone, bicycle, machete, sickle, spade, hoe and water pump. Since they are dichotomous variables, we applied the Multiple Correspondence Analysis (MCA), which allows us to analyse a pattern of relationships existing among several categorical variables (Abdi and Valentin, 2007).

Tanzania has the highest level of on-farm monthly income (195.2 USD). Ethiopia and Malawi show the highest proportion of farmers accessing credit (35% and 28%, respectively). Access to input subsidies is low in all country-cases except in Tanzania, where about 66% of farmers can benefit from incentives to purchase agricultural inputs.

The fourth group of variables includes households' human and social assets: number of family members, membership in farmers' associations, and access to extension and advisory services. Information access and association membership positively influence technology adoption and innovation (Chowdhury et al., 2014). Malawi has the highest proportion of farmers who are members of interest groups (26.8%), while Ethiopia has the highest rate of farmers accessing extension services (38.9%).

The last group of variables captures households' environmental contexts: agro-ecological zone (semi-arid or sub-humid); and climate variations, proxied by households' perception of changes in the intensity and frequency of extreme climate events such as floods, droughts and erratic rainfalls. Households in semi-arid areas and farmers perceiving changes in weather and climatic patterns are more willing to adopt CSA practices (Deressa et al., 2011; Elum et al., 2017; Masud et al., 2017).

4.4. Interaction effects and country-group comparison

Interaction terms can be introduced to deepen understanding of the relationships among the independent variables considered in the model. They indicate non-causal associations and are used when an independent variable is expected to have different effects on the model outcome, depending on the value of another independent variable included in the same equation model (Cox, 1984). A three-step process was adopted to define the interaction terms included in the present analysis: (i) the set of potential interactions merging each regressor with the country-group variable was defined; (ii) the existence of the interaction was detected using the Analysis of Variance (ANOVA); (iii) only the interactions whose results were statistically significant were introduced into the model. Here, we defined interactions combining the country-group categorical variable with the economic, human and social assets explanatory variables (the only groups found to be statistically significant in the ANOVA), under the hypothesis that the relationship between such regressors and CSA adoption intensity differs across countries.

4.5. Issues in model estimation: multicollinearity and endogeneity

Given the number of explanatory variables and the cross-sectional nature of the sample, the adoption estimation model presented in the study might have been affected by multicollinearity and endogeneity problems.

Multicollinearity exists when one predictor variable in a regression model can be linearly predicted from the others with a substantial degree of accuracy (Farrar and Glauber, 1967). We used the variance inflation factor (VIF) and the condition number test to detect multi-collinearity among explanatory variables. We can exclude the possibility of multicollinearity problems because: the condition number is lower than 30[9]; all explanatory variables have a tolerance higher than 0.2 or 0.1[10]; VIF is lower than 5[11]. Endogeneity arises when an explanatory variable (such as income) may be jointly determined by the decision to adopt a practice. Following Davidson and MacKinnon (1993), we used the Durbin-Wu-Hausman augmented regression test to detect endogeneity problems. The test is formulated by including the residuals of each endogenous right-hand side variable in the original regression model. First, we specified the potential endogenous variable (income) as a function of all the other exogenous variables and a defined instrumental variable (income diversification). Second, we estimated the fractional regression model using the residual terms obtained from the previous stage. Income residuals were not found to be statistically significant, confirming the consistency of the estimator (see supplementary material). However, we have not been able to analyse other explanatory variables potentially affected by endogeneity (e.g. access to extension and advisory services) because of the difficulties encountered in selecting proper instrumental variables. This means that potential endogeneity problems might persist in the estimated model.

5. Results and discussion

In this section, we present and discuss the analytical findings of econometric model estimation (see regression's coefficients reported in Table 5). We discuss only the explanatory variables that were found to be statistically significant in the regression output.

5.1. Households' demographics

Male-headed households show higher adoption intensity than female-headed ones. This is not surprising, because women in Africa often suffer from social and cultural discrimination, have lower education levels and face constrained resource and service access (Pender and Gebremedhin, 2007). Household heads' age is found to positively influence the level of adoption intensity. This is consistent with previous studies showing that older farmers have more knowledge and experience, allowing them to benefit more from technology than younger ones (Mwangi and Kariuki, 2015).

Household heads' education level also positively influences adoption intensity. This supports earlier analyses showing that a higher level of education can stimulate households' resource use consciousness and ability to receive, decode and understand information about technological improvements (Guarini et al., 2018).

5.2. Households' physical assets

Farmland size does not influence adoption intensity. This implies that both small and large farms may strategically adopt CSA options, and that other farm characteristics drive the adoption of specific strategies to cope with climate change.

There is a positive relationship between livestock rearing and adoption intensity. This confirms that mixed crop-livestock systems, considered the backbone of smallholder production in many developing countries (Herrero and Thornton, 2010), are important to climate change adaptation. Improved grazing management might produce manure that could be used to benefit crop production through organic fertilisation, which could then reduce the use of chemical fertilizers (Sumberg, 2002). The positive effect of crop-livestock systems is mainly linked with CSA packages where

[9] The condition number is computed by finding the square root of the maximum eigenvalue divided by the minimum eigenvalue of the matrix. If the condition number is above 30, the regression may have severe multicollinearity (Belsley, 1991).

[10] Tolerance is equal to $1 - R^2_j$, where R^2_j represents the coefficient of determination of a regression of explanator j on all the explanators. Tolerance of less than 0.20 or 0.10 and/or a VIF of 5 or 10 and above indicates a multicollinearity problem (O'Brien, 2007).

[11] The variance inflation factor (VIF) is the quotient of the variance in a model with multiple terms by the variance of a model with one term alone, and quantifies the severity of multicollinearity. It is equal to $1/\ 1 - R^2_j$ (James et al., 2013).

Table 5
Results of the econometric model.

		Coeff		St. Err (Robust)	z
Households' demographics	Household head gender	0.122	***	0.031	3.94
	Household head age	0.002	*	0.001	1.81
	Household head education	0.050	*	0.026	1.89
Households' physical assets	Cropland area	0.000		0.000	0.27
	Asset index	−0.026		0.085	−0.31
	Livestock	0.149	***	0.031	4,76
	Chemicals	0.056	**	0.028	1.98
Households' economic assets	Income	0,000		0.000	1.32
	Ethiopia#Credit access	−0.104	***	0.035	−2.98
	Tanzania#Credit access	0.151	*	0.088	1.72
	Malawi#Credit access	0.188	***	0.058	3.27
	South Africa#Credit access	0.170		0.141	1.20
	Ethiopia#Subsidies access	−0.129		0.089	−1.44
	Tanzania#Subsidies access	0.206	*	0.112	1.85
	Malawi#Subsidies access	0.132		0.102	1.29
	South Africa#Subsidies	0.327	*	0.171	1.91
Households' human and social assets	HH members	0.025	***	0.007	3.72
	Ethiopia#EASs access	0.213	***	0.036	5.90
	Tanzania#EASs access	−0.083		0.098	−0.84
	Malawi#EASs access	−0.059		0.061	−0.97
	South Africa#EASs access	−0.492	***	0.089	−5.53
	Agricultural groups	0.018		0.038	0.49
Environmental context	Climate change experience	0.498	***	0.043	11.49
	Semi-arid AEZ	0,180	***	0.028	6.52
	Tanzania	−0.667	***	0.076	−8.82
	Malawi	−0.343	***	0.051	−6.73
	South Africa	−0.091	*	0.049	−1.85

Source: own elaboration.
*significant at 10%, ** significant at 5%, *** significant at 1%.

the use of organic fertilizers is key. Livestock activities might conflict with climate-smart practices based on crop-residue use (i.e. mulching), however, as they represent an immediate source of animal feeding.

Use of chemicals positively affects adoption intensity. Indeed, many CSA practices require adequate chemical levels to have beneficial effects on crop yields. For example, herbicides are used jointly with minimum tillage, and integrated pest management complements other soil management strategies (Heeb et al., 2019).

5.3. Households' economic assets

Households' access to external economic resources like credit and subsidies affects adoption intensity. Results show that access to credit increases CSA intensity in Tanzania and Malawi[12], but decreases it in Ethiopia. The impact is not statistically significant in South Africa. Additional economic resources stimulate investments in innovative production practices in Malawi and Tanzania (Simtowe and Zeller, 2006). The results for Ethiopia may be explained by the agricultural credit systems in the country-cases. National statistics show that in Ethiopia, only 5% of total credit is directed to the agricultural sector, while in Malawi and Tanzania, the percentages rise to 24% and 10% respectively (FAO, 2019). Where credit is severely constrained, farmers use it to implement conventional practices more intensively. Access to input subsidies is positively related to CSA intensity in Tanzania and South Africa. This result is not surprising given the complementary use of improved seeds and chemical inputs in most CSA packages.

5.4 Households' human and social assets

The number of household members determines the increase in adoption intensity. Since household size is considered a proxy measure of labour availability, this result confirms that larger households have the capacity to overcome constraints related to time-consuming CSA practices, e.g. weeding when minimum tillage is practiced (Rusu et al., 2009).

Access to extension and advisory services has positive effects on CSA intensity in Ethiopia. This is in line with our expectations given the role of extension activities in knowledge and information dissemination. Ethiopia has recently invested massively in a public agricultural extension system, which is the largest in Africa (Berhane et al., 2018). Extension agents represent a link between innovators and users, facilitating technology access at the farmer level. Households exposed to innovation-diffusion programmes are more aware of the benefits of CSA, are stimulated to adopt what they have learned and can even influence other farmers in the area (Genius et al., 2013). Access to extension services is negatively related to adoption intensity in South Africa. This result could be due to the low quality of services provided to sampled households, as confirmed by our survey.

[12] The interaction effect depends on the other covariates and can have different signs for different observations, making simple summary measures of the interaction effect difficult (Ai and Norton, 2003). Considering the present study, the results should be interpreted as follows: the positive effect of credit access is greatest in Tanzania (- 0.104 + 0,151 = 0.047) followed by Malawi (- 0.104 + 0,188 = 0.084) and South Africa (- 0.104 + 0,170= 0.066).

5.5. Environmental context

Households' location affects adoption intensity. The relations between socio-economic and environmental factors become more complex if we consider local context (Laureti et al., 2014). Households located in arid or semi-arid agro-ecological zones (such as in Ethiopia) adopt more climate-smart intense technology packages. CSA includes many water-harvesting and conserving techniques (e.g. mulching, cover cropping, minimum tillage, tied ridging, planting pits) which are more effective in dryland areas, where low rainfall and high evapotranspiration often limit crop productivity.

Perception of climate-related extreme events such as floods, droughts and erratic rainfall increases adoption intensity. This is not surprising given the expected positive effects of CSA technology in supporting climate change adaptation (Grothmann and Patt, 2005).

6. Conclusions and implications

6.1. Conclusions

This paper starts from the premise that climate-smart agriculture is a path African smallholders should follow to transition towards a cleaner production food system. As in other sustainability transitions, technological innovation plays a critical role. Here, a cross-sectional econometric analysis is applied to primary data on sustainable farming practices in the cereal-legume farming systems of Ethiopia, Malawi, South Africa and Tanzania.

Results have shown that adoption intensity of innovation technology packages is higher: (i) in semi-arid agro-ecological zones and in climates where water availability may be limiting; (ii) where there is a perception of increasingly frequent extreme events and erratic rainfall patterns due to climate change; and (iii) in mixed crop-livestock systems. Simultaneous implementation of CSA practices can sustainably improve farm productivity and be a strategy for adapting to multiple risks and potential weather shocks. However, CSA fails to achieve its full potential due to low levels of adoption among smallholders and SMEs' difficulties in scaling up innovation.

A twofold approach should be implemented. On one side, adoption barriers for marginalised farmers must be removed. Investments are needed to promote effective education and quality extension programs, which should prioritize female-headed households, young farmers and mixed crop and livestock systems. Access to inputs and financial resources should be improved through promotion of both formal (e.g., rural financial institutions) or informal (e.g., village loan and saving groups) credit opportunities and appropriate infrastructure and marketing channels for inputs. Development of labour markets will lift the labour scarcity constraint and ease the adoption of labour-consuming innovation technologies. Investments in generating and disseminating weather-related information among smallholders are expected to improve climate perception and overall CSA adoption. On the other side, business and contractual links between technology-ready smallholders and small-to-medium enterprises must be created to permit the scaling-up and development of the industrial model. This will be enabled by greater availability of scientific and practical evidence about CSA technologies, partnerships between enterprises and researchers, and farmers' field trials and demonstrations.

6.2. Implications

Large-scale adoption of CSA technologies will create the societal changes needed to foster sustainable development in Africa. However, investments, policies and action plans should account for the drivers and limiting factors of technology adoption. They should be evidence-based and tailored to specific geographical contexts, accounting for the structural, socio-economic and agro-ecological heterogeneity of the farming sector. SMEs involved in scaling-up and developing industrial applications require appropriate information about their potential clients' expected responses. Research and extension services can also help SMEs acquire new knowledge and skills, which they can then share with their customers. More applied research is therefore needed to expand the base data, especially where information is scarce, and to allow comparisons like the one presented here.

Improvement of overall socio-economic conditions should create a favourable practical and regulatory environment for SMEs to develop an industrial model for CSA. To this extent, national policies to cope with climate change already include CSA as adaptation strategy. The Ethiopia National Adaptation Plan aims at improving food security through increased climate-smart agricultural productivity. The South African National Climate Change Strategy identifies CSA as a possible adaptation method. Alternative farming systems based on improved and diversified crop production and using appropriate water management technologies are identified as priorities in the National Adaptation Programmes of Action of Malawi and Tanzania.

Strategies to increase adoption intensity should consider common geographical and climatic traits at the national level, but also evaluate local business models. Incentive measures, such as providing ecological compensation to adopters or giving them opportunities to access climate-related financing, will encourage farmers to adopt CSA practices.

CRediT authorship contribution statement

Giacomo Branca: Conceptualization, Methodology, Validation, Resources, Writing - original draft, Writing - review & editing, Supervision, Project administration, Funding acquisition. **Chiara Perelli:** Methodology, Formal analysis, Investigation, Data curation, Writing - original draft, Visualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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