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Adoption of climate-smart agricultural practices and their influence on the technical efficiency of maize production under extreme weather events

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ABSTRACT

Malawi experiences frequent and intense extreme weather events that affect rain-fed household maize production. Thus, households have adopted various climate-smart agriculture (CSA) practices to cushion maize production from the adverse effects of extreme weather events, particularly drought episodes. This study examines the drivers of CSA practices' adoption and their influence on the technical efficiency of maize production among drought-affected households. Based on a conditional logit model, the study finds drought episodes substantively enhancing the adoption of organic manure by 76% and soil and water conservation by 29%. The Cobb-Douglas Stochastic Frontier Analysis reveals that households are 63% technically efficient, implying that they can increase current maize production by 37%. A two-stage Tobit model further shows that concurrent adopting organic manure and inorganic fertilizers in the same farm significantly improves maize production's technical efficiency by 18% and is more noticeable among drought-affected households. This study, therefore, advocates for simultaneous adoption of organic and inorganic fertilizers to enhance the effect of CSA practices on the technical efficiency of maize production under intensifying drought episodes. Besides, the study recommends championing gender-targeting extension services to augment the benefits of CSA practices among female farmers. Ultimately, the study results contribute to the existing literature on improving agricultural productivity under varying weather conditions.

1. Introduction

Agriculture remains the cornerstone of Sub-Sahara Africa's (SSA) economic transformation and achievement of Sustainable Development Goals (SDGs) [1]. Several SSA countries, including Malawi, have adopted agriculture as their pathway out of poverty. It is the primary source of livelihood, accounting for 60% of the regions labor force and 40% of Gross Domestic Product (GDP) (Bjornlund et al., 2020). By 2050, SSA's population is expected to double to 2.1 billion, with a 60% increase in food demand (Ittersum et al., 2016). Over the past decades, food production in SSA has been volatile and failed to meet the population demand due to high dependence on rain-fed agriculture, poor agricultural practices, and extreme weather events such as droughts, dry spells and floods [2]. El Nino Southern Oscillation events have amplified drought and flood episodes in the region, and temperatures have continuously increased by 1.6 °C–2 °C, while precipitation declined by 4% between 1990 and 2018 [3]. In the region, temperature is predicted to increase by 1.0–3.0 °C by 2060. Furthermore, high poverty levels and limited credit markets have exacerbated SSA's vulnerability to extreme weather events [4]. These factors have contributed to SSA's weak agricultural adaptive capacity to extreme weather events [5].

In Malawi, agriculture accounts for 28% of GDP, 80% of export earnings, 64% of the workforce, and 85% of household livelihoods [6]. The sector is dualistic, comprising smallholder (70%) and estate (30%) sub-sectors. Smallholder farmers' landholding sizes have diminished from 1.53 ha (ha) in 1968 to 0.4 ha in 2020 following rapid population growth [7,8]. The crop sub-sector accounts for over 80% of the agricultural sector and 17% of GDP. As a staple food, maize dominates the crop sub-sector and is cultivated by over 92% of households [7]. Women contributes 70% of the total labour-force in the crop sub-sector [9], nevertheless, they have limited access and use of agricultural input, insecure land tenure systems and informal institutions governing farm management [10]. Despite maize production determining national and household food security, its impact is limited by rain-fed dependence, small landholding sizes, low soil fertility, and poor agricultural practices [9,11]. With overwhelming evidence of extreme weather events by 2040

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(DoDMA, 2018 [6]; and without adaptation, maize production stands to be adversely affected [4,7,12].

In the recent past, Malawi has experienced increasing dry days by almost 27% and late on-set of rainfall during main cropping seasons, resulting in crop failures and over 6.5 million people being food insecure (World Bank, 2016; [4]. Seven major drought episodes have occurred between 1990s and 2020, reducing maize production by 48%, affecting over 32 million people, and downscaling GDP by 21.5% (DoDMA, 2018). These realities, compounded by rapid population growth and high poverty levels, have negatively affected the technical efficiency of maize production and the food security status of the country [6,13].

Following the adverse effects of drought episodes on maize production, the Government of Malawi (GoM) and several other stakeholders, including households, have championed various climate change adaptation strategies [14]. The Government has promoted Climate-Smart Agriculture (CSA), which integrates climate responsiveness in agriculture at the household level [8,15]. CSA concepts include conservation agriculture, sustainable land management, and agroforestry practices [16]. While the CSA concept is new and still evolving, many of its practices have existed before [17,18]. Besides externally inspired CSA, households have adopted locally enthused CSA practices [6]. Nonetheless, the rate of adopting these CSA practices is still not consistent with investment, and extreme weather events are predicted to indisputably reduce maize production by 10.8% by 2040 [3,19].

CSA practices present an opportunity to address the effects of extreme drought episodes and enhance the sustainability of maize production in Malawi [3]. The challenge, however, is that in Malawi, households have operationalized CSA practices differently, with various local translations and nomenclatures across several communities [17]. Some households have even abandoned already adopted CSA practices due to information asymmetry on the ground [20,21]. Contrary to recommendations of adopting CSA as a package [22], most households have undertaken only two of the five CSA practices, and allied implementation has often been short-lived [11]. Consequently, farmers have failed to derive the full potential benefits of CSA on enhancing maize production, thereby increasing poverty incidences and food insecurity at the household level [11]; Khataza et al., 2018). Additionally, limited research on the drivers and the climate resilience of CSA has facilitated low adoption at the household level [9,23]. Moreover, most households lack information on the technically efficient CSA practices that induce maize productivity under extreme weather conditions [4,19]. Thus, additional studies on the drivers and the technical efficiency of CSA practices are assertive to cope with extreme weather events in Malawi [5,51,55].

Therefore, this paper examines drivers of CSA practices' adoption and their influence on the technical efficiency of maize production under extreme drought episodes. It uses a panel dataset representing farming households in Malawi for 2010/2011 to 2016/2017. While using a conditional logit model (CL), the study assesses drivers of adopting various CSA practices. It also evaluates CSA practices' influence on the technical efficiency of maize production through the application of a two-stage Tobit model. This study's contribution to the existing literature on extreme drought episodes is four-fold. First, it provides evidence regarding the drivers and the effects of CSA practices on maize production in Malawi. Second, it minimises CSA dis-adoption through isolating efficient CSA practices at household level. Third, the study enhances the adoption of climate resilient CSA practices that have substantial effects on the technical efficiency of maize production. Finally, it ensures suitability, flexibility and sustainability of CSA practices by mainstreaming indigenous knowledge in climate adaptation programming. Overall, the study adds to the existing SDGs' literature on improving agricultural productivity under intensifying weather events.

2. Research methodology

2.1. Study area

The study was conducted in rural farming communities in Malawi affected by extreme drought episodes (see Fig. 1). Malawi is a landlocked country and relies on rain-fed maize production for national food security. District altitudes vary from below 500–1500 m above sea level. Malawi has one annual rainy season from November to April, with average precipitation varying from 725 mm to 2500 mm. It has experienced drought episodes since 1980s, with extreme drought events becoming more pronounced in the recent past, with Chikwawa, Chiradzulu, Karonga, Mulanje, Nsanje and Phalombe being the most affected

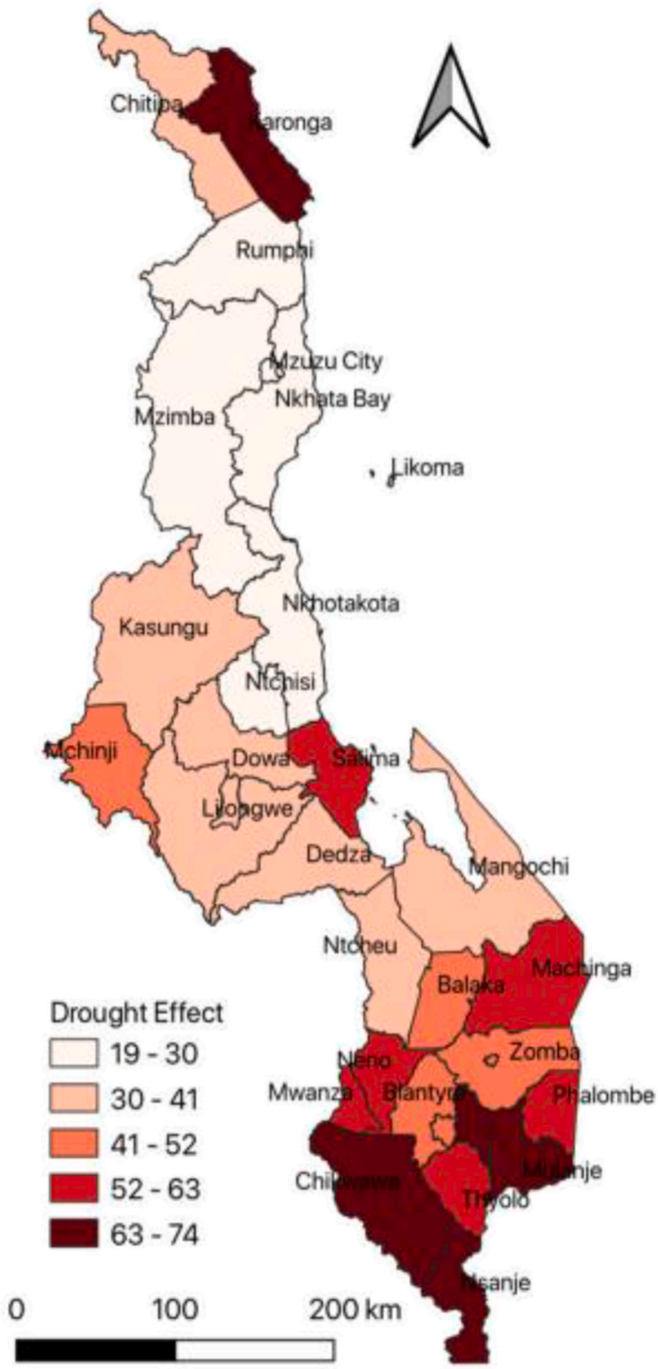

Fig. 1. Proportion Distribution of drought-affected households in Malawi.

districts. Several models have predicted increasing vulnerability, intensity, magnitude and frequency of extreme drought events (DoDMA, 2018; [12]. Apart from the high poverty levels and limited adaptive capacity [23], El Niño and La Niña phenomena have further intensified the country's climate vulnerability [3].

2.2. Conditional fixed effect logit model

In this study, the random utility theory informs the framework of examining household decisions over various CSA choices [24] and is described in two-fold. First, the objects of various CSA practices over which farmers have preferences, namely, organic manure (MAP), soil and water conservation (SWC), maize improved varieties (MIV) and legume intercropping (MLI), cushion maize production from the adverse effects of extreme drought episodes. Second, household attributes such as age, education, gender and other socioeconomic factors determine various CSA practices' choice behaviour.

The independence of irrelevant alternatives (IIA) assumption of the multinomial logit (MNL) model assumes that the choice of one CSA practice does not influence the choice of another [25–27,53]. On the contrary, households in the study area combine CSA practices in the same plot, thus ruling out use of the MNL [4,17]. Several models that allow for correlation across various CSA practices, however, exist, viz., the multinomial probit (MNP) and the conditional logit (CL) [28]. This study adopts the CL due to its flexibility to estimate either a standard, uniform, or log-normal choice distribution [29,30]. Following Hoffman and Duncan [31] and Heckman (1981), we also considered the CL appropriate because CSA decisions are a function of household characteristics. The study thus specifies the panel-based CL model as in equation (1).

$$CSA_{ijt} = \{ \begin{array}{l} 1 \ if \ CSA^*_{ijt} = \sum_{j=0}^{J} \beta_j M_{ijt} + \omega_i R_{ijt} + \alpha_i + \varepsilon_{ijt} > 0 \\ 0 \ if \ CSA^*_{ijt} = \sum_{j=0}^{J} \beta_j M_{ijt} + \omega_i R_{ijt} + \alpha_i + \varepsilon_{ijt} \leq 0 \end{array} \tag{1}$$

where CSA_{ijt} takes a value of 1 if a household adopts any CSA practice including MAP, SWC, MIV, MLI and otherwise, zero. The M_{ijt} is a vector of age, education, farm size, literacy, cell-phone ownership, household size, distance to district headquarters, slope, soil quality and soil type. R_{ijt} represents dummies for drought experience, access to credit as well as extension services. The β and ω_i are unknown parameters to be estimated by the model. The α_i is treated as a random component, while the ε_{ijt} is the error term, with zero mean and constant variance.

2.3. Cobb-Douglas Stochastic Frontier Analysis (SFA)

This study defines technical efficiency as the plot manager's ability to generate optimal maize output from a given technology. It further strongly assumes that drought episodes partially widen the gap between the observed and frontier outputs, which correspondingly determine household technical inefficiency, ceteris paribus. However, a production function is devoid of any economic intuition unless it has some specified structural properties such as utility maximization [32,33].

Various scholars have examined technical efficiency using either a parametric or a non-parametric approach. The parametric approach uses stochastic frontier analysis (SFA), while the non-parametric uses data envelopment analysis (DEA). A key advantage of the SFA over DEA is its ability to split the random error term's impact from the inefficiency effect [33,34]. Inadequate record keeping and high illiteracy rates among smallholder farmers popularly favour the SFA use [32]. Farrell (1957) developed the SFA, which Aigner et al. [35] as well as Meeusen and van den Broeck [36] extended to evaluate technical efficiency across various fields.

The SFA has been used to investigate technical efficiencies of crop production. Musaba [37] and Mango et al. [32] adopted the SFA to study the technical efficiency of smallholder farmers' maize production in Zambia and Zimbabwe, respectively. Mehmood et al. [38] employed the SFA to assess the influence of liquidity constraints on wheat producers' technical efficiency in Pakistan. Some studies have used the SFA to examine the technical efficiency of maize production in Malawi, using cross-section data and with bias on demographic factors (Chirwa, 2008; [39]. In this study, we use panel data to investigate the influence of CSA practices on the technical efficiency of maize production in Malawi, thereby contributing to the existing literature on improving agricultural productivity [23]. We adopt the Cobb-Douglas specification because of its flexibility, excitability and interpretability [34]. The panel-based maximum likelihood estimated Cobb-Douglass SFA model is expressed as in equation (2).

$$lny_{ijt} = \sum_{j=0}^{J} \beta_j lnx_{ijt} + \sum_{m=1}^{M} \lambda_m D_{ijt} + \alpha_i + \upsilon_{ijt} + u_{ijt} \tag{2}$$

where lny_{ijt} is the log of yield in kg/ha for plot-manager at time point. lnx_{ijt} is a vector of various inputs, namely, farm size, fertilizer, seed, labor and organic fertilizer. The D_{ijt} denotes dummies for soil quality, slope and drought experience. The λ_m and $\beta_j$are unknown parameters, while α_i is the individual fixed effect. The u_{ijt} is the technical inefficiency which is derived through its exponential while the υ_{ijt} is the random error, with zero mean and constant variance.

2.4. Two-stage panel-based censored Tobit model

This study adopts a two-stage panel-based censored Tobit model to analyse the influence of CSA on the technical efficiency of maize production under extreme drought episodes. First, the study employs a bivariate panel-based Probit model to predict the CSA practices farmers adopt, while accounting for possible endogeneity [23]. The study presents a panel-based Probit model as in equation (3):

$$A_{ijt} = \sum_{j=0}^{J} \omega_j H_{ijt} + \alpha_i + \kappa_{ijt} \tag{3}$$

where A_{ijt} takes a value of 1 if the household adopts any CSA practice as mentioned above, and zero otherwise. The H_{ijt} is a vector of education, age, gender, farm size, household size, mobile phone, access to extension services and credit. The ω_j stands for the unknown parameters to be estimated. The κ_{ijt} is the white noise, with zero mean and constant variance, while the $\alpha_i$is as presented previously.

Second, the study employs a panel-based Tobit model as in equation (4):

$$\widehat{u}_{ijt} = \omega_0 + \sum_{j=1}^{J} \omega_j \widehat{Z}_{ijt} + \gamma_j K_{ijt} + \alpha_i + \varepsilon_{ijt} \tag{4}$$

where $\widehat{u}_{ijt}$ is the technical efficiency score predicted from equation (2). $\widehat{Z}_{ijt}$ is a vector of CSA practices values estimated from equation (3) such as $\widehat{MAP}$, $\widehat{SWC}$, $\widehat{MIV}$and $\widehat{MLI}$, and K_{ijt} is a vector that includes variables like access to subsidy and credit, land productivity, livestock ownership, gender, literacy, household size and marital status. The ω_j and γ_j are the unknown parameters to be estimated by the model. The ε_{ijt} is the error term with zero mean and constant variance, while the α_i is as prior-defined.

2.5. Data and sampling design

The study uses a panel based household dataset (2010/2011–2016/2017), which was compiled by the NSO and the World Bank through the Integrated Household Panel Surveys (IHPS). It was collected within a two-stage cluster sampling design covering 208 enumeration areas, and representative at the national, urban/rural, regional, and district levels, [7]. The IHPS instruments included households, agriculture, fishery, and community questionnaires. Between 2010/2011 and 2016/2017, the IHPS asked all sampled households to state whether they experienced any drought episodes. Consequently, we define households reporting experience of any drought episodes as drought-affected community (DAC) households, otherwise non-drought-affected community (NDAC) households. The IHPS captured data on household socioeconomic characteristics (such as age, marital status, education, household size, mobile phone ownership, credit accessibility, extension services), extreme weather events (drought and dry spell) and plot characteristics such as plot area, slope, soil quality and type [7,13]. It also captured farm level data like labor, farm holding size, seed, inorganic fertilizers, CSA practices (such as organic fertilizer, soil and water conservation, improved maize varieties, intercropping), crops cultivated and harvest.

This study has sample size of 1329 households in 2010, 1311 households in 2013, and 1193 households in 2016/2017. The IHPS data shows several households experiencing extreme drought episodes, with half of households reporting the effect of extreme drought in 2010/2011 (51%), 34% in 2013 and 46% in 2016/2017 cropping seasons. In this study, drought episodes negatively affect the technical efficiency of maize production, and adoption of CSA practices strengthens the climate resilience of maize production at the household level. Finally, this study complements household interviews with IHPS community (qualitative) focus group interviews.

3. Results and discussions

3.1. Summary statistics of household socioeconomic characteristics and plot-level characteristics

Table 1 presents summary statistics for drought-affected (DAC) and non-drought-affected (NDAC) communities. Table 1 shows that males (75%) head most households in DAC and NDAC communities. The mean household head age was 44 years, with a mean household size of 5 persons. Two-thirds of household heads have ever attended school, with the majority having attained senior primary education. Table 1 also shows that household location in relation to agricultural markets has a bearing on input accessibility. Almost half of households own a working mobile phone. These results are in line with [7].

Table 1 further indicates that households cultivate maize on an average farm size of 0.48 ha, with female farmers having 0.41 ha. Half of the cultivated farms have loamy soils, with substantial differences between DAC (63%) and NDAC (56%) households. About 62% of the households have good soil quality and flat farm. Female farmers produce 370 kg less than their male counterparts. Table 1 shows significant differences of DAC maize yield between 2010 and 2017, with no substantial disparity among NDAC over the same period.

Fig. 2 shows the distribution of households adopting various CSA practices. The figure reveals increasing adoption of various CSA practices between 2010 and 2016/2017. Most households (65%) implement two to three of the five CSA practices. Furthermore, about 76% of households apply NPK fertilizers, which increased from 37.5 kg per acre (2010) to 54 kg per acre (2017). More male farmers (78%) apply NPK relative to their female counterparts (72%), thus explaining resource constraints among female farmers (see Fig. 2). The study also finds that 21% of households use organic fertilizer, applying on average about 178 kg per acre (see Table 1). The study finds a considerable increase in organic fertilizer application between 2010 (126.5 kg) and 2017 (321.6 kg). Besides, more than half of the households implement SWC techniques such as terraces (5%), erosion control bunds (26%), sandbags (1%), vetiver grass (8%), water harvest bunds (1%) and ditches (4%). Additionally, half of the respondents plant MIV and its adoption rose from 46% in 2010 to 56% in 2017. Qualitative data rationalizes that the increase in adoption of MIV among farming households is due to the previous adverse effect of drought episodes on maize production.

3.2. Adoption of climate smart agricultural practices

Table 2 presents the drivers of CSA practices among DAC and NDAC households based on the conditional fixed effects logit model. Factors such as household head's education, distance to district headquarters, slope and soil quality significantly influence households' decision to adopt SWC techniques. Furthermore, households with steep slopes, poor soil quality and drought experience have higher probabilities of adopting the various SWC techniques. Nevertheless, the study finds no significant differences in terms of drivers affecting SWC adoption between DAC and NDAC households. These results are in line with Nguyen et al. [40]; Darkhwh et al. [41] and Teshome et al. [42].

Literacy and extension services substantially affect the MIV adoption. For instance, most literate households cultivate MIV due to the understanding of extension messages on improved varieties. Qualitative data shows that farmers have information on the merits and demerits of various maize varieties, which presents a freedom of choice among households. Interestingly, Table 2 demonstrates extension services and drought episodes as the only factors essentially influencing MIV adoption among DAC. These findings conform to those of Katengeza et al. [19]and; Ayedun [49].

The study also observes that gender and drought episodes significantly influence maize-legume intercropping decision. The study finds several male farmers intercropping maize with legumes compared to female farmers. The study further notices that drought episodes significantly enhance intercropping of maize with leguminous crops. Besides, qualitative data explains that intercropping maize with legumes reduce run-off water and enhance nitrogen fixation. Conversely, the study finds slightly above half of the households (56%) still practicing maize monocropping despite increased drought episodes. These results are similar to those of Bouwman et al. [43]; Timothy et al. [44] and Simtowe et al. [45].

Table 2 further indicates that credit accessibility, age and drought experience substantively influence household adoption of organic fertilizer. Qualitative data reveals that households access credit to hire labor for composite manure production. Similarly, the study notes elder people engaging in organic fertilizer while household with larger farms practise fallow cultivation.

3.3. Cobb Douglas stochastic frontier analysis

Table 3 highlights the maximum likelihood estimated results of a Cobb-Douglas Stochastic Frontier Analysis (SFA) between DAC and NDAC households. The study notes slopes, soil quality, labor, inorganic fertilizer, seed, farm size and drought experience significantly influence maize production. Households that apply NPK fertilizer enhances maize production by at least 3 kg. Similarly, labor improves maize yield by 26 kg in NDAC and 35 kg in DAC households. Table 3 also shows that farm size yields higher returns than any factor of production. Likewise, organic fertilizer improves maize production by 15 kg in NDAC and 8 kg in DAC households. The study finds farms with steep slopes having lower maize yield by 4 kg in DAC and 8 kg in NDAC. Qualitative data clarifies that farm with steep slopes experience excessive soil erosions, while farms with loamy soils have better soil structure and water filtration. Drought episodes have reduced maize yield by 20% and these results are in line with McCarthy et al. [4].

Despite the negative effect of drought on maize production, the study finds DAC households reporting higher yields per ha than NDAC counterparts (see Fig. 3). Accordingly, the chi-square test shows a significant correlation between yield and experience drought episode, and there is a considerable difference between maize yield by DAC and NDAC. Moreover, maize yield has significantly increased from 922 kg per ha in 2010 to 1720 kg per ha in 2016 among DAC households due to adoption various CSA practices.

Table 1
Summary statistics of household socioeconomic characteristics [2010–2016/2017].

		2010			2013			2016			POOLED 2010–2016					DIFF_TEST	
	UNIT_M	TOTAL	DAC	NDAC	TOTAL	DAC	NDAC	TOTAL	DAC	NDAC	TOTAL	DAC	NDAC	MHHD	FHHD	DAC/NDAC	M/FHHD
Matched sample	%	35%	51%	49%	34%	37%	63%	31%	46%	54%		44%	56%	75%	25%		
Matched sample size	Number	1329	672	657	1311	479	832	1193	554	639	3833	1705	2128	2872	961		
Gender	Yes/No	0.76	0.73	0.79	0.76	0.76	0.75	0.73	0.76	0.70	0.03	0.05	0.01	0.03	0.02	***	
Married	Yes/No	0.79	0.76	0.81	0.78	0.80	0.77	0.77	0.79	0.75	0.75	0.75	0.75	0.75	0.25		
HH size	Number	5.04	4.86	5.22	5.55	5.75	5.44	5.47	5.58	5.37	0.78	0.78	0.78	0.97	0.20		***
Age	Years	43.47	43.45	43.49	46.47	45.97	46.76	48.42	48.66	48.21	5.35	5.35	5.35	5.65	4.46		***
Literacy	Yes/No	1.38	1.38	1.37	1.33	1.35	1.33	1.37	1.34	1.39	46.02	45.84	46.17	44.64	50.15		***
School attended	Yes/No	1.21	1.24	1.19	1.20	1.18	1.21	1.15	1.14	1.16	1.36	1.36	1.36	1.28	1.59		***
Class reached	Years	6.22	5.71	6.70	6.20	5.99	6.32	5.68	5.52	5.82	1.19	1.19	1.19	1.15	1.32		***
Mobile phone ownership	Yes/No	0.46	0.39	0.53	0.55	0.48	0.60	0.72	0.75	0.70	6.04	5.72	6.29	6.38	4.76	***	***
Distance to main road	Km	1.05	1.13	0.98	1.07	1.19	1.00	1.02	1.07	0.98	0.57	0.53	0.61	0.66	0.31	***	***
Distance to ADMARC	Km	7.61	8.07	7.14	7.90	8.40	7.61	7.78	7.50	8.03	1.05	1.13	0.99	1.05	1.03	***	
Distance to HQ	Km	51.14	44.50	57.93	25.24	23.18	26.42	27.30	29.62	25.29	7.76	7.98	7.59	7.48	8.60	**	***
Sandy soils	Yes/No	0.22	0.23	0.22	0.19	0.25	0.16	0.27	0.31	0.25	0.23	0.26	0.21	0.22	0.26	***	**
Loamy soils	Yes/No	0.53	0.57	0.48	0.54	0.47	0.58	0.59	0.63	0.56	0.55	0.56	0.54	0.56	0.52		**
Clay soils	Yes/No	0.22	0.18	0.25	0.26	0.27	0.25	0.35	0.31	0.39	0.27	0.25	0.29	0.28	0.26	***	
Good soils	Yes/No	0.48	0.50	0.45	0.42	0.44	0.41	0.62	0.64	0.60	0.50	0.53	0.48	0.51	0.47	***	**
Fair soils	Yes/No	0.40	0.35	0.44	0.42	0.38	0.45	0.45	0.45	0.44	0.42	0.39	0.45	0.42	0.43	***	
Poor soils	Yes/No	0.13	0.15	0.11	0.15	0.18	0.14	0.15	0.17	0.14	0.14	0.17	0.13	0.14	0.17	***	**
Flat slope	Yes/No	0.56	0.55	0.57	0.57	0.57	0.57	0.61	0.63	0.58	0.58	0.58	0.57	0.59	0.55		**
Slight steep	Yes/No	0.33	0.32	0.35	0.31	0.28	0.32	0.49	0.47	0.51	0.37	0.36	0.39	0.37	0.39	*	
Moderate slope	Yes/No	0.08	0.10	0.06	0.09	0.12	0.08	0.15	0.16	0.15	0.11	0.12	0.09	0.11	0.10	***	
Hilly	Yes/No	0.03	0.03	0.02	0.03	0.03	0.03	0.04	0.04	0.04	0.03	0.03	0.03	0.03	0.03		
Seed	Kg	13.08	13.00	13.17	14.22	14.82	13.88	20.49	21.30	19.78	15.78	16.21	15.43	16.13	14.74		**
Labor	Hours	55.90	55.39	56.42	32.33	34.54	31.05	23.42	25.01	22.04	37.73	39.66	36.18	39.62	32.07	***	***
Farm size	Acre	1.00	0.97	1.03	0.95	0.90	0.98	1.59	1.63	1.56	1.17	1.16	1.17	1.22	1.00		***
Inorganic fertilizer	Kg	37.46	37.09	37.85	32.22	29.94	33.54	53.72	53.16	54.20	40.73	40.30	41.07	43.90	31.25		***
Organic fertilizer	Kg	126.55	51.91	202.90	99.68	92.92	103.57	321.63	338.44	307.05	178.08	156.53	195.34	196.47	123.12		
Manure Application	Yes/No	0.14	0.13	0.15	0.19	0.20	0.18	0.31	0.33	0.29	0.21	0.22	0.20	0.21	0.22		
NPK Fertilizer Application	Yes/No	0.81	0.78	0.84	0.74	0.71	0.76	0.74	0.75	0.72	0.76	0.75	0.77	0.78	0.72	*	***
SWC	Yes/No	0.57	0.54	0.59	0.50	0.45	0.54	0.65	0.64	0.67	0.57	0.55	0.59	0.56	0.60	***	**
Extension Services	Yes/No	0.41	0.46	0.37	0.73	0.69	0.75	0.91	0.92	0.91	0.67	0.66	0.67	0.68	0.62		***
Access to subsidy	Yes/No	1.00	1.00	1.00	0.53	0.55	0.52	0.42	0.42	0.41	0.61	0.64	0.59	0.61	0.61	***	
Credit Accessibility	Yes/No	0.11	0.09	0.13	0.22	0.24	0.21	0.24	0.27	0.22	0.19	0.19	0.19	0.20	0.16		**
Improved varieties	Yes/No	0.46	0.43	0.50	0.48	0.50	0.47	0.57	0.59	0.56	0.50	0.50	0.51	0.53	0.42		***
Intercropping	Yes/No	0.44	0.55	0.33	0.57	0.63	0.53	0.66	0.63	0.69	0.45	0.51	0.40	0.42	0.53	***	***
Drought	Yes/No	0.51	1.00	–	0.37	1.00	–	0.46	1.00	–	0.44	1.00	–	0.44	0.45		
Pest infestation	Yes/No	0.09	0.12	0.06	0.23	0.29	0.19	0.13	0.24	0.04	0.15	0.21	0.10	0.16	0.11	***	***
Yield	Kg/Acre	552.06	439.01	667.69	607.87	483.17	679.66	736.13	818.88	664.39	628.44	574.85	671.38	698.34	419.54		***

NOTE: t statistics in parentheses: *p<0.05, **p<0.01, ***p<0.001.

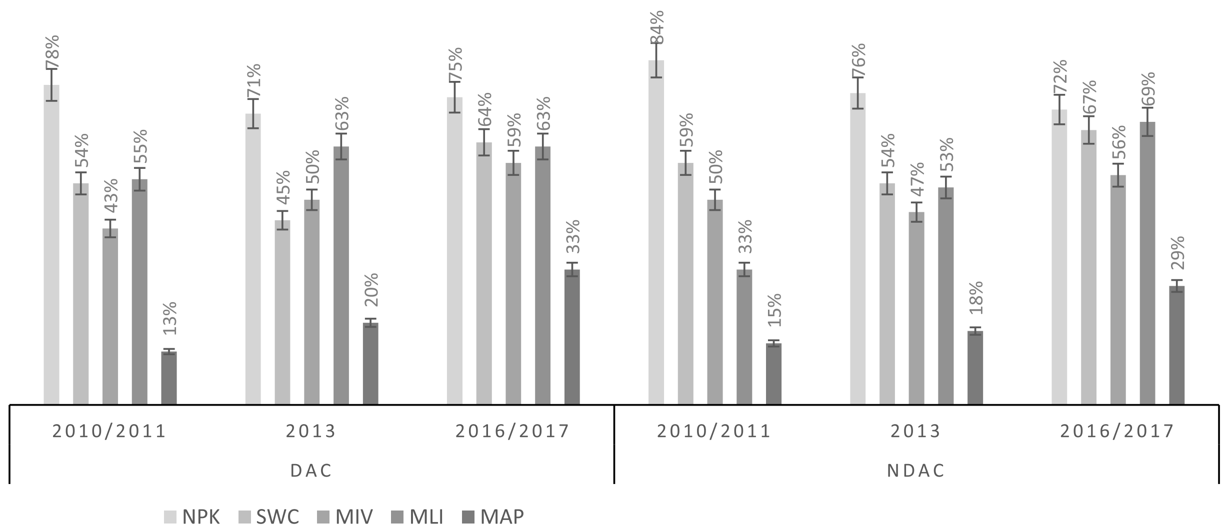

Fig. 2. Distribution of DAC and NDAC households adopting various CSA practices between 2010/2011 and 2016/2017].

3.4. Influence of CSA on technical efficiency of maize production

Fig. 4 illustrates the distributions of technical efficiency for DAC and NDAC households. The study finds households being 63% technically efficient, implying that farmers can reduce current input use by 37% to achieve the same production level. The student's t-test reveals a substantial difference between the technical efficiency of DAC (62%) and NDAC (64%) households. About 74% of both DAC and NDAC households have an efficiency score above 50%. Almost 22% of DAC versus 18% of NDAC households have technical efficiency below 50%, indicating more production loss among DAC than NDAC.

Table 4 provides results from a two-stage panel-based censored Tobit model, which assess CSA practices' influence on the technical efficiency of maize production. In the first step, the study removes the potential endogeneity of CSA choices through the use of CSA-related predicted values, while the second stage evaluates the effect of CSA practices on the technical efficiency of maize production. The study notes that SWC adoption significantly improves the technical efficiency of maize production for both DAC and NDAC households by 2%. Qualitative data reveals contour-farming and erosion control bunds conserve soil moisture and increase water infiltration rate. These findings are consistent with Kumawat et al. [46] and Abate et al. [48].

Similarly, the study finds the cultivation of improved varieties other than local varieties enhances the technical efficiency of maize production by 3% in NDAC and DAC. Qualitative data shows that farmers cultivate early maturing and drought-resistant improved varieties. Furthermore, households that intercropped maize with legume enhance the technical efficiency by 2% in both DAC and NDAC. Nonetheless, the study finds more DAC (51%) than NDAC households (40%) intercrop maize with beans, pigeon peas and groundnuts. Intercropping generally enhances soil fertility through soil moisture retention and nitrogen fixation [47].

Additionally, the study records that concurrently adopting organic fertilizer and inorganic fertilizer strongly increases the technical efficiency of maize production by 18%. Furthermore, simultaneously applying organic manure and inorganic fertilizer is more effective and evident among DAC households. This study also observes that land productivity positively influences the technical efficiency of maize production. Nevertheless, the study notices negative relationship between livestock ownership and credit accessibility, on the one hand, and the technical efficiency of maize production, on the other hand. In other words, there is limited complementarity between livestock, credit and maize production [38]. Household heads' gender, literacy, marital status and family size substantively affect the technical efficiency of maize production (see Table 4). The study finds female farmers less technically efficient than male farmers due to limited access to improved varieties and credits for procuring inorganic fertilizers.

Imperatively, this study attempts to combine various methodologies to understand the drivers and the influence of CSA on the technical efficiency of maize production between DAC and NDAC households under extreme drought episodes. Thus, the study has partly contributed to the evidence on attaining SDGs targets on improving agricultural productivity. However, the study has not tested some hypotheses due to use of secondary data, which lacked some disaggregated data for CSA practice' specific techniques. Thus, the study has not address the following research questions: (i) what is the effect of specific contour bunds, drainage ditches, terrenes and others on the technical efficiency, and (ii) what concurrent application of organic and inorganic fertilizer is optimal to enhance the technical efficiency of maize production? Additionally, land is very critical in transforming agriculture in Malawi [6], hence, a study which assesses the effects of these specific SWC or MIV or MLI with varying land tenure systems becomes informative to customary land regularization policies in the country. Therefore, the study suggests that future research should include such researchable hypotheses to thoroughly inform CSA implementation under both extreme drought episodes and varying land tenure systems.

4. Conclusion and policy recommendations

This study examines the drivers of CSA practices' adoption and their influence on the technical efficiency of maize production under extreme weather events. The study uses a three-wave panel dataset (2010/2011, 2013 and 2016/2017) containing 3800 randomly sampled households. To address the research objectives, the study adopts a Conditional Logit (CL) model to assess drivers of CSA practices' adoption and the two-stage Tobit regression to evaluate their influence on the technical efficiency of maize production.

Based on the CL model, the study finds that farm size, mobile phones, extension, slope and soil quality as well as drought significantly influence the adoption of soil and water conservation, organic fertilizer, improved varieties and legume intercropping. Furthermore, drought episodes considerably enhance the adoption of soil and water conservation (29%), maize improved varieties (23%) and organic fertilizer application (76%). There is a strong bias of maize mono-cropping in the study area, especially among households with large farms. Nonetheless, the study finds more households intercropping maize with legumes in DAC than in NDA communities. Besides, the results reveal an inverse relationship between distance to the district office and the likelihood of

Table 2
Results of Conditional Logit regression output [2010–2016/2017].

	NDAC				DAC				POOLED			
CSA PRACTICES:	SWC	IMV	MLI	OMA	SWC	IMV	MLI	OMA	SWC	IMV	MLI	OMA
Gender (Male=1)	0.038	−0.490***	0.304*	−0.189	0.113	−0.126	0.415*	−0.220	0.046	−0.334**	0.363***	−0.205
	(0.220)	(-3.32)	(2.200)	(-0.89)	(0.550)	(-0.65)	(2.270)	(-0.69)	(0.350)	(-2.87)	(3.320)	(-1.18)
Credit (Access=1)	0.027	−0.121	0.014	0.438*	0.366	−0.108	0.035	0.505	0.142	−0.114	0.011	0.423*
	(0.160)	(-0.85)	(0.100)	(2.140)	(1.670)	(-0.53)	(0.180)	(1.670)	(1.080)	(-0.98)	(0.090)	(2.520)
Cellphone(Own=1)	0.010	−0.108	0.074	−0.166	−0.022	−0.117	0.056	−0.095	0.002	−0.112*	0.062	−0.147
	(0.130)	(-1.73)	(1.230)	(-1.70)	(-0.18)	(-1.09)	(0.550)	(-0.62)	(0.030)	(-2.08)	(1.200)	(-1.82)
Age (Years)	−0.001	0.0120**	0.007	0.011	0.005	0.009	0.005	0.007	0.001	0.0118***	0.00613*	0.00948*
	(-0.11)	(3.110)	(1.870)	(1.880)	(0.870)	(1.640)	(1.080)	(0.810)	(0.200)	(3.820)	(2.130)	(1.970)
Literate (Yes=1)	0.321*	−0.359**	0.147	0.131	0.057	−0.241	0.326*	−0.610*	0.197	−0.285**	0.226*	−0.122
	(2.050)	(-2.69)	(1.140)	(0.640)	(0.310)	(-1.41)	(2.020)	(-2.14)	(1.670)	(-2.73)	(2.260)	(-0.74)
HHsize (Number)	0.035	−0.007	0.030	0.025	0.023	−0.070	0.043	−0.022	0.032	−0.027	0.036	0.012
	(1.170)	(-0.26)	(1.190)	(0.620)	(0.580)	(-1.94)	(1.290)	(-0.37)	(1.350)	(-1.30)	(1.810)	(0.350)
Distance to HQ	−0.470*	−0.226	−0.784***	−0.142	−0.939*	−0.162	−0.594	0.053	−0.542**	−0.235	−0.739***	−0.080
	(-2.01)	(-1.10)	(-4.18)	(-0.48)	(-2.29)	(-0.47)	(-1.79)	(0.120)	(-2.69)	(-1.35)	(-4.54)	(-0.33)
Slope (Flat=1)	−2.125***	−0.115	0.230*	−0.098	−1.821***	−0.085	0.219	0.519	−2.007***	−0.096	0.236**	0.102
	(-15.89)	(-0.98)	(2.030)	(-0.55)	(-11.09)	(-0.55)	(1.470)	(1.950)	(-19.48)	(-1.02)	(2.630)	(0.700)
Soil Quality(Good=1)	−0.280*	0.071	0.162	−0.244	−0.532**	0.086	0.145	0.086	−0.363***	0.071	0.144	−0.126
	(-2.09)	(0.620)	(1.450)	(-1.39)	(-3.23)	(0.570)	(1.000)	(0.350)	(-3.51)	(0.780)	(1.640)	(-0.89)
Soil Type(Clay=1)	0.069	0.257	0.135	0.441*	0.050	0.282	0.001	−0.265	0.070	0.260*	0.076	0.195
	(0.410)	(1.780)	(0.960)	(2.020)	(0.270)	(1.640)	(0.010)	(-0.92)	(0.560)	(2.360)	(0.720)	(1.130)
Extension(Access=1)	−0.061	0.237*	0.078	0.314	−0.123	0.370*	−0.289*	−0.094	−0.081	0.276**	−0.061	0.157
	(-0.45)	(2.060)	(0.700)	(1.690)	(-0.73)	(2.390)	-(1.99)	(-0.35)	(-0.78)	(3.030)	(-0.70)	(1.040)
Land Area(Ha)	−0.004	−0.005	−0.007	−0.098	−0.208**	0.111	0.005	−0.093	−0.051	0.001	0.001	−0.093
	(-0.30)	(-0.96)	(-0.61)	(-1.54)	(-2.78)	(1.750)	(0.320)	(-1.36)	(-1.29)	(0.300)	(0.290)	(-1.94)
Drought(Yes=1)									0.292**	0.231*	−0.463***	0.759***
									(2.770)	(2.460)	(-5.15)	(5.150)
Constant	0.066	0.465	−0.830**	−1.234**	0.600	0.541	−1.299***	0.123	0.160	0.368	−0.857***	−1.014**
	(0.210)	(1.640)	(-3.05)	(-2.87)	(1.500)	(1.460)	(-3.62)	(0.190)	(0.640)	(1.620)	(-3.93)	(-2.87)

NOTE: t statistics in parentheses: *p<0.05, **p<0.01, ***p<0.001.

Table 3
Results from a cobb douglas stochastic frontier analysis (SFA) [2010–2016/2017].

DEP_VARIABLE: LN_YIELD (KG/ACRE)		COBB-DOUGLAS SFA				
	UNIT	NDAC	DAC	MALE	FEMALE	POOLED
lnfertilizer	Kilogram	0.0306*	0.0498**	0.087***	0.096**	0.0348**
		(2.16)	(2.67)	(4.23)	(3.17)	(3.05)
lnfarmSize	Acre	0.485***	0.512***	0.611***	0.560***	0.493***
		(19.10)	(16.90)	(21.89)	(11.51)	(24.99)
lnlabor	Hours	0.263***	0.352***	0.0102	0.094***	0.295***
		(8.66)	(9.03)	(0.96)	(3.60)	(12.08)
lnseed	Kilogram	0.0124*	0.00859	0.130***	0.142*	0.0114**
		(2.15)	(1.31)	(4.34)	(2.55)	(2.62)
lnManure	Kilogram	0.150***	0.0823*	−0.0329	−0.142	0.115***
		(5.34)	(2.48)	(-0.73)	(-1.78)	(5.31)
Slope	Steep (Yes/No)	−0.055	−0.0443	0.0715	0.128	−0.0371
		(-1.37)	(-0.92)	(1.59)	(1.64)	(-1.20)
Soil_type	Sandy (Yes/No)	−0.123*	−0.0578	−0.107*	0.0216	−0.0843*
		(-2.46)	(-1.07)	(-2.04)	(0.25)	(-2.29)
Soil_quality	Good (Yes/No)	0.0820*	0.132**	0.217***	0.313***	0.101**
		(2.06)	(2.76)	(4.95)	(3.99)	(3.29)
Drought	Affected (Yes/No)			−0.514***	−0.0514	−0.203***
				(-5.63)	(-0.30)	(-6.63)
Constant		0.883***	0.647***	0.641	1.079	0.806***
		(16.04)	(10.27)	(0.02)	(0.03)	(19.68)
Usigma (cons)		4.826**	15.05*	0.683***	0.722***	7.406**
		(2.61)	(2.25)	(21.45)	(10.88)	(3.27)
Vsigma (cons)		0.641***	0.715***	0.0871***	0.0965**	0.717***
		(22.07)	(20.66)			(35.17)
N		2127	1705			3832

NOTE: t statistics in parentheses: *$p<0.05$, **$p<0.01$, ***$p<0.001$.

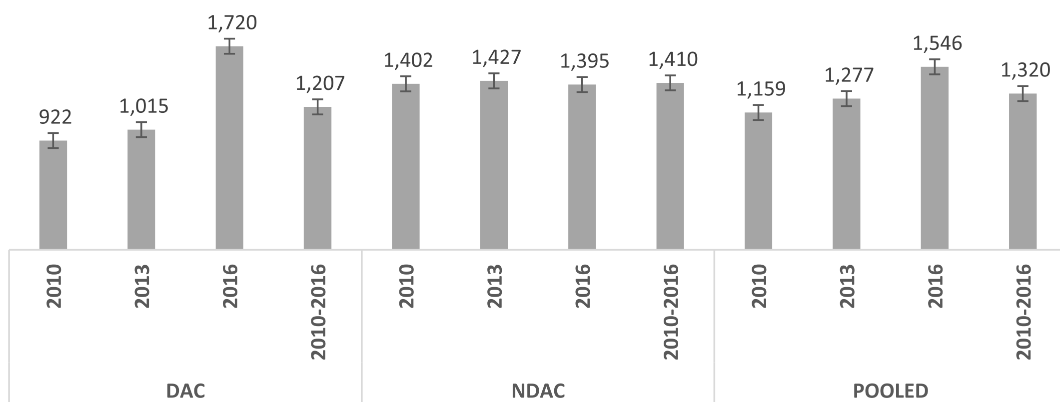

Fig. 3. Average maize yield (kg ha^{-1}) among households affected and not affected by drought [2010–2016/2017].

adopting CSA practices due to reduced extension service visits. Additionally, the study notices a negative relationship between credit accessibility and the technical efficiency of maize production due to limited complementarity between off and on-farm household activities.

Furthermore, a Cobb-Douglass Stochastic Frontier Analysis (SFA) shows that inorganic fertilizer, farm size, labor, seed and organic manure remarkably influence maize productivity. Contrarily, drought episodes negatively affect maize production by around 20%. The study finds households being 63% technically efficient with varying scores between DAC and NDAC households, implying that the current technical efficiency can, on average, be improved by 37%. In terms of gender, the study finds female farmers 5% less technically efficient than male farmers because female farmers have limited access to agricultural inputs. A two-stage panel-based censored Tobit model reveals positive and substantive influence of adopting CSA practices on the technical efficiency of maize production. Remarkably, the study finds SWC and MIV enhancing the technical efficiency of maize production by 9% and 15%, respectively. The study further notices the concurrent adoption of organic fertilizer and inorganic fertilizer in the same farm improving the technical efficiency by 18%, with the effect heavily observed among DAC households. The study also notes that household head's literacy and marital status as critical in determining the technical efficiency of maize production. Additionally, the study finds DAC households (1720 kg per ha) having higher yields that NDAC households (1400 kg per ha) and this is attributed to CSA practices' adoption.

In general, the study recommends simultaneous adoption of organic and inorganic fertilizer at farm-level to enhance the technical efficiency of maize production. Besides, the study proposes gender targeting extension services in promoting CSA practices since women have limited access to agricultural inputs, insecure land tenure systems, and informal institutions governing farm management. Moreover, the study proposes future studies to assess the effect of specific techniques of SWC, namely, terraces, contour bunds, vetiver grass and ditches on the technical efficiency of maize production under both extreme drought episodes and different land tenure security systems.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence

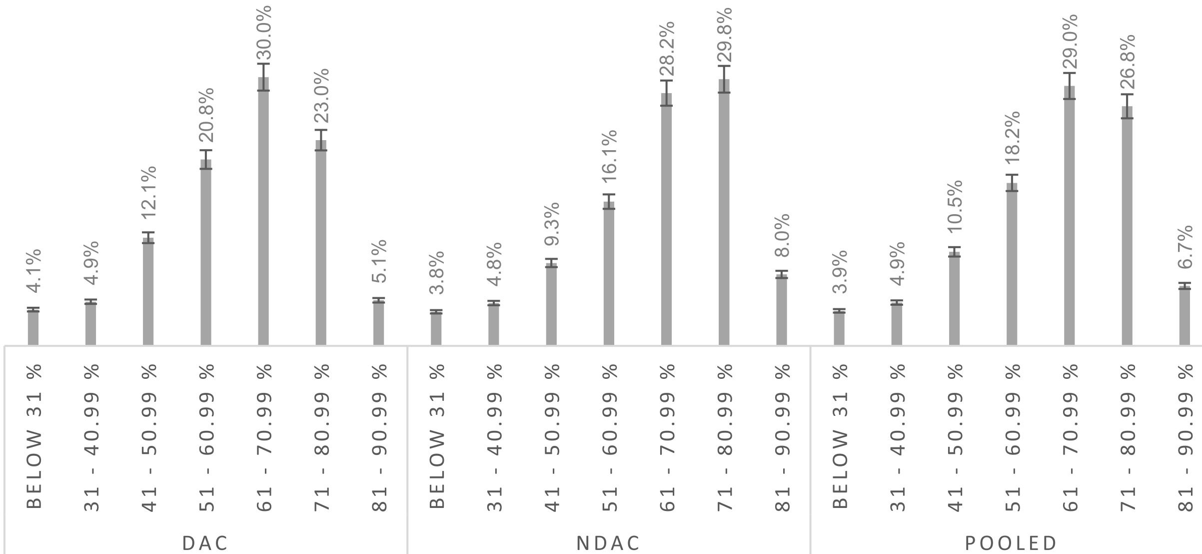

Fig. 4. Distribution of the technical efficiency score between DAC and NDAC households [2010–2016/2017].

Table 4
Results of a two-stage censored Tobit model [2010–2016/2017].

DEP_VARIABLE: EFFICIENCY		POOLED	DAC	NDAC	MALE	FEMALE
SWC	Yes/No	0.102**	0.176	0.108*	−0.0596	0.217
		(2.63)	(1.87)	(2.02)	(-1.03)	−1.82
MIV	Yes/No	0.180***	0.277***	0.160**	−0.0093	0.0873
		(4.57)	(4.15)	(2.64)	(-0.18)	−0.77
MLI	Yes/No	0.0468	0.0411	0.0175**	−0.0894	−0.15
		(1.21)	(0.05)	(3.10)	(-1.54)	(-1.29)
NPK*MAP	Interaction	0.184**	0.350**	0.154	0.132	−2.176
		(3.16)	(2.86)	(1.79)	(0.22)	(-0.74)
NPK	Yes/No	0.0504***	0.0414*	0.0674***	0.01	0.041
		(5.16)	(2.03)	(4.45)	(0.85)	(0.78)
MAP	Yes/No	0.0313	0.0445	0.0807	−0.0658	−0.375*
		(1.24)	(0.86)	(1.31)	(-0.86)	(-2.23)
Access to subsidy	Yes/No	0.011***	0.047***	0.066*	0.018***	0.068***
		(4.32)	(7.33)	(2.08)	(6.83)	(5.34)
Land Productivity	Yield/Area	0.048	0.064***	0.042	0.0216	0.0375
		(0.65)	(3.49)	(0.45)	(0.32)	(0.67)
Livestock	Yes/No	−0.099***	−0.013	−0.086***	−0.018***	−0.011*
		(-6.50)	(-0.48)	(-3.57)	(-9.50)	(-2.27)
Credit	Accessibility	−0.0293	0.0382	−0.0455	−0.0183	0.0283
		(-2.33)	(0.18)	(-2.34)	(-1.11)	(0.70)
Gender	Male/Female	0.279***	0.266***	0.280***	7.331***	3.628***
		(50.93)	(30.26)	(36.14)	(22.85)	(23.38)
Literacy	Yes/No	0.0416***	0.0457***	0.0465***	−0.101	−0.131
		(8.63)	(5.50)	(6.63)	(-1.50)	(-1.04)
HH size	Number	0.00854***	0.00459*	0.00651***	−0.0559***	−0.0492
		(7.19)	(2.54)	(3.87)	(-3.91)	(-1.52)
Married	Yes/No	0.300***	0.301***	0.319***	0.783**	0.158
		(45.76)	(29.12)	(35.06)	(2.65)	(0.91)
sigma_u (cons)		0.139***	0.137***	0.130***	1.123***	1.141***
		(44.20)	(33.09)	(33.82)	(32.80)	(16.98)
sigma_e (cons)		0.0631***	0.0607***	0.0642***	0.441***	0.495***
		(43.83)	(21.75)	(24.22)	(17.77)	(8.45)
N		2546	1136	1410	1090	316

NOTE: t statistics in parentheses: *p<0.05, **p<0.01, ***p<0.001.

the work reported in this paper.

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Further reading

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