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Can smallholder farmers buffer rainfall variability through conservation agriculture? On-farm practices and maize yields in Kenya and Malawi

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Abstract

Reduced tillage, permanent ground cover and crop diversification are the three core pillars of Conservation Agriculture (CA). We assess and compare on-farm effects of different practices related to the three pillars of CA on maize yields under ENSO-driven rainfall variability in Kenya and Malawi. Reduced tillage practices increased yields per hectare by 250 kg on average in Malawi under below-average rainfall conditions and by 700 kg in Kenya under above-average rainfall, but did not have any significant effect on yields under below-average rainfall conditions in Kenya. Ground cover had a positive impact on yields in Malawi (dry conditions) but not in Kenya (both dry and wet conditions), where mixed crop and livestock systems limited this practice. Crop diversification had positive impacts in Kenya (both dry and wet conditions), where maize-legume crop rotation is practiced, but not in Malawi where landholdings are too small to allow rotation. Our findings suggest that isolated CA techniques can have positive effects on yields even after only a few years of practice under variable rainfall conditions. This strengthens empirical evidence supporting the value of CA in resilience building of agricultural systems, and suggests that both full and partial adoption of CA practices should be supported in areas where climate change is leading to more variable rainfall conditions.

1. Introduction

The 2015/16 El Niño event was one of the strongest on record (Jacox *et al* 2016) with global impacts including droughts, flooding and extreme weather events. This had catastrophic impacts on agricultural production and subsequently food security. Countries in the Horn of Africa, East and southern Africa experienced widespread crop failures, predominantly affecting smallholder farmers leading to a significant humanitarian response to prevent famine (Feeny and Chagutah 2016). Although uncertainty surrounds the future impact of climate change on the frequency and intensity of El Niño events (Collins *et al* 2010), climate change is predicted to cause similar conditions on a more frequent basis (Rosenzweig *et al* 2001, Niang *et al* 2014). Therefore, understanding the impact of such weather conditions on smallholder farmers and designing resilience solutions is crucial.

One solution developed to combat erratic rainfall is Conservation Agriculture (CA), the combination of three soil management practices: minimal soil disturbance through reduced tillage, permanent organic soil cover

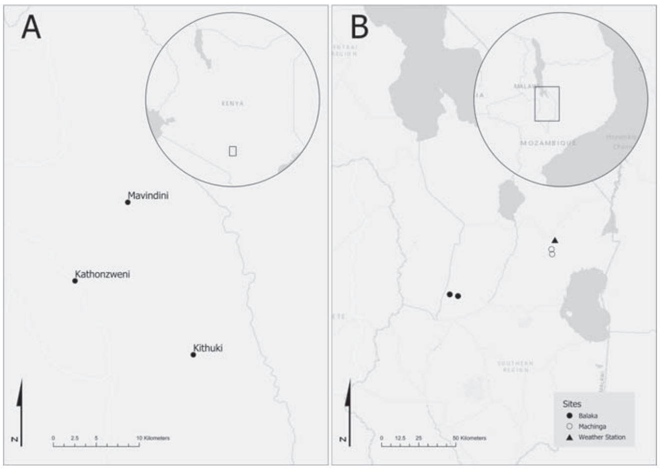

Figure 1. Location of study areas in Kenya (A) and Malawi (B).

through cover crops or mulching, and intercropping or crop rotation (FAO 2008). CA is expected to provide environmental benefits through reduced soil erosion, enhanced soil moisture retention, soil carbon sequestration and improved soil fertility through the accumulation of biomass, thereby stabilizing crop yields through periods of enhanced climate variability (Pretty and Bharucha 2014). From a livelihoods perspective, the increased productivity and resilience to climate variability is expected to positively impact household food security and capacity to reinvest in future agricultural production (Rusinamhodzi *et al* 2011).

To date, evidence of the benefits of CA is mainly available from a series of controlled experimental studies on farms and within agricultural research stations. These suggest that CA increases maize yield in 80% of cases (Thierfelder *et al* 2015) and can increase resilience to climate stress (Steward *et al* 2018). However, there are often important caveats, for example a meta-analysis found that while maize yields increased with CA, the benefits were often only visible after 20 years of practice and depended on high inputs of nitrogen fertiliser (Rusinamhodzi *et al* 2011). More recent reviews, however, found no effect of the time since CA implementation on yields (Steward *et al* 2018). Doubts remain over possible negative impacts of CA techniques on yields and resilience under certain conditions (Giller *et al* 2009). For example, reduced tillage can improve the retention of soil moisture in sandy soils, but might reduce porosity and increase compaction in clay soils. Reduced tillage may also lead to higher weed burdens, particularly under monocrops (Nichols *et al* 2015).

This study contributes to CA literature by: (1) assessing CA performance under variable climate conditions, (2) focusing on actual farm plots and (3) evaluating the performance of other agricultural practices underaken by farmers that are not the CA pillars. Few studies have focused on yields from farmers' fields that are not under experimental controls. CA is extensively promoted across sub-Saharan Africa (Kimaro *et al* 2016) where heterogeneous farming systems and temporal variability add further complexity (Giller *et al* 2015) which can substantially affect CA performance (Rosenstock *et al* 2014). In field conditions, CA takes place along multiple, complementary agricultural practices that influence yields beyond the individual or combined effects of CA subpractices (Vanlauwe *et al* 2014).

The variable rainfall conditions experienced during the 2015/16 El Niño in East and Southern Africa provided the opportunity to simultaneously examine the performance of CA in both high and low rainfall conditions. In this paper we assess maize grain yields in smallholder farming contexts in Kenya, where the 2015/2016 event led to above-average rainfall, and in Malawi, where farmers experienced low rainfall and prolonged dryspells (Tozier de la Poterie *et al* 2018). Our study aimed to determine: (1) whether maize yields under CA perform better than those under conventional tillage strategies in both high and low rainfall conditions, (2) if particular aspects of CA cultivation (minimal tillage, soil cover, intercropping) and related practices influence maize yields and (3) how the interactions of these practices with other agricultural techniques influence maize yields.

2. Methods

2.1. Study areas

In Kenya, rainfall is bimodal, with one rainfall episode from March to May (MAM) and another from October to December (OND). The Kenyan study took place in Makueni County, in the semi-arid zone of south-east Kenya (figure 1(a)). Mean annual rainfall is 644 mm, with 50%–60% of the total annual rainfall occurring during OND, the main growing season (Gichuki 2000). Rural areas are inhabited by agro-pastoralists who depend on rain-fed agriculture and livestock keeping. Farming households rely on crop farming for about 65% of their income, with maize (*Zea mays*) being the main cultivated crop (Ifejika Speranza *et al* 2008). Farmers were trained from 2008 to 2009 in CA-related techniques through outreach programmes by the Center for Training and Integrated Research in Arid and Semi-arid Lands Development (CETRAD), with an adoption rate of 10%. Most farmers have at least 2–3 years practice of CA and some have up to 12 years.

Malawi has a sub-tropical climate with a unimodal rainfall regime (Mutegi *et al* 2015) and one growing season from November to April. Subsistence farming is the main livelihood, supporting over 80% of the population (Zant 2018). Research took place in the Balaka and Machinga Districts in southern Malawi (figure 1(b)). Mean annual rainfall is 831 mm (Ntaja Meterological Station, 1970–2016). These districts were purposively selected due to them having experienced some, but not total, maize crop loss during the 2015/16 season. Maize is the main food crop cultivated in both districts. In Machinga, CA has been practised for three years, having been promoted through the NGO Total Land Care, with an adoption rate of 1.5%. CA was introduced in Balaka in 2007 by the FAO and has been promoted by various organisations since then, leading to an adoption rate of 5.5%.

2.2. The 2015/16 El Niño

The 2015/16 El Niño heavily affected Malawi with low rainfall, erratic timing and prolonged dry spells. This led to widespread crop failure, rendering 6.7 million people food insecure (Botha *et al* 2018). In Kenya, the impacts of El Niño were less severe, with above-average rainfall in OND 2015 leading to improved harvests (FEWS NET KENYA 2016). However, flooding occurred in the west of the country and increased rainfall during this time was associated with an increase in cholera cases (Moore *et al* 2017).

To characterize rainfall in the Kenyan study area, we compiled daily rainfall estimates from the TARCAT (TAMSAT African Rainfall Climatology and Time Series) dataset based on Meteosat images (Maidment *et al* 2014, Tarnavsky *et al* 2014). For Malawi, we used meteorological data from the rainfall station at Ntaja, Machinga District (figure 1(b)).

2.3. Data collection

Data collection took place from June to August 2016 in both countries. Households were surveyed using questionnaires (Kenya $n = 134$; Malawi $n = 201$) that collected both quantitative and qualitative data on crop production, including yields, cultivation methods and the use of agricultural inputs. Given the low numbers of CA farmers, a random stratified sampling framework was developed.

In Malawi, agricultural extension support is administered through geographical divisions termed extension planning areas (EPAs), which are divided into administrative areas known as sections, containing several villages. Interviews with government extension staff at district, EPA and section level identified two sections in both Balaka and Machinga where an Agricultural Extension Development Officer (AEDO) was present and where CA took place. Within each section discussions with focus groups, village leaders and the AEDO enabled lists of CA farmers to be produced from which participants were randomly selected. Based on registered numbers we conducted questionnaires with at least 25 CA farmers in each section, representing 50% of registered farmers across the two sections. Non-CA farmers were selected randomly from village household lists. In Kenya, farmers were randomly selected from a list of CA farmers provided by the CETRAD agricultural support programme. Non-CA farmers were randomly selected.

In both countries, focus group discussions were conducted with groups of CA and non-CA farmers. These were used to inform the development of the household questionnaire, the experience of the 2015/16 season and the practice of farming using an illustrated list of CA and related practices.

In Malawi, households tend to farm several small plots of land, which are not grouped together. On average both CA and non-CA farmers had 2.33 plots of land ($\max = 7$, $\min = 1$) which have an average size of 0.4 ± 0.27 ha ($\min = 0.002$ ha, $\max = 2.02$ ha). Different crops are grown in different plots, and different cultivation techniques were practiced on different plots, giving a total of 346 plots.

In Kenya, farmers tend to plant maize on a single contiguous plot every year in rotation with cowpeas (*Vigna unguiculata*), pigeon peas (*Cajanus cajan*) and green grams (*Vigna radiata*). These legumes are invariably planted through traditional ploughing methods. For maize, farmers usually applied reduced tillage and ploughing to different sub-sections of the plots. In this case, we made a general estimate of the areas under these practices (see supplementary material 1 available online at stacks.iop.org/ERL/14/115007/mmedia). As part of CETRAD extension programmes, farmers were used to monitor their harvests and could provide data for the 2014 and 2015 OND growing seasons, but only for the total of the contiguous maize plot. Of the sampled households, 103 had valid data on maize yields. Farmers almost exclusively practiced CA for maize cultivation. They had access to an average of 5 plots of land ($\max = 12$, $\min = 1$), with an average size of 3.6 ± 3.3 ha ($\max = 20$ ha, $\min = 0.4$ ha).

2.4. Data analysis

We tested the effects of two groups of predictors: (1) the interacting CA pillars; and (2) other related practices, on maize yields for 2015 in Malawi and for 2014 and 2015 in Kenya. CA pillars and other practices were aggregated from the primary list of practices in the survey (table 1). As many farmers failed to harvest anything, leading to zero-inflated data, we used a two-step modelling approach in the R statistical programme (R Core Team 2016) using the lme4 package (Bates *et al* 2015): (1) generalised linear mixed-effects

Table 1. Number of households using CA related and other agricultural practices.

	Kenya		Malawi	
	n ho households	%	*n* ho households	%
CA pillar components				
Reduced tillage[a] and zero tillage)	49	47.6	69	24.9
Ground cover	20	19.4	95	34.3
– Mulching only	3	2.9	71	25.6
– Cover crop only	15	14.6	4	1.4
– Mulching and cover crop	2	1.9	20	7.2
Crop diversification	68	66.0	226	81.6
– Intercropping only	2	1.9	162	58.5
– Crop rotation only	61	59.2	21	7.6
– Intercropping and crop rotation	5	4.9	43	15.5
Combinations of CA pillars				
Reduced tillage only	18	17.5	1	0.4
Ground cover only	3	2.9	9	3.2
Crop diversification only	30	29.1	146	52.7
Reduced tillage and ground cover only	0	0.0	9	3.2
Reduced tillage and crop diversification only	21	20.4	3	1.1
Ground cover and crop diversification only	7	6.8	21	7.6
All three pillars used	10	9.7	56	20.2
No CA pillar used	14	13.6	32	11.6
Other practices				
Herbicide use	11	10.7	39	14.1
Composting	93	90.3	152	54.9
Fertilizer use	16	15.5	208	75.1
Drought tolerant varieties	32	31.1	53	19.1
Cutoff drains	62	60.2	28	10.1
Planting basins (Zai pits)	31	30.1	33	11.9
Terracing	47	45.6	—	—
Early planting	41	39.8	166	59.9
Pesticide use	41	39.8	—	—
Ridges (box or contour ridges)	54	52.4	116	41.9
Water harvest	25	24.3	—	—
Weeding (hand, hoe or oxen)	—	—	252	91.0
Agroforestry (incl. alley cropping)	—	—	97	35.0
Hybrid seeds	—	—	208	75.1
Banking	—	—	80	28.9

[a] Includes 'hand ripping', 'oxen ripping', 'hand subsoiling' and 'zero tillage' practices.

models (GLMM) with a binomal error structure to test whether maize yields met a miniumum threshold based on the requirements of an average household and farm size; and (2) linear mixed-effects models (LMM) of log(yield) excluding zeros to test the effect of different practices on yields.

GLMM were used to test whether practices alter the chance of a farming household meeting their maize requirements for food security. Thresholds were calculated as a function of average farm and household size, per person calorific requirement, post harvest loss, milling efficiency and plate wastage (supplementary material 2). Maize yields thresholds were estimated at 834 kg maize/ha for Kenya, and 840 kg maize/ha for Malawi.

In GLMM, the difference of odds ratios (OR) between treatment and control indicates the effect of practices on the likelihood of meeting the yield threshold. OR is equal to the exponent of the sum of the intercept and the practice B-coefficient of the GLMM. An increase in OR for the practice when compared to the control means that the practice increases the likelihood of meeting the yield threshold, and a decrease means the opposite.

To control for spatial-autocorrelation, farmers nested within villages were included as a random effect in all models. For the Kenya case, farm coordinates were available and Moran's test confirmed that the random-effect of village successfully controlled for spatial auto-correlation. Model performance was assessed through the conditional pseudo R-squared coefficients (R2c) for both fixed and random effects, and the marginal pseudo R-squared (R2m) for fixed effects only, using r.squaredGLMM function in R (Nakagawa and Schielzeth 2013). GLMM model

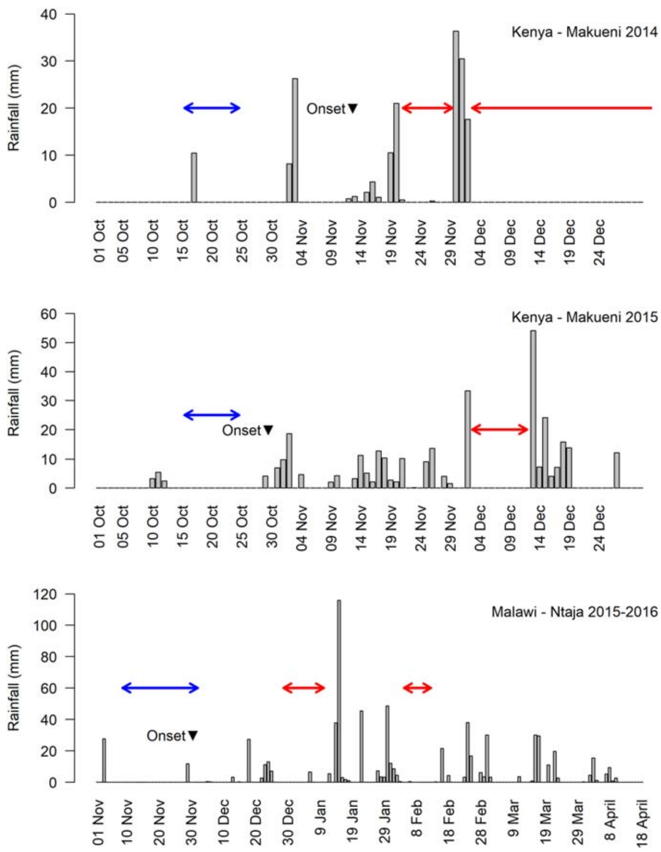

Figure 2. Estimated rainfall during maize growing seasons in the study areas. Blue arrows represent the usual period of onset of rains; red arrows represent dry spells longer than five days.

power was also assessed through the percentage of correctly predicted observations in the original data.

In models exploring the performance of CA pillars, we also tested if the inclusion of random-effects for other commonly practiced techniques improved model performance. For Kenya, none of these practices improved model performance. For Malawi, hoe-weeding and banking (where ridges are reinforced when the crops are growing) were retained as random-effects in CA models. All models were averaged using 95% confidence set and Bayesian information criterion (BIC).

3. Results

3.1. Kenya

3.1.1. Rainfall

In Kenya, the Makueni area received 172 mm of rainfall between October and December 2014, and 386 mm between October and December 2015. These numbers could be underestimations, given the limitations of TAMSAT data in capturing non-convective rains (Seyama *et al* 2019). In both seasons the onset of rainfall, defined as a period of at least five consecutive days with a total of at least 20 mm of rainfall (Ifejika Speranza *et al* 2008), occurred, later than the usual period when farmers expect the rains (16th–25th October). In OND 2014 (figure 2(upper)), rainfall was very erratic, with less than 20 mm recorded during the 10 days following onset, which indicates a failed start (Ifejika Speranza *et al* 2008). Furthermore, the rains stopped completely after 3rd December with the next rainfall recorded on 20th January 2015, representing a dry spell longer than 30 d. In OND 2015, regular rains followed onset, which can be considered a successful start. A dry spell occurred in early December but did not exceed 10 d (figure 2(middle)).

3.1.2. Practices

Table 1 shows the number and proportion of farmers using different combinations of CA pillars and other land management practices. Crop diversification is mainly performed through crop rotation. Due to scarce adoption of mulching and the use of cover crops, we have little data on ground cover only or ground cover combined with reduced tillage. No practices were auto-correlated except contour ridges and terracing, which are mutually exclusive and had an 85% negative correlation.

3.1.3. Maize yields

In 2014, 24 of 103 (23.3%) farmers met the threshold maize requirement and 20 farmers obtained no yield. In 2015, 46/103 (44.7%) farmers met the threshold and only one farmer obtained no yield. When excluding failed harvests, mean yield was 660.18 ± 765.33 (SD) kg ha^{-1} ($n = 83$) in 2014 and 1029.93 ± 1136.00 kg ha^{-1} ($n = 102$) in 2015.

Table 2. Effect of practices on maize yield thresholds and yield amounts.

Model Dependent variable Function used	Generalised linear mixed-effects models (GLMM) Maize yield thresholds reached (yes/no) glmer	Linear mixed models (LMM) Maize grain yields (kg ha^{-1}) lmer
Kenya case—2014 Interacting CA pillars	$n = 103$ *Significant predictors ($p < 0.05$):* Control: odds ratio OR = 0.22 (standard error margin SEM 0.12–0.40) Crop diversification: OR = 0.63 (SEM 0.38–1.03) R2m = 98.7%, R2c = 98.8% Overall model power: 67.8%	$n = 83$ *Significant predictors ($p < 0.05$):* Control: 311.50 (SEM 249–390) kg ha^{-1} R2m = 6.4%; R2c = 18.8%
Other practices	*Significant predictors* ($p < 0.05$): Herbicide use: OR = 2.42 (SEM 0.99–5.88) Fertilizer + Diversification + Herbicide: OR = 29.79 (SEM 3.01–294.87) Control: OR = 0.34 (SEM 0.13–0.90) *Borderline significant predictors* ($p < 0.1$): Crop diversification: OR = 0.87 (SEM 0.51–1.48) Fertilizer: OR = 1.67 (SEM 0.71–3.96) R2m = 35.1%, R2c = 64.6% Overall model power: 54.3%	*Significant predictors* ($p < 0.05$): Control: 457.50 (SEM 255–821) kg ha^{-1} Composting: 180.34 (SEM 113–286) kg ha^{-1} *Borderline significant predictors* ($p < 0.1$): Herbicide use: 837.61 (SEM 610–1149) kg ha^{-1} R2m = 15.4%, R2c = 32.0%
Kenya case—2015	$n = 103$	$n = 102$
Interacting CA pillars	No significant predictors R2m = 98.3%, R2c = 99.1% Overall model power: 85.4%	*Significant predictors* ($p < 0.05$): Control: 561.85 (SEM 465–678) kg ha^{-1} Crop diversification: 745.53 (SEM 628–885) kg ha^{-1} Reduced tillage: 1273.52 (SEM 860–1885) kg ha^{-1} R2m = 8.3%, R2c = 46.9%
Other practices	*Significant predictors* ($p < 0.05$): Zai pits: OR = 421.75 (SEM 35.57–5001.26) R2m = 23.4%, R2c = 59.7% Overall model power: 83.5%	*Significant predictors* ($p <$ 0,05): Control: 599.73 (SEM 447–805) kg ha^{-1} Reduced tillage: 1343.10 (SEM (898–2008) kg ha^{-1}) R2m = 12.8%, R2c = 41.1%
Malawi case—2015/16	$n = 327$	$n = 277$
Interacting CA pillars	*Significant predictors* ($p < 0.05$): Control: OR = 0.124 (SEM 0.075–0.201) Ground cover: OR = 0.475 (SEM 0.316–0.712) R2m = 33.2%, R2c = 52.1% Overall model power: 83.6%	*Significant predictors* ($p < 0.05$): Control: 247.35 (SEM 197–310) kg ha^{-1} Reduced tillage: 505.12 (SEM 413–618) kg ha^{-1} Ground cover: 432.18 (SEM 350–533) kg ha^{-1} R2m = 15.4%, R2c = 47.8%
Other practices	*Significant predictors ($p < 0.05$):* Banking: OR = 0.054 (SEM 0.032–0.089) Ground cover: OR = 0.551 (SEM 0.399–0.762) Control: OR = 0.190 (SEM 0.13–0.277) R2m = 19.3%, R2c = 44.3% Overall model power: 86.2%	*Significant predictors* ($p < 0.05$): Control: 244.70 (SEM 216–278) kg ha^{-1} Banking: 152.85 (SEM 133–176) kg ha^{-1} Fertiliser: 325.74 (SEM 285–372) kg ha^{-1} Reduced tillage: 391.22 (SEM 326–470) kg ha^{-1} Ground Cover: 350.73 (SEM 296–415) kg ha^{-1} R2m = 13.8%, R2c = 54.5%

3.1.4. Effect of practices on maize yields

Table 2 summarizes the ORs, respectively the estimate values exponents of significant predictors for yield thresholds and yield amounts in 2014 and 2015 (for the full model results, see supplementary material 3).

In 2014, control farmers had an OR of 0.22, meaning that the chances of meeting the threshold is 5 times less without the use of CA practices. Adding crop diversification, in this case mainly rotation, increases the OR to 0.63, meaning that although the chances of meeting the threshold were still lower than 50% (OR lower than 1), they increased with this practice. There is no evidence that other CA component practices or their interactions had an effect. Other practices such as herbicide use and fertilizer use both increased the OR of meeting the yield threshold from 0.34 to 2.41 and to

1.67, respectively. A combination of crop diversification, fertilizer and herbicide use increased the OR to 29.79.

Regarding yield amounts, CA pillars had no detectable effect on yields, but non-results should be interpreted with caution as data were lacking for some interactions and yield values were aggregated across CA and non-CA practices within the Kenya maize plots. The use of herbicides increased yields from 457.49 kg ha^{-1} (control value) to 837.61 kg ha^{-1} (+83.09%) but composting reduced yields to 180.34 kg ha^{-1} (−60.58%).

In 2015, the use of planting basins (zai pits) drastically increased the OR of meeting the yield threshold to 421.75 compared to 1.67 in the control.

For yield amounts, there was also no evidence for interactions between CA practices. Taken alone, reduced tillage increased yields from 561.85 to 1273.52 kg ha^{-1} (+126.67%). Diversification also increased yields from 561.85 to 745.53 kg ha^{-1}. Adding other practices did not improve the model and the effect of reduced tillage remained significant with a yield increase of 123.95% from 599.73 kg ha^{-1} (control) to 1343.10 kg ha^{-1}.

3.2. Malawi case

3.2.1. Rainfall

Meteorological data from the Ntaja rainfall station indicate that in 2015 there were single day rainfall events on 1st October (30.1 mm), 3rd November (27.6 mm), and 29th November (11.8 mm). Dry conditions continued until the 18th–25th December (61.5 mm) and returned until 12th–18th January 2016 when 165 mm of rain fell. Farmers reported replanting three times during this period due to false onsets. It was not until mid-January that the onset of more consistent rainfall came (figure 2(bottom)).

3.2.2. Practices

Crop diversification occurs mainly through intercropping and ground cover through mulching (table 1). Due to large adoption of ground cover, there are little data on reduced tillage only and reduced tillage in combination with crop diversification. There were positive correlations higher than 50% between hand ploughing and hoe weeding, hand weeding and mulching, mulching and zero tillage, whereas there were negative correlations between hoe weeding and zero tillage, hand ploughing and mulching, hand ploughing and zero tillage.

3.2.3. Maize yields

Of the 346 farmed plots, 19 were removed from analysis due to insufficient data. Of the remaining 327 plots, 50 had complete harvest failure in 2015/16. In plots where harvest was attained (277 plots), 54 (19.5%) met the threshold for maize yield. When excluding failed harvests, mean yield was 463.81 ± 560.74 (SD) kg/ha. The median yield was 247.1 kg ha^{-1}.

3.2.4. Effect of practices on maize yields

For 2015/16, the OR was 0.12 for meeting the maize yield threshold for control farmers (table 2). Adding ground cover increased the OR to 0.475. Considering additional practices shows that banking reduces the OR to 0.054 while ground cover still increases the OR of meeting the yield threshold to 0.551 compared to 0.19 in the control.

Regarding yield amounts, reduced tillage increased yield from 247 kg ha^{-1} (control) to 505 kg ha^{-1} (+111.2%) and ground cover increased yield to 432 kg ha^{-1} (+70.2%).

Adding other practices to assess their yield effect showed that fertilizer use increased yield from 245 kg ha^{-1} (control) to 326 kg ha^{-1} (+33.1%), but banking reduced yields to 153 kg ha^{-1} (−37.6%). In this model, reduced tillage increased yield to 391 kg ha^{-1} (+59.5%) and ground cover increased yield to 351 kg ha^{-1} (+43.3%).

4. Discussion

These results demonstrate that several techniques associated with CA made a significant difference to maize yields under both dry and wet rainfall conditions. Under below average rainfall conditions in Malawi (2015/16), ground cover increased the chance to meet minimal yield thresholds and increased resilience. Reduced tillage increased yields by 250 kg ha^{-1} on average.

Under the above-average rainfall conditions in Kenya in 2015, we did not observe the negative effect of reduced tillage techniques on yields found in other cases (Hussain *et al* 1999). Instead, reduced tillage led to an average yield increase of 700 kg ha^{-1}. The observation that the use of planting basins ('zai pits') also increased the chance to reach yield thresholds suggests that they can have a protective effect even under above-average rainfall conditions. This might be due to the sandy soils that dominate in the Makueni region (Saiz *et al* 2016). The rainfall total of 386 mm and the higher yields in OND 2015 compared with 2014 also suggest that the El Niño conditions in 2015 were beneficial for maize cultivation and did not correspond to excessive rainfall.

Despite positive effects of some techniques on yields, we found no significant effects of the interactions between the three CA pillars in both sites. This will be due to the relative recent CA adoption in the area (Rusinamhodzi *et al* 2011), or it could be linked with the small number of farmers who adopted full CA. The observation that some techniques can increase yields even individually is encouraging for farmers who struggle to adopt the full CA package. For example, in Kenya, land availability allows crop rotation involving maize and legumes, which increases the chance to meet food security thresholds under dry conditions and increases yields in wetter conditions. The fact that legumes are planted by ploughing hampers middle and long-term effects of reduced tillage on maize. The lack of benefits of crop diversification in Malawi results from the widespread use of intercropping rather than crop rotation, due to small landholdings (Ngwira *et al* 2012).

Our results highlight the importance of considering CA practices in interaction with techniques that are usually not included in the three-pillar framing. For example, soil fertility management appears crucial, as the beneficial role of fertilizer use in the 2014 Kenya case and the 2015 Malawi case shows. Vanlauwe *et al* (2014) have suggested including fertilizer use as a 'fourth principle' of CA. Our findings also show that, other technical factors such as weed management play a key role, as the benefits of herbicide use suggest.

Besides the complex interaction between CA pillars and related techniques, observing CA performance on actual farm contexts brings further challenges. One is the difficulty in finding a diverse and balanced adoption of different practices to allow comparison. For example in Kenya, the use of mulching and cover crops was limited due to the fact that maize stalks are traditionally used as fodder. Though cover crops achieved a higher adoption rate, it remains relatively marginal. In Malawi, mulching was more widespread and led to benefits. The use of ground cover is favoured by small landholdings (Grabowski and Kerr 2014) but discouraged in mixed crop-livestock systems (Jaleta *et al* 2013). Intercropping appears a solution to solve this trade-off (Ngwira *et al* 2012) but is dependent on markets for seed input and sale of intercropped produce. These considerations show that multi-scale dynamics, such as local resource and labour availability, markets and agricultural development policies strongly and selectively influence the adoption of CA pillars and related practices (Corbeels *et al* 2014). Although there is intense debate as to whether the lack of application of all principles can still be termed CA, it is evident that these practices can be beneficial in isolation and yield benefits can be enhanced by their interactions under both below and above-average rainfall conditions.

5. Conclusion

This study provides empirical evidence from wet and dry years across sub-Saharan Africa to demonstrate on-farm benefits of individual CA practices. This provides important information on how the nature of CA adoption across different practices in a real-world farm situation can provide similar yield and climate resilience benefits to those observed across controlled field trial studies. We show that adoption of individual practices can be beneficial in some cases. Greater adoption of alternative methods of cultivation can have significant impacts not only on increasing resilience within rural households but also on improving soil quality. This illustrates that agricultural interventions are not 'one size fits all' and should adapt to consider agro-ecological and social conditions, encouraging flexibility in adoption guidelines. It remains necessary to examine more carefully the adoption rates and effects of specific agricultural techniques related with CA that go beyond reduced tillage and the standard three-pillar package.

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Data availability statement

The data that support the findings of this study are available from the corresponding author upon request. The data are not publicly available for ethical reasons.

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