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Use of Integrated Soil Fertility Management Technologies in Malawi: Impact of Dry Spells Exposure

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1. Introduction

Droughts in many parts of sub-Saharan Africa (SSA) are frequent and severe with devastating impacts especially on agriculture and food security (Benson and Clay, 1998). One way to identify a drought is when average seasonal rainfall is below 75% of the normal. In addition, dry spells within a rainfall season turn into a drought if they last for more than three months (Chabvungma et al., 2015). Coupled with poor soil fertility and poor water retention capacity of the soils, 60% of SSA is vulnerable and 30% extremely vulnerable to drought (Benson and Clay, 1998). For the past four decades, SSA countries have faced a risk of failed cropping season with 10–40% probability due to drought. In the mid-1980s for example, drought resulted in the worst famine in Africa, affecting 20 countries and endangering the lives of 35 million people. The most affected regions were eastern and southern Africa, particularly the countries of Ethiopia, Kenya, Malawi, Mozambique and Zimbabwe (Shiferaw et al., 2014).

In Malawi, a country heavily dependent on rain-fed agriculture (Government of Malawi, 2011b), frequent and prolonged dry spells and low levels of nitrogen use are major causes of low crop productivity resulting in persistent food insecurity (Weber et al., 2012). Another problem faced by Malawi's agricultural sector is over-dependence on maize as a staple crop (Smale, 1995). Maize production is highly vulnerable to drought; maize productivity can be reduced by up to half when a severe drought occurs, especially during grain filling phase (CIMMYT, 2013). Over the past two decades, Malawi's maize production has been significantly low in drought years such as 1991/92, 2001/02 and 2004/05 (Denning et al., 2009; Msowoya et al., 2016; Nangoma, 2007).

Efforts to enhance maize productivity through increased drought resilience, nutrient application and nutrient maintenance are thus important to achieve sustainable food security. Such efforts require complementary investments in organic and inorganic integrated soil fertility management (ISFM) technologies and high yielding and drought tolerant crop varieties. ISFM technologies increase nutrient intake, protect the soils against degradation and minimize nutrient depletion through enhanced soil organic matter and biological activity (Vanlauwe et al., 2015; Weidmann and Kilcher, 2011). ISFM ensures nutrient balance and efficient management of soil fertility through combinations of inorganic fertilizer, organic resources, soil and water conservation technologies and crop diversification. Over time, ISFM technologies increase crop yields and yield stability.

In this paper, we use a four-wave panel dataset for Central and Southern Malawi to examine use and use intensity of two ISFM technologies – organic manure and maize-legume intercropping – and how exposure to dry spells influences their use. Organic manure and maize-legume intercropping are not new technologies to Malawian smallholders, and our longitudinal data enable an improved understanding of how the technologies have been used for a period of close to 10 years. We examine the degree to which farmers' use of organic manure and maize-legume intercropping is associated with previous experiences of dry spells, holding constant other key factors. This issue has been largely unexplored in the literature. It is reported that conservation agriculture practices can minimize the drought sensitivity of crop yields in "normal" rainfall years (Kilcher, 2007; Makate et al., 2017a; Makate et al., 2017b; Muzari et al., 2012) but may also reduce crop yield in years of high or low rainfall (Corbeels et al., 2014).

Previous research in Malawi suggests that use of organic manure increases with inorganic fertilizer use and fertilizer price (Holden and Lunduka, 2012), tenure security (Kassie et al., 2015), knowledge of manure making (Kilcher, 2007; Mustafa-Msukwa et al., 2011) and household labor availability (Chatsika, 2016; Mustafa-Msukwa et al., 2011; Snapp et al., 2002). The probability of using maize-legume intercropping has been shown to be limited by the yield advantage of maize over legumes, pest susceptibility, and a lack of appropriate legume genotypes (Kerr et al., 2007; Ortega et al., 2016). Other factors shown to influence maize-legume intercropping are market access, output prices, availability and cost of improved legume seeds, farm size and exposure to weather shocks (Asfaw et al., 2014; Kassie et al., 2015; Kerr et al., 2007; Kilcher, 2007; Ortega et al., 2016). Silberg et al. (2017) also reported that use of maize-legume intercropping increases with previous sales of legumes and noted that technologies such as organic manure and inorganic fertilizer are likely to be applied on plots where intercropping is practiced.

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We test two related hypotheses in this paper: one, exposure to early-season and late-season dry spells increases the likelihood of using organic manure; two, exposure to early-season and late-season dry spells increases the likelihood of using maize-legume intercropping. We combine household panel survey data from 2006 to 2015 and daily rainfall data from 2003 to 2015 from the Malawi's Department of Climate Change and Meteorological Services (DCCMS). We use the daily rainfall data from DCCMS to generate dry spell and rainfall distribution variables. While farmers' perception/memory of recent dry spells is an option to capture a dry spell exposure variable, this perception variable may be subjective (Duinen et al., 2015) and therefore biased. As such, we construct objective dry spell variables using daily rainfall data to minimize biased estimates. On the other hand, farmers' perceptions regarding the drought conditions on their own farm may be more accurate and take into account local heterogeneity in weather and soil conditions. Indeed, Holden and Quiggin (2017) failed to find evidence of endogeneity of farmer perception variables using data from 2012 for the sample of farmers studied herein. As such, we have estimated additional models controlling for farmer perceptions of dry spell, using data that excludes the year 2006 because of data unavailability.

In this study, dry spells are measured as the number of consecutive days (at least five) with a total precipitation below 20 mm after the onset of the rainy season.[1] We then identified the longest early-season and late-season dry spell in each of the previous three seasons of a survey year and these are the dry spell variables included in the regression analysis. Dry spells are common during Malawi's rainfall season and local meteorologists consider a dry spell as drought if their duration is three-to-four months or longer (Chabvungma et al., 2015).

Severity of dry spells has been increasing in Malawi and other parts of SSA in recent years and the use of drought-resilient technologies can help farmers adapt. For example, estimates from EM-DAT (2018) show that in 2005 the country experienced a drought that was described by local meteorologists as one of the worst in 60 years (Chabvunguma and Munthali, 2008). Approximately 30% of the country's population (over 4 million people) was affected by a subsequent hunger crisis and needed emergency food aid (Denning et al., 2009). There were also reported extensive droughts in 2008 and 2012 that affected many people. In 2015, the country reported early-season floods and late-season droughts. The early-season floods affected approximately 1.1 million people, 230,000 were displaced, and 176 and 172 people were reportedly killed and missing, respectively (Government of Malawi, 2015). The late-season drought was responsible for the poor maize harvest in 2015, estimated at 25–30% lower than the previous five-year average (FEWS NET, 2015).

2. Background

2.1. Major Weather Patterns in Malawi

Malawi has a sub-tropical climate with three major seasons. First is a cool, dry winter season between May and August before a hot, dry season from September to October. The hot, dry season is followed by the warm-wet season from November to April during which about 95% of the annual rainfall takes place. On average, the country receives 725 mm to 2500 mm of rainfall (DCCMS, 2006). Climate variability is high and weather extremes such as droughts, mid-season dry spells and floods represent severe threats to livelihoods (Chabvungma et al., 2015). The severity has increased in recent times because of climate change, population growth, urbanization and environmental degradation (FAO, 2012). Focusing on the nine-year period of our surveys, we show in Fig. 1 the average annual rainfall and maize production across the country. Annual rainfall was lowest in 2015 with an average of 918 mm while the highest was reported in 2008. It is, however, surprising that the higher rainfall in 2008 resulted in low maize production which was 19.4% less than the previous season (2007) (Government of Malawi, 2009).

2.2. Organic Manure

Organic manure is an organic matter-based technology (Snapp et al., 1998) whose sources include farm yard manure, compost manure, green manure, crop residues and household refuse (Chilimba et al., 2005; Government of Malawi, 2012; Holden and Lunduka, 2012; Kabuli and Phiri, 2006; Snapp et al., 1998). The advantage of this technology is that it enhances soil organic matter and essential nutrients such as nitrogen (N), phosphorus (P) and potassium (K) (NPK) (Mafongoya et al., 2006; Thierfelder et al., 2015a, 2015b). The technology also increases nutrient and water use efficiency, nutrient maintenance and soil pH (Heerink, 2005; Mafongoya et al., 2006; Nyasimi et al., 2017).

Organic manure is not a new technology to smallholder farmers in Malawi (Andersson and D'Souza, 2014). In fact, organic matter-based technologies can be traced back to indigenous knowledge as early as the 1970s (Mango et al., 2017). In the early 2000s, the government embarked on a campaign to promote the use of compost manure, farmyard manure and crop residues (Chilimba et al., 2005). At the national level, only 15.2% of maize plots used organic manure in 2002/03 and 2003/04 and 12.7% in 2008/09 and 2009/10 (Snapp et al., 2014).

There are several challenges to widespread use of organic manure. The first challenge is unguaranteed and unbalanced quality of nutrients. Different organic sources contain different quantities of nutrients with varying ranges (Chilimba et al., 2005; Mafongoya et al., 2006). Another reason for low use of organic manure in Malawi is that few households have livestock. As a result, available amounts of organic manure are often insufficient to meet nitrogen and other nutrient requirements for maize production (Mafongoya et al., 2006). The third challenge is the high labor requirement for making and transporting organic manure. Household labor availability may thus constrain adoption. Furthermore, because organic manure technology may be slow in releasing nutrients and it takes time to build soil nitrogen, crop yield response takes time to materialize (Snapp et al., 1998). A final challenge is there are trade-offs between using crop residues and household refuse for soil cover (mulching) versus using it for animal fodder or incorporating it as manure in the soil for more quick release of nutrients (Valbuena et al., 2012).

2.3. Maize-legume Intercropping

Maize-legume intercropping is a farming practice in which the maize crop is mixed with one or more leguminous crops. This technology can improve crop productivity and enhance the sustainability of maize-based cropping systems (Snapp et al., 2002). Empirical evidence has shown that these systems increase soil productivity through biological nitrogen fixation and conservation of soil nutrients (Government of Malawi, 2012; Snapp et al., 1998). Apart from the agronomic benefits, legume intercropping provides environmental benefits through reduced soil erosion, improved water infiltration and carbon sequestration; it also increases crop and food diversity by providing high protein grain and edible leaves (e.g. beans and cowpea leaves). All these benefits are achieved at a low cost and low risk for the farmer (Government of Malawi, 2012; Kamanga et al., 2010; Kerr et al., 2007; Woomer et al., 2004). In Malawi, the most common legumes that have been intercropped with maize are beans in the Central Region and pigeon peas in the Southern Region (Waddington, 1990; Waldman et al., 2017).

Maize-legume intercropping, like organic manure, is also an old technology among smallholder farmers not only in Malawi but also in Africa as a whole (Okigbo and Greenland (1976) in Silberg et al., 2017).

[1] Personal communication (February 18, 2016) with Charles L. Vanya (Principal Meteorologist with DCCMS)

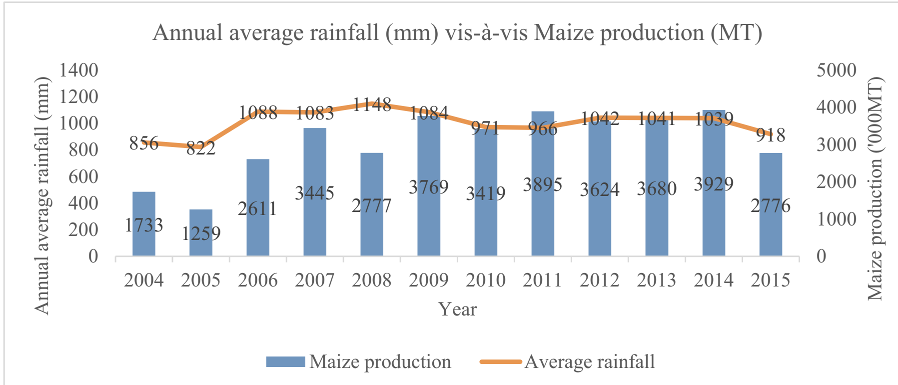

Fig. 1. Maize production and rainfall over time.
Source: Ministry of Agriculture, Irrigation and Water Development (production data) and DCCMS (rainfall data).

In Malawi, Heisey and Smale (1995) reported that maize-legume intercropping was common until the late 1960s, but since that time there has been a decline in use of this technology for reasons we describe below.

One, government's policies that encourage sole cropping. The 1965 Land Act, for example, promoted production of cash crops, mainly tobacco. The result was an increase in tobacco production and a decline in food production (Kydd and Christiansen, 1982). To enhance food production the government offered higher prices for maize (Silberg et al., 2017). Coupled with minimal effort from the government to promote intercropping, the higher maize price policy resulted in increased maize monocropping. The farm input subsidy is another policy strategy that encouraged monocropping of maize and minimal diversification (Chibwana et al., 2012; Harrigan, 2008). Recently, however the program has enhanced access to both maize and legume seeds and this may increase maize-legume intercropping. Chinsinga and Poulton (2014), however, noted that access to legume seeds is relatively poor and the government has not done enough to promote intercropping.

Other problems limiting intercropping are scarcity of factors (especially labor), delayed returns, high opportunity cost and inadequate extension support (Silberg et al., 2017). Sometimes returns to intercropping may take two or more seasons to materialize, and farmers who rely on immediate gains from the technology are likely to dis-adopt the technology after one or two seasons. Kassie et al. (2013) noted that limited funding to agricultural extension services is another challenge that may constrain adoption of intercropping. Limited market access and low and variable legume prices are other factors affecting use of maize-legume intercropping (Ortega et al., 2016; Silberg et al., 2017).

3. Methodology

3.1. Conceptual Framework

This section develops a conceptual model of household agricultural production decisions under the combined effects of weather risk and low soil fertility. Farmers make input decisions before weather conditions are revealed and determine production outcomes, which subsequently form the basis for consumption decisions in the current year and next year's input decisions. Production decisions are made as a first step to maximize weighted probability utility of returns in different states of nature (Holden and Quiggin, 2017). Given low crop productivity due to low soil fertility and erratic rains and assuming risk aversion, farmers would be interested to choose a mix of drought-resilient and soil nutrient enhancing technologies to enhance production. Such inputs in our case include inorganic fertilizer (F), organic manure (M), maize-legume intercropping (I), and other inputs (X). Let the production function be specified as

$$Y = Y[N(F, M, I), X, \varepsilon], \tag{1}$$

where N represents soil nutrients from inorganic fertilizer, organic manure, and maize-legume intercropping, while ε is climate risk and has a distribution function of G(.), which outcome is not known to the farmer at planting time (Ding et al., 2009; Koundouri et al., 2006).

This model has several interesting features. First, we assume that farmers are rational and will use a given technology based on their perception that it is yield enhancing.[2] In our case, farmers will be motivated to apply organic manure and/or maize-legume intercropping because they expect maize production to be higher on plots with the technologies than plots without the technologies. These two technologies enhance organic matter and nutrient content in the soil and promote nutrient retention which is essential for maize production (Government of Malawi, 2012; Heerink, 2005; Mafongoya et al., 2006; Snapp et al., 1998). There are, however, possible tradeoffs between technologies with immediate production gains and those with long-term but delayed production benefits. Farmers often chose technologies with immediate production gains over those with delayed production effects (Corbeels et al., 2014). This suggests that the farmers' adoption decisions are reversible after one or more seasons and the likelihood of this can be high for technologies with delayed benefits.

Second, farmers are faced with recurring dry spells. A severe drought can reduce maize yields by as much as half of its average (CIMMYT, 2013). Production under drought will therefore benefit from drought-tolerant technologies. Empirical evidence has shown that conservation technologies have potential to reduce the negative impact of drought on crop yields by enhancing soil and moisture conservation (Kilcher, 2007; Makate et al., 2017a; Makate et al., 2017b; Muzari et al., 2012). Organic manure and maize-legume intercropping are potentially drought-tolerant because they enhance rainwater infiltration and water retention capacity. We therefore expect that maize production under drought conditions would be higher for adopters of organic manure and/or maize-legume intercropping. Assuming farmers observe this high maize production under drought for plots with organic manure and/or maize-legume intercropping vis-à-vis plots without, use of these technologies would increase in the ensuing years.

Organic manure and maize-legume intercropping may take more than two-three seasons to build soil organic matter (Silberg et al., 2017; Snapp et al., 1998), which is essential for moisture retention. This may then result in dis-adoption of the technologies after one or two seasons of use. In addition, Corbeels et al. (2014) observed that in some sites adoption of conservation agriculture technologies may result in low yields during high rainfall or during low rainfall. This may also affect use and use intensity over time. We leave for a future study the

[2] Alternatively, the technology may be cost-saving, for example because it is labor-saving.

empirical analysis of the impact of using these technologies on crop yield.

In this paper, we are interested in testing the hypothesis that farmers respond to previous exposure to dry spells by using maize-legume intercropping and organic manure. This builds on the assumptions that these technologies reduce the damages from dry spells and that farmers who test or use the technologies and are exposed to such dry spells are likely to discover this benefit. Given that our data is in three-year intervals, we construct dry spell variables lagged three years. These variables are likely to influence farmers' beliefs about the likelihood of different states of nature as well as the likely outcomes for alternative technologies they have already used under different states of nature. We take into account the possibility that risk preferences and behavior of farmers could be related to their level of wealth. We therefore control for wealth by including proxies such as the value of assets and tropical livestock units (TLU).

We are particularly interested in dry seasons that occur early and late in the rainy season. Early-season dry spells may affect the germination rate of maize, and a technology that retains water and improves germination rate under water stress would be appealing to farmers. On the other hand, late-season dry spells affect grain filling, a critical growth stage when maize needs enough water. As discussed, organic manure and maize-legume intercropping enhance water retention at this critical stage of maize production. We therefore expect a positive impact of early-season and late-season dry spells on use and use intensity of organic manure and maize-legume intercropping.

Third, the farmers' decision to use a given technology will not only be affected by production factors but also by consumption preferences. For example, edible legumes are likely to be intercropped with maize (Kerr et al., 2007) for consumption purposes especially due to market failure. Valbuena et al. (2012) also observed trade-offs for crop residues and household refuse for different options such as animal feed and making organic manure. The opportunity cost of organic manure use may affect its use by farmers. We control for consumption preferences by including in the model the distance to agricultural markets and legume price variables, while the opportunity cost is controlled for by the inclusion of the TLU variable.

3.2. Model Specification and Estimation Strategy

Based on the conceptual model presented in Section 3.1, we model the farmer's decision to use organic manure and/or maize-legume intercropping first as a binary decision. Farmers will have to decide either to apply organic manure or not. Similarly, they will have to decide either to intercrop or not. Having modelled the binary use decision, we then model the intensity of use decision. We decompose these use decisions as follows:

$$C_{it} = \beta_0 + \beta_1 W_{dt} + \beta_2 S_{it}^{f} + \beta_3 D_{it} + \beta_4 F_{it} + \beta_5 P_{it}^{f} + \beta_6 P_{dt}^{y} + \beta_7 R_{it} + \beta_8 H_{it} + \beta_9 T_t + \alpha_i + \varepsilon_{it} \tag{2}$$

where C_{it} is the dependent variable and represents different values for use and intensity of use. In use estimation, C_{it} is a dummy, equal to one if household i used organic manure (maize-legume intercropping) in year t, and equal to zero otherwise. For intensity of organic manure use, C_{it} is measured as quantity of organic manure applied in kilograms per hectare (kg/ha) and is log transformed. For maize-legume intercropping, use intensity, C_{it}, is defined as the share of total household cultivated land that is intercropped and varies between zero and one [0,1].

W_{dt} is a vector of previous early-season and late-season dry spells (one-to-three-year lags) measured as longest number of days. These are the key variables in our model. $\widehat{\beta}_1$ is a vector of coefficients of interest testing the main study hypotheses that previous exposure to dry spells promotes the use of organic manure and/or maize-legume intercropping. We have also controlled for farmers' perceptions of recent droughts in separate models that exclude 2006 data due to data unavailability in that year.

Presently there are many public and private sector efforts in Malawi promoting use of both organic and inorganic fertilizer technologies. The Government of Malawi (GoM) has been promoting the use of inorganic fertilizer through the Farm Input Subsidy Program (FISP). Through its Agricultural Sector Wide Approach (ASWAp) it has been promoting sustainable land management (SLM) practices that build soil fertility, prevent soil erosion, and conserve rain water, including organic manure and maize-legume intercropping (Government of Malawi, 2011a). To control for government interventions in the study areas we have only included a FISP (S_{it}^{f}) variable (receipt of fertilizer subsidy coupon) due to data limitations. Non-governmental organizations (NGOs) have also been actively involved in promoting use of conservation technologies. However, due to data limitations, we do not directly control for NGO interventions. We rely on time-invariant controls to partly control for time-invariant government and NGO interventions.

In Eq. (2), D_{it} is distance to agricultural markets, a proxy for access to farm inputs. F_{it} is (log of) fertilizer used (kg/ha) by household i at time t, which we assume positively influences use of organic manure as reported by Holden and Lunduka (2012). We also control for input and output prices by including the commercial fertilizer[3] real price (NPK and Urea) (P_{it}^{f}) and annual average real maize and legume grain prices[4] in district d at time t (P_{dt}^{y}). We expect the fertilizer price to directly or indirectly affect use of organic manure and maize-legume intercropping. The higher fertilizer price reduces demand for inorganic fertilizer and this may indirectly increase or reduce use of ISFM technologies depending on whether the technologies are complements or substitutes.

R_{it} is a dummy variable for the Southern region. Household characteristics that affect use of organic manure and maize-legume intercropping are represented by vector H_{it}. These variables include (log of) farm size (ha), distance to the farm (km), (log of) male and female labor (adult equivalent/ha), (log of) off-farm labor (adult equivalent/ha), (log of) livestock endowment (tropical livestock units), (log of) the values of asset holdings in Malawi Kwacha (MK), sex of the household head (1 = female), education of the household head (years) and age of the household head (years). T_t are year dummies (2006 is the reference) which control for price variation across years, α_i captures individual time-invariant effects, while ε_{it} is the error term.

The parameters in Eq. (2) are estimated using the correlated random effects (CRE) models as proposed by Mundlak (1978) and Chamberlain (1984). In this approach we include means of time-varying farm household characteristics. The CRE is chosen over other approaches in order to control for unobserved heterogeneity. The approach allows unobserved heterogeneity to be correlated with observed covariates and sample selection (Wooldridge, 2010a). While household fixed effects (FE) could be another option, the incidental parameters problem associated with this approach (Wooldridge, 2009; Wooldridge, 2010a) makes CRE our preferred option. The CRE model avoids the incidental parameters problem in non-linear models, identifies average partial effects (not just parameters), can be combined with the related control function (CF) approach for nonlinear models with heterogeneity and endogeneity and can be extended to unbalanced panels. The CRE method was used by Holden and Lunduka (2012) in Malawi and Arslan et al. (2014) in Zambia.

We model the binary (zero/one) decisions to use organic manure and use maize-legume intercropping, using a probit estimator (Wooldridge, 2010b), while the decision on the quantity of organic manure to apply is modelled using a tobit estimator to account for those who do not use the technology (Tobin, 1958). We model the area share under intercropping using a fractional probit estimator to constrain the

[3] Fertilizer price includes both commercial and subsidized fertilizer and is at farm household level. On the other hand, output price is at farmer district level.

[4] Data on annual average output prices is from the Ministry of Agriculture, Irrigation and Water Development.

predicted value between zero and one (Wooldridge, 2011).

The two technologies, organic manure and maize-legume intercropping, though independent equations could have correlated errors. The technologies have greater benefits when adopted together on the same parcel or plot. This suggests that estimating the equations jointly could increase efficiency of the results. However, since we use only household level data in this paper, we are not be able to assess whether the household uses the two technologies on the same plot or on different plots. As a robustness check, we apply the conditional mixed process (CMP) procedure proposed by Roodman (2011) that allows estimating the equations jointly, using a systems approach. This procedure uses Zellner's Seemingly Unrelated Regression (SUR) (Zellner, 1962) concept. The CMP also allows testing for cross-equation constraints and we present the test results in Table 6.

3.3. Attrition, Sample Selection, and Endogeneity

A common problem in longitudinal data is attrition, which is the loss of sample members between the first and subsequent waves of data collection (Fitzgerald et al., 1998; Wooldridge, 2010b). We first conducted a simple probit test to assess whether attrition was random and therefore ignorable. Separate tests were conducted for organic manure and maize-legume intercropping outcome variables. We found a chi-square of 118.68 and 127.74 in organic manure and maize-legume intercropping outcome variables, respectively, with a very high p-value (0.0000) in both cases. We therefore rejected the null hypothesis that attrition was random.

Fortunately, as noted by Fitzgerald et al. (1998), unbiased estimation is possible even when attrition is high, provided that the proper adjustments are made. In this study, attrition bias is partly addressed by controlling for time-constant unobservable factors that affect attrition by using the CRE models – an alternative to household fixed-effects (FE). The approach however does not control for the systematic differences between those who attrite and those who remain in the sample. The second option proposed by Fitzgerald et al. (1998) and Wooldridge (2010b) is controlling for attrition bias due to observables by using an inverse probability weights (IPW) approach. IPW is however not available in non-linear models used in this paper – CRE models.

Attrition is not the only problem faced in the empirical modelling. The models could also suffer from endogeneity, which makes identification of causal effect difficult because of biased estimates. The possible causes of endogeneity in our setting include self-selection of farmers in using inorganic fertilizer, reverse causality and unobserved heterogeneity. Reverse causality arises when the dependent variable is a causal factor of an explanatory variable of interest. For example, the intensity of using maize-legume intercropping could be a function of farm size and at the same time could influence the operational farm size. The problem of unobserved heterogeneity may cause omitted variable bias. While we address the problem of unobserved heterogeneity by using the CRE procedure, self-selection and reverse causality may still result in biased estimates.

To control for endogeneity bias of fertilizer use intensity in both organic manure and maize-legume intercropping models and of farm size in intercropping models, we propose a two-step control function (CF) approach (Petrin and Train, 2010; Wooldridge, 2011). An alternative is an instrumental variable (IV) approach (Wooldridge, 2010b). We first apply the Durbin-Wu-Hausman's test of endogeneity suggested by Hausman's (1978) before applying the CF approach. In this procedure, we estimate the reduced form equations with the potential endogenous variables and compute residuals. The residuals are included in the structural equations with organic manure and maize-legume intercropping and we observe their significance. If the residuals are significant at 10% level of significance or lower, then we reject exogeneity of the potential endogenous variables and hence the CF approach should be used.

3.4. Data and Study Areas

We use four waves of panel data collected through household surveys conducted in 2006, 2009, 2012 and 2015 in six districts in Central and Southern Malawi. The districts are Kasungu and Lilongwe in Central Region; Chiradzulu, Machinga, Thyolo and Zomba from Southern Region. These districts are agro-ecologically at different elevation zones and receive different amounts of rainfall. Zomba for example is drought prone (World Bank, 2010) while Thyolo lies in the high plateau and hilly areas receiving over 1200 mm annual rainfall. The rest of the districts lie in the medium altitude zone and enjoy high average rainfall ranging from 800 to 1200 mm annually (Bunda College, 2008).

The initial sampling of the households in 2006 used a multistage sampling approach following the 2004 Integrated Household Survey Two (IHS2) (Lunduka, 2009). The first stage was purposive sampling of the six districts with the primary goal of capturing dynamics in land issues. The second stage was simple random sampling of enumeration areas (EAs) where two were randomly sampled in Thyolo, Chiradzulu and Machinga districts, while three were sampled in Zomba, Kasungu and Lilongwe. Third, from each EA, 30 households were randomly sampled giving a total of 450 respondents. Of these 450 households, 378 were resurveyed in 2009, and 350 in 2012 and 2015, resulting in four rounds of unbalanced panel data (Table 1).

One drawback is that our sample size is small and may not be representative at the national level (Lunduka et al., 2013). However, Chibwana et al. (2012) observed that rural households in Malawi share similar characteristics such that our sample may provide important insights with respect to uptake of organic manure and maize-legume intercropping. Furthermore, our sample covers Central and Southern regions of Malawi where 89% of the population lives. The Southern region, where four of our six districts are located, has the highest population share, smallest farm sizes, and lowest rainfall among the three regions of the country.

Our dataset has some important advantages. One, we have a long panel of four waves, which is rare in most large surveys. An exception is the nationally representative IHS data, which also has four waves. Two, we have detailed farm level information where plots were measured with a Global Positioning System (GPS) device with minimal area measurement errors. Unlike the IHS data, where initial rounds did not measure all household plots, in our data all household plots were measured using GPS in all the four waves. Area measurement error has been found to be a substantial problem leading to biased estimates of areas and area productivity in farm surveys in SSA, including in Malawi (Carletto et al., 2015; Holden and Fisher, 2013). Above all, the districts in our study capture spatial and intertemporal variability in rainfall distribution and vulnerability to dry spells as discussed in paragraph one of this section. The data also capture land dynamics (Lunduka, 2009) where households in Southern Region districts have small land holdings (Matchaya, 2007; Tchale, 2009) and are therefore likely to

Table 1
Study areas.

District	Sample size					Technology use		FISP
	2006	2009	2012	2015	Total	Organic manure	Intercropping	
Thyolo	62	51	47	47	207	0.53	0.60	0.78
Zomba	86	84	76	79	325	0.39	0.65	0.64
Chiradzulu	53	35	36	34	158	0.65	0.86	0.64
Machinga	51	49	47	45	192	0.41	0.51	0.49
Kasungu	102	88	83	81	354	0.43	0.35	0.45
Lilongwe	96	71	61	64	292	0.40	0.24	0.44
Total	450	378	350	350	1528	0.45	0.50	0.55

Figures on organic manure, intercropping and FISP are based on balanced data with 314 households for each panel.

Table 2
Use of organic manure and maize-legume intercropping.

Year	Mean	Applied manure (1 = yes)		Manure quantity (kg/ha)		Intercropping (1 = yes)		Farm size share-Intercropping	
2006	Mean	0.30		4582.37		0.29		0.25	
	[Conf. interval]	0.25	0.35	3060.17	6104.57	0.24	0.34	0.21	0.30
2009	Mean	0.44		5186.08		0.44		0.23	
	[Conf. interval]	0.39	0.50	2522.18	7849.99	0.38	0.49	0.19	0.27
2012	Mean	0.50		4545.71		0.52		0.33	
	[Conf. interval]	0.45	0.56	2059.80	7031.61	0.46	0.57	0.28	0.37
2015	Mean	0.54		6827.96		0.75		0.43	
	[Conf. interval]	0.49	0.60	3729.65	9926.27	0.70	0.80	0.39	0.47

These figures are based on balanced data with 314 households for each panel.

intensify use of land-saving technologies such as maize-legume intercropping compared to households in Central Region districts.

The districts exhibit different patterns of use of organic manure and maize-legume intercropping as reported in Table 1. These figures are indicative and we use only the balanced data. Maize-legume intercropping is dominant in the Southern Region districts with our Chiradzulu sample having a use rate of 85% compared to 24% in Lilongwe in Central Region. Some of these areas have had active promotion of intercropping technologies by agricultural extension and development projects (Waldman et al., 2017) hence high use rates. Additionally, the share of households with access to fertilizer subsidies from the Farm Input Subsidy Program is high in the Southern Region districts with the highest reported in Thyolo (78%) while Kasungu in the Central Region is the lowest with 44%. The level of FISP may have an implication on use of both organic manure and maize-legume intercropping. The FISP package contains maize seed and from 2007/08 also legume seed of which better access to both can encourage farmers to increase intercropping, while good access to inorganic fertilizer may affect organic manure and maize-legume intercropping use through complementarity or substitution effects. Holden and Lunduka (2012) reported a complementary relationship between fertilizer subsidy receipt and organic manure in Malawi, while Alabi et al. (2016) observed a crowding-out effect of fertilizer subsidy receipt on organic manure in Nigeria.

A semi-structured questionnaire was used to collect data on household and plot level characteristics but our primary unit of analysis in this paper is the farm household. The household panel data were merged with daily rainfall data from the Department of Climate Change and Meteorological Services from 2003 to 2015. We collected the rainfall data from all weather stations in our survey districts. These include: Chiradzulu in Chiradzulu district; Kaluluma and Kasungu in Kasungu; Bunda, Chitedze and Kamuzu International Airport in Lilongwe; Chikwewo, Liwonde and Ntaja in Machinga, Bvumbwe and Thyolo in Thyolo and Chancellor College, Chingale and Makoka in Zomba district. We used data from the closest weather station to our sampled enumeration areas where the household data were collected in each district. These weather stations were Chiradzulu, Kasungu, Chitedze, Ntaja, Bvumbwe and Chancellor College. We merged the household and rainfall data at enumeration area level. This implies that data from one weather station were used for multiple enumeration areas in each district.

The rainfall data allowed us to generate dry spell and rainfall distribution variables. As discussed in Section 1, we defined a dry spell as the consecutive number of days (at least five) where total rainfall precipitation is below 20 mm after the onset of the rains. We identified the longest early- and late-season dry spells in each of the three previous seasons of a survey year. The early-season dry spell coincides with the planting period that is from November/December to January. We first identified the onset of the rains in each year at each weather station and constructed an early-season dry spell variable. On the other hand, the late-season dry spell coincides with the maize flowering period that is between February and early March. We used maize as a benchmark for calculations since maize is the main staple crop in Malawi and is grown by over 90% of smallholder farmers (Denning et al., 2009). Past exposure to dry spells may affect probability expectations about rains in the current season as well as the expected performance of alternative technologies based on past experiences. These expectations may then affect use and use intensity of organic manure and maize-legume intercropping if the technologies are perceived to affect the outcome of drought on crop yields. We also included rainfall distribution variables such as average rainfall (lagged three seasons (mm)) and December and February average rainfall (mm) for the survey years.

The dependent variables organic manure and maize-legume intercropping were measured differently. First, use of organic manure and maize-legume intercropping were measured as dummy variables, equal to one for households using the technology and equal to zero otherwise. Intensity of use for organic manure was measured as quantity of organic manure applied in kilograms per hectare (kg/ha) while for maize-legume intercropping use intensity was defined as the share of total cultivated land under intercropping. For organic manure, respondents were asked how much organic manure was applied on each plot they used organic manure. We used standard measures of collecting this data such as ox-carts, wheelbarrows, 50-kg and 90-kg bags, and 5-litre and 20-litre buckets. We then used the standard conversion rates to estimate the quantity of manure in kilograms applied per hectare of land.

The data indicate an increase in use of organic manure from 30% of the households in 2006 to 54% in 2015 and from 29% to 75% for maize-legume intercropping (Table 2) based on balanced panel data. For intensity, we obtained estimates for users and the data show an increase in organic manure use between 2006 (4582 kg/ha) and 2015 (6828 kg/ha), while the share of farmed area allocated to maize-legume intercropping also increased from 25% (2006) to 43% (2015).

3.5. Summary Statistics of Independent Variables By Year

Table 3 presents summary statistics (means and proportions) for the explanatory variables used in this paper for each panel round based on balanced data. The data show considerable variation over time in exposure to early- and late-season dry spells. For example, 2006 has the longest one-year lag of late-season dry spells of about 13 days on average while 2012 has the longest two-year lag of early-season dry spells of about 11 days. The three-year average annual rainfall is lowest for 2006 in our sample area and highest in 2009. For government intervention variables, we notice a decrease for fertilizer subsidy access from 73% of the households in 2012 to 54% in 2015. Number of extension visits decreased from 2.7 times in 2009 to 1.1 in 2015.

Input and output prices show that the fertilizer real price increased from 57 Malawi Kwacha (MK)/kg in 2006 to MK138/kg in 2015. For output prices, we used lagged values as indicators of household's naïve expectations. The one-year lag of maize grain real price was higher in 2009 than in 2006, lower in 2012 than in 2009, and increased between 2012 and 2015. Some of the observed price variations could be explained by policy and weather changes. The data also shows that the quantity of inorganic fertilizer applied per hectare of land increased

Table 3
Summary statistics of independent variables by year.

Variable	2006	2009	2012	2015	Total
Drought and rainfall distribution					
Longest early dry spell (1-year lag), days	7.66	6.46	5.61	4.93	6.16
Longest early dry spell (2-year lag), days	10.09	9.49	10.50	7.66	9.43
Longest early dry spell (3-year lag), days	7.68	7.77	7.71	7.73	7.72
Longest late dry spell (1-year lag), days	12.72	11.69	10.65	6.20	10.31
Longest late dry spell (2-year lag), days	9.34	6.30	7.81	10.24	8.42
Longest late dry spell (3-year lag), days	9.61	9.64	9.66	9.65	9.64
3 year average rainfall (mm)	5.49	6.03	5.80	5.80	5.78
December average rainfall (mm)	6.35	7.41	7.40	7.40	7.14
February average rainfall (mm)	5.58	6.37	6.36	6.36	6.17
Government interventions					
Number of extension visits		2.74	0.53	1.07	1.45
Fertilizer subsidy (1 = yes)	0.38	0.55	0.73	0.54	0.55
Distance to market (km)	4.35	4.36	4.20	4.25	4.29
Social networks					
Input credit access (1 = yes)		0.10	0.07	0.08	0.08
Farm organization (= yes)		0.19	0.20	0.17	0.19
Regional variables					
Southern region (1 = yes)	0.56	0.58	0.59	0.58	0.58
Inputs, input price and output prices					
Fertilizer price (MK[a]/kg)	57.26	77.54	70.37	137.73	85.72
Maize price - 1 year lag (MK[a]/Kg)	38.17	53.29	26.89	45.15	40.88
Pigeon peas price - 1 year lag (MK[a]/Kg)	102.26	73.11	119.68	138.16	108.30
Household physical and livestock assets					
Farm size (ha)	1.00	1.17	1.21	1.14	1.13
Asset value (MK[a])	3709.05	4237.10	2468.16	6418.28	4208.15
Tropical livestock unit	1.10	1.52	1.17	0.53	1.08
Fertilizer quantity (Kg/ha)	154.32	234.31	196.56	155.89	185.27
Household characteristics					
Male family labor (adult equivalent/ha)	2.83	3.64	3.60	4.13	3.55
Female family labor (adult equivalent/ha)	2.53	3.47	3.26	3.78	3.26
Off-farm labor (adult equivalent/ha)	0.14	0.20	0.35	0.25	0.24
Household head sex (1 = male)	0.21	0.22	0.23	0.37	0.25
Education of household head (years)	7.43	5.24	5.20	5.36	5.81
Household size	5.38	5.39	5.38	5.59	5.43
Age of household head (years)	42.59	45.75	50.09	50.89	47.33
Plot Characteristics					
Plot distance (m)	924.29	596.58	738.24	846.42	776.38
Sandy soil	0.34	0.21	0.22	0.20	0.24
Loam soil	0.54	0.50	0.54	0.72	0.57
Clay soil	0.12	0.29	0.24	0.08	0.18
Flat slope	0.61	0.62	0.62	0.48	0.58
Moderate slope	0.33	0.34	0.32	0.44	0.36
Steep slope	0.06	0.04	0.06	0.08	0.06
High soil fertility	0.21	0.16	0.19	0.05	0.15
Medium soil fertility	0.49	0.65	0.71	0.74	0.65
Low soil fertility	0.30	0.19	0.10	0.21	0.20

[a] Values in Malawi Kwacha (MK) are deflated with consumer price indices (CPI) using 2010 prices. The figures in this table are based on balanced data of 315 households for each panel.

between 2006 and 2009, but has been decreasing since then. This trend could reflect the scale of FISP, which has been scaled back in recent years. The combined effect of availability of fertilizer through FISP and good rains, for example, enhances output supply, which also affects output price. We expect these factors to affect farmers' investment decisions in organic manure and maize-legume intercropping directly or indirectly. The data also suggest that there has been a slight change in owned farm size from 2006 to 2015. We also report plot characteristics such as plot distance and perceived soil type, slope and soil fertility.

4. Results and Discussions

We begin by discussing the potential endogeneity problem in our estimation as mentioned in Section 3.3. The inorganic fertilizer and farm size variables may be endogenous to the outcome variables due to self-selection of users and reverse causality, respectively. We proposed applying the two-step control function (CF) approach as applied by Papke and Wooldridge (2008) and Gebreeyesus (2015) to control for endogeneity bias. As a first step, we applied a Durbin-Wu-Hausman's test of endogeneity suggested by Hausman (1978). In this test, we first estimated first-stage regressions with potential endogenous variables using a panel tobit for inorganic fertilizer and a linear probability model for farm size. We then generated residuals that were included in the structural equations for organic manure and maize-legume intercropping. The results are presented in Table A1. The results show that both residuals are insignificant in the organic manure and maize-legume intercropping equations. This implies that we cannot reject exogeneity of the inorganic fertilizer and farm size variables in our sample and suggests that the CF approach may not be necessary. We therefore estimated the organic manure and maize-legume intercropping equations excluding the residuals in the CRE framework.

Table 4 presents results for use and use intensity of organic manure, while we present results for use and use intensity of maize-legume intercropping in Table 5. We used the CRE probit for use of organic

Table 4
Use and use intensity of organic manure with CRE models.

Variable	Use of organic manure		Log manure (kg/ha)	
	CRE probit	CMP	CRE tobit	CMP
Longest early dry spell (1-year lag), days	0.032*	0.024	0.104***	0.177
	(0.02)	*(0.02)*	*(0.02)*	*(0.11)*
Longest early dry spell (2-year lag), days	−0.024	−0.020	−0.020	−0.146
	(0.02)	*(0.01)*	*(0.02)*	*(0.09)*
Longest early dry spell (3-year lag), days	0.056	0.041	0.167***	0.792**
	(0.04)	*(0.05)*	*(0.05)*	*(0.31)*
Longest late dry spell (1-year lag), days	0.029***	0.025***	0.050***	0.170***
	(0.01)	*(0.01)*	*(0.01)*	*(0.06)*
Longest late dry spell (2-year lag), days	−0.075***	−0.065***	−0.040	−0.341***
	(0.02)	*(0.02)*	*(0.03)*	*(0.13)*
Longest late dry spell (3-year lag), days	0.007	−0.004	0.138**	0.489
	(0.04)	*(0.05)*	*(0.06)*	*(0.36)*
3 year average rainfall (mm)	−0.175	−0.183*	0.147	−0.338
	(0.12)	*(0.10)*	*(0.13)*	*(0.71)*
December average rainfall (mm)	0.079	0.085*	0.090	0.008
	(0.05)	*(0.05)*	*(0.06)*	*(0.34)*
February average rainfall (mm)	−0.158***	−0.152***	−0.173***	−0.489
	(0.05)	*(0.05)*	*(0.05)*	*(0.33)*
Log-commercial fertilizer (kg/ha)	−0.002	0.003	0.006	0.102
	(0.02)	*(0.02)*	*(0.02)*	*(0.13)*
Fertilizer subsidy, dummy	0.012	0.013	0.149	−0.484
	(0.10)	*(0.09)*	*(0.11)*	*(0.63)*
Log-farm size (ha)	0.132	0.097	0.364*	0.788
	(0.19)	*(0.16)*	*(0.20)*	*(1.05)*
Southern region	0.826***	0.762***	1.292***	2.551
	(0.26)	*(0.24)*	*(0.28)*	*(1.59)*
Distance to market (km)	−0.045**	−0.042**	0.020	−0.293**
	(0.02)	*(0.02)*	*(0.02)*	*(0.14)*
Fertilizer price (Mk/kg)	0.001*	0.001**	0.000	0.006**
	(0.00)	*(0.00)*	*(0.00)*	*(0.00)*
1-year lag maize price (Mk/kg)	0.036***	0.032***	0.004	0.197***
	(0.01)	*(0.01)*	*(0.01)*	*(0.08)*
1-year lag legume price (Mk/kg)	0.002**	0.002**	0.002	0.004
	(0.00)	*(0.00)*	*(0.00)*	*(0.01)*
Log-male labor (adult equivalent/ha)	0.162	0.127	−0.542***	1.577
	(0.17)	*(0.13)*	*(0.18)*	*(1.01)*
Sex of household head (1 = female)	0.025	0.019	0.325***	−0.292
	(0.11)	*(0.09)*	*(0.12)*	*(0.60)*
2009 year dummy	−0.157	−0.165	0.723***	−1.852
	(0.25)	*(0.23)*	*(0.26)*	*(1.56)*
2012 year dummy	1.010***	0.884***	1.222***	5.478***
	(0.21)	*(0.19)*	*(0.23)*	*(1.28)*
2015 year dummy	0.675***	0.560***	2.357***	3.519***
	(0.20)	*(0.17)*	*(0.23)*	*(1.17)*
Constant	−3.160***	−2.588***	−5.856***	−26.947***
	(0.99)	*(1.00)*	*(1.18)*	*(6.75)*
Prob > chi^2	0.000	0.000	0.000	0.000
Observations	1527	1527	1527	1527

Significance levels: *10%, **5%, ***1% and we report robust standard errors in the parenthesis. Full results of this table with all control variables are reported in the appendix in Table A2.

manure and maize-legume intercropping while we used the CRE tobit and the CRE fractional probit for organic manure use intensity and farm size share under intercropping, respectively. The first two columns of the tables are results on use of the technologies while the third and fourth columns are for use intensity. The first and third columns for each table are models where equations have been estimated independently while in the second and fourth columns we report results from joint estimation of organic manure and intercropping equations in a systems approach using the CMP procedure.

In Table 6, we report the associated cross-equation correlation matrix from the CMP estimation. The correlation matrix reports negative but insignificant correlations between use intensity of organic manure and maize-legume intercropping. These results are similar with the findings of Arslan et al. (2017) who reported negative but insignificant correlations between organic fertilizer and intercropping technologies. The results suggest that we cannot reject the hypothesis that the errors from the two equations (organic manure and intercropping) are uncorrelated. While this could suggest that, the two technologies are not dependent, in our case it could be because we are using household level panel data where it is impossible to assess whether households use both technologies on the same plot/parcel when households have more than one parcel.

In Table A4, we present results where we included additional control variables such as farmer perception of recent droughts, lagged use of organic manure and maize-legume intercropping, number of visits of agricultural extension officers, access to input credit dummy and participation in farmer organization dummy. These models are run without 2006 data because these variables are not available for 2006.

The first main hypothesis we test in this paper is that exposure to dry spells increases the likelihood of using organic manure. The results in Table 4 show that one-year lag of early-season dry spells is positive and significantly associated with use and use intensity of organic

Table 5
Use and use intensity of maize-legume intercropping with CRE models.

Variable	Use of intercropping		Farm size share under intercropping	
	Probit	CMP	Fractional probit	CMP
Longest early dry spell (1-year lag), days	0.200*	0.094***	0.020***	0.073***
	(0.11)	*(0.02)*	*(0.00)*	*(0.02)*
Longest early dry spell (2-year lag), days	−0.143	−0.018	−0.004	−0.017*
	(0.09)	*(0.01)*	*(0.00)*	*(0.01)*
Longest early dry spell (3-year lag), days	0.816***	0.155***	0.039***	0.124***
	(0.30)	*(0.05)*	*(0.01)*	*(0.04)*
Longest late dry spell (1-year lag), days	0.173***	0.046***	0.011***	0.038***
	(0.06)	*(0.01)*	*(0.00)*	*(0.01)*
Longest late dry spell (2-year lag), days	−0.360***	−0.037*	−0.009*	−0.055***
	(0.13)	*(0.02)*	*(0.01)*	*(0.02)*
Longest late dry spell (3-year lag), days	0.522	0.128**	0.031***	0.115**
	(0.34)	*(0.06)*	*(0.01)*	*(0.05)*
3 year average rainfall (mm)	−0.065	0.130	0.080***	0.086
	(0.73)	*(0.11)*	*(0.03)*	*(0.10)*
December average rainfall (mm)	−0.029	0.083	0.022**	0.088*
	(0.33)	*(0.05)*	*(0.01)*	*(0.05)*
February average rainfall (mm)	−0.520*	−0.168***	−0.046***	−0.145***
	(0.31)	*(0.05)*	*(0.01)*	*(0.04)*
Log-commercial fertilizer (kg/ha)	0.076	0.006	0.000	−0.001
	(0.13)	*(0.02)*	*(0.01)*	*(0.02)*
Fertilizer subsidy, dummy	−0.444	0.132	0.031	0.094
	(0.61)	*(0.10)*	*(0.02)*	*(0.08)*
Log-farm size (ha)	0.882	0.342*	−0.025	−0.086
	(1.11)	*(0.18)*	*(0.04)*	*(0.15)*
Southern region dummy	2.333	1.231***	0.229***	1.057***
	(1.64)	*(0.25)*	*(0.06)*	*(0.22)*
Distance to market (km)	−0.290**	0.019	0.005	0.014
	(0.12)	*(0.02)*	*(0.00)*	*(0.02)*
Fertilizer price (Mk/kg)	0.005*	0.000	0.000	0.000
	(0.00)	*(0.00)*	*(0.00)*	*(0.00)*
1-year lag maize price (Mk/kg)	0.188**	0.004	0.002	0.004
	(0.07)	*(0.01)*	*(0.00)*	*(0.01)*
1-year lag legume price (Mk/kg)	0.004	0.002*	0.000	0.001
	(0.01)	*(0.00)*	*(0.00)*	*(0.00)*
Log-male labor (adult equivalent/ha)	1.653	−0.485***	−0.101***	−0.311**
	(1.04)	*(0.16)*	*(0.04)*	*(0.14)*
Sex of household head (1 = female)	−0.289	0.299***	0.024	0.100
	(0.62)	*(0.10)*	*(0.02)*	*(0.07)*
2009 year dummy	−1.642	0.667***	−0.044	0.022
	(1.50)	*(0.25)*	*(0.05)*	*(0.21)*
2012 year dummy	5.441***	1.133***	0.159***	0.489***
	(1.24)	*(0.21)*	*(0.05)*	*(0.15)*
2015 year dummy	3.726***	2.157***	0.298***	1.162***
	(1.15)	*(0.19)*	*(0.04)*	*(0.15)*
Constant	−27.755***	−5.394***	−0.949***	−3.908***
	(6.62)	*(1.10)*	*(0.22)*	*(0.87)*
Prob > chi^2	0.000	0.000	0.000	0.000
Observations	1527	1527	1527	1527

Significance levels: *10%, **5%, ***1% and we report robust standard errors in the parenthesis. Full results of this table with all control variables are reported in the appendix in Table A3.

manure. The results are, however, not significant using the CMP framework and this could be because the errors from the two equations are insignificantly correlated as reported in Table 6. We however find similar results for models with additional controls in Table A4. Similarly, one-year lag of late-season dry spells is positive and significantly correlated with use and use intensity of organic manure and the results are robust where CMP reports similar results.

There is an inconsistent effect of two-year and three-year lags of both early-season and late-season dry spells on use and use intensity of organic manure. The two-year lag of early-season dry spells is negative but insignificantly correlated with use and use intensity of organic manure, while the two-year lag of late-season dry spells is negative and significantly associated with both use and use intensity. On the other hand, the three-year lag of both early- and late-season dry spells is positive and significantly correlated with use intensity. Another interesting result is the negative and significant correlation between average rainfall in February and use intensity of organic manure.

The second main and related hypothesis we test is that exposure to previous dry spells increases use and use intensity of maize-legume intercropping. The results in Table 5 show a positive and significant correlation of one-year and three-year lags of early-season dry spells and one-year lag of late-season dry spells with use and use intensity.

Table 6
Correlation matrix from the CMP regressions.

Technology	Maize-legume intercropping	Farm size share under intercropping
Manure use	0.058 *(0.236)*	
Log manure		−0.028 *(0.378)*

The correlation matrix is separate for use and use intensity equations. Figures in parenthesis are standard errors. The correlations of the errors are insignificant.

The results are similar with the CMP estimation. With respect to the two-year lag of both early-season and late-season dry spells, we find an inconsistent correlation with use and use intensity of maize-legume intercropping. The two-year lag of early-season dry spell is negative but insignificantly correlated with both use and use intensity, while the two-year lag of late-season dry spell is negative and significantly related to both use and use intensity of maize-legume intercropping. It is also interesting that average rainfall in February is associated with less likelihood of using maize-legume intercropping while the average rainfall in December has a positive and significant association with use intensity.

We highlight three main findings from the full set of results. One, farmers in our sample respond to exposure to previous dry spells by using organic manure and maize-legume intercropping as drought-resilience enhancing ISFM technologies. This suggests that farmers develop weather expectations from previous weather conditions and influence production decisions of the following season. Crop production, particularly maize production, which dominates in Malawi, is susceptible to dry spells, especially late-season dry spells, and farmers are willing to invest in technologies that minimize the impacts. While irrigation might be considered an option, the high investment and maintenance costs in SSA (Inocencio, 2007; Woodhouse et al., 2017) limit most smallholder farmers from using this technology. Organic manure and maize-legume intercropping offer farmers options to hedge against late-season dry spells in particular by enhancing rainwater infiltration rates and conserving soil moisture through organic matter and soil cover.

A second key finding is that the recent weather shocks (i.e. one-year lag of early-season and late-season dry spells) are more influential than long-term weather conditions (e.g. two- and three-year lags) in building farmers' weather expectations. This interesting result could suggest that smallholder farmers are myopic. While research indicates that occurrence of climatic shocks creates fear and worry among smallholder farmers of a reoccurrence and leads to increased investments in adaptive mechanisms that hedge against resulting losses (Van Den Berg et al., 2009), among our sample households such adaptive behavior occurs only the case for an immediate dry spell shock.

Three, the inconsistent correlation between long-term weather conditions and use of ISFM technologies could mean that farmers do not observe production benefits of these technologies under early- and late-season dry spells after one year of experience. This could be related to the observation by Snapp et al. (1998) and Silberg et al. (2017) that the agronomic benefits of organic manure and maize-legume intercropping, respectively, may delay for more than two seasons. Thus, the positive impact of the one-year lag could be associated with perceived impacts of the technologies on crop production under dry spells, while the inconsistent impact of the two- and-three-year lags could be associated with delayed benefits. Farmers are impatient for immediate production gains and are more likely to dis-adopt or reduce usage of a technology with poor first-year results. Corbeels et al. (2014) reported that farmers tend to put more weight on immediate needs over future benefits of a given technology. Thus, the inconsistent impact of two- and three-year lags of early- and late-season dry spells may not necessarily mean that farmers are not responding to long-term dry spell exposure but rather they are more interested in immediate benefits over medium to long-term benefits.

Controlling for input and output prices, the results show that the commercial fertilizer price is positively association with use of organic manure and maize-legume intercropping. There is also a positive and significant relationship between lagged maize price and use intensity of organic manure and use of maize-legume intercropping. These results suggest that farmers are somewhat price responsive. The higher price for commercial fertilizer, which effectively reduces demand for inorganic fertilizer, is associated with a higher likelihood of using organic manure. This indirect effect of fertilizer price on organic manure indicates that inorganic fertilizer and organic manure technologies are partly substitutes. Farmers make a systematic trade-off by investing in organic manure when the fertilizer price is increased. As for output prices, higher maize and legume prices from the previous season provide an incentive for farmers to use organic manure and practice maize-legume intercropping. Relative to the opportunity cost for labor for making organic manure, a higher output price signifies higher expected profits and increases the probability of using the technology. These results concur with the findings of Silberg et al. (2017) where previous sales of legumes enhanced use of maize-legume intercropping.

It is also interesting to note that male household labor has a negative and significant relationship with use intensity of maize-legume intercropping. The result may suggest that the technology is labor-saving. While the amount of labor per unit is increased (a form of land use intensification) (Waddington et al., 2007), the amount of labor per unit output may decline because it is not necessary to prepare separate land for two or more crops. Legumes may also help to suppress weeds under a maize crop and then reduce the need for weeding. While our results point in this direction, we leave the assessment of labor requirements for another study.

Controlling for additional variables in Table A4 we notice that number of agricultural extension visits is positive and significantly correlated with both use and use intensity of organic manure. Similarly, participation in a farmer organization is associated with a higher likelihood of using organic manure. We used extension visits as a proxy for government interventions in the study areas. It should be mentioned that these results should be taken as associations rather than causal relationships, because we did not control for potential endogeneity of these variables. Our results are therefore only indicative of the great potential of agricultural extension services for promoting use of organic manure. We also controlled for drought perception variables in Table A4. We find unexpected negative associations between perception to drought and use of ISFM technologies. We again do not discuss these results because we did not control nor test for potential endogeneity of perception variables. Finally, we notice that the lagged use of organic manure and intercropping are insignificant in current use of organic manure and intercropping respectively. These results suggest that the CRE framework adequately controls for unobserved heterogeneity in our sample.

5. Conclusions and Policy Implications

Using four waves of panel data spanning nine years, our results show for our Central and Southern Malawi sample households that maize-legume intercropping increased from 29% in 2006 to 75% in 2015 and use of organic manure increased from 30% to 54% over the same period. Our results demonstrate that use and use intensity of organic manure and maize-legume intercropping are positively associated with exposure to early-season and late-season dry spells. The positive correlation of dry spells with use of ISFM technologies implies that farmers respond to occurrence and risks associated with dry spells and may perceive that such technologies help them to hedge against resulting production losses. We leave for future research to investigate how efficient these technologies are in achieving this objective. However, with the Government of Malawi taking an active role in promoting these technologies, there is need for collective and coordinated efforts to ensure that appropriate climate-smart technologies are available and disseminated to farmers. While irrigation technology is an expensive option due to high investment and maintenance costs, ISFM technologies offer smallholder farmers lower-cost options to hedge against late-season dry spells by conserving soil moisture.

Another interesting conclusion that requires policy attention is the inconsistent effect of two- and three-year lags of early-season and late-season dry spells on use and use intensity of ISFM technologies. Farmers seem to have myopic weather expectations as recent weather shocks appear more influential than long-term weather conditions. Another possible explanation is delayed benefits of the technologies as literature reports that the benefits may take a long time to manifest (Silberg et al., 2017; Snapp et al., 1998). While further research is needed to confirm this hypothesis, our findings underscore the need for agricultural extension services to go beyond promoting the use of ISFM technologies to also ensure that farmers are aware of potential long-term benefits and how to use the technologies. Sharing the risks of delayed production benefits with the farmers could be another option of enhancing use and use intensity. This could be in the form of incentives in the first two to three seasons of use. Jointly promoting ISFM technologies could also help minimize dis-adoption rates of technologies with delayed benefits. For example, joint use of organic manure, inorganic fertilizer and intercropping could allow farmers to benefit from inorganic fertilizer, which has immediate production benefits, while organic manure and intercropping build organic matter and soil nutrients for long-term and sustainable effects.

Table A1
First stage regression results for test of endogeneity of fertilizer use and farm size.

Variable	Potential endogenous variable: fertilizer			Potential endogenous variable: farm size		
	Fertilizer use	Organic manure use	Intercropping use	Farm size	Organic manure use	Intercropping use
Log-commercial fertilizer (kg/ha)	1.193	1.193	0.003	0.003	0.042**	
	(1.08)	*(1.05)*	*(0.00)*	*(0.02)*	*(0.02)*	
Residual from fertilizer use	*−1.188*	*−1.149*				
	(1.08)	*(1.05)*				
Log-farm size (ha)	0.477*	−0.461	−0.307	0.803	0.915	
	(0.27)	*(0.57)*	*(0.56)*	*(0.61)*	*(0.60)*	
Residual from farm size	*−0.697*	*−0.674*				
	(0.63)	*(0.62)*				
Fertilizer subsidy, dummy	1.641***	−1.696	−1.638	−0.002	0.254***	0.249***
	(0.15)	*(1.77)*	*(1.73)*	*(0.02)*	*(0.09)*	*(0.09)*
Longest early dry spell (1-year lag), days	−0.057**	0.058	0.046	−0.004	−0.007	−0.017
	(0.03)	*(0.06)*	*(0.06)*	*(0.00)*	*(0.02)*	*(0.02)*
Longest early dry spell (2-year lag), days	0.026	−0.029	−0.022	−0.002	0.004	0.009
	(0.02)	*(0.03)*	*(0.03)*	*(0.00)*	*(0.01)*	*(0.01)*
Longest early dry spell (3-year lag), days	−0.122*	0.195	0.245*	0.007	0.046	0.101**
	(0.07)	*(0.14)*	*(0.13)*	*(0.01)*	*(0.04)*	*(0.04)*
Longest late dry spell (1-year lag), days	−0.042***	0.056	0.033	0.000	0.006	−0.015*
	(0.02)	*(0.05)*	*(0.04)*	*(0.00)*	*(0.01)*	*(0.01)*
Longest late dry spell (2-year lag), days	−0.070**	0.032	0.078	−0.007**	−0.047***	0.002
	(0.03)	*(0.08)*	*(0.08)*	*(0.00)*	*(0.02)*	*(0.02)*
Longest late dry spell (3-year lag), days	−0.121	0.152	0.211	0.007	0.003	0.067
	(0.08)	*(0.14)*	*(0.13)*	*(0.01)*	*(0.04)*	*(0.05)*
3 year average rainfall (mm)	−0.020	−0.135	0.062	0.039	−0.186*	0.012
	(0.19)	*(0.11)*	*(0.11)*	*(0.04)*	*(0.11)*	*(0.11)*
December average rainfall (mm)	0.413***	−0.367	−0.290	0.084***	0.065	0.128*
	(0.08)	*(0.44)*	*(0.44)*	*(0.01)*	*(0.07)*	*(0.07)*
February average rainfall (mm)	−0.185**	0.119	0.080	−0.042***	−0.071	−0.104**
	(0.08)	*(0.20)*	*(0.20)*	*(0.01)*	*(0.05)*	*(0.05)*
Southern region dummy	−0.886**	1.374	1.506	0.000	0.322	0.487**
	(0.43)	*(0.98)*	*(0.97)*	*(.)*	*(0.23)*	*(0.23)*
Log asset value (MK)	0.148***	−0.149	−0.136	0.001	0.026**	0.034***
	(0.02)	*(0.16)*	*(0.16)*	*(0.00)*	*(0.01)*	*(0.01)*
Log TLU	−0.066	0.048	−0.112	0.004	−0.033	−0.191***
	(0.12)	*(0.10)*	*(0.10)*	*(0.01)*	*(0.07)*	*(0.07)*
Distance to market (km)	−0.028	−0.016	0.042	−0.007	−0.044**	0.014
	(0.03)	*(0.03)*	*(0.03)*	*(0.01)*	*(0.02)*	*(0.02)*
Fertilizer price (Mk/kg)	−0.005***	0.007	0.007	0.000	0.002***	0.002***
	(0.00)	*(0.01)*	*(0.01)*	*0.00*	*(0.00)*	*(0.00)*
1-year lag maize price (Mk/kg)	0.063***	−0.068	−0.060	−0.001	0.008**	0.013***
	(0.01)	*(0.07)*	*(0.07)*	*(0.00)*	*(0.00)*	*(0.00)*
1-year lag legume price (Mk/kg)	0.002	0.002	0.004**	0.000*	0.003***	0.006***
	(0.00)	*(0.00)*	*(0.00)*	*0.00*	*(0.00)*	*(0.00)*
Log-male labor (adult equivalent/ha)	0.322	−0.308	−0.574	−0.112***	0.152	−0.129
	(0.26)	*(0.39)*	*(0.38)*	*(0.03)*	*(0.14)*	*(0.14)*
Log-female labor (adult equivalent/ha)	−0.197	0.344	0.368	−0.073**	0.161	0.191
	(0.26)	*(0.25)*	*(0.24)*	*(0.03)*	*(0.14)*	*(0.14)*

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Table A1 (*continued*)

Variable	Potential endogenous variable: fertilizer			Potential endogenous variable: farm size		
	Fertilizer use	Organic manure use	Intercropping use	Farm size	Organic manure use	Intercropping use
Log-off farm labor (adult equivalent/ha)	1.367***	−1.193	−1.496	0.044	0.400**	0.045
	(0.28)	*(1.47)*	*(1.44)*	*(0.03)*	*(0.16)*	*(0.16)*
Sex of household head (1 = female)	−0.053	0.093	0.383***	−0.007	0.035	0.327***
	(0.16)	*(0.11)*	*(0.11)*	*(0.02)*	*(0.09)*	*(0.09)*
Education of household head (years)	0.038**	−0.030	−0.041	−0.001	0.016*	0.004
	(0.02)	*(0.04)*	*(0.04)*	*(0.00)*	*(0.01)*	*(0.01)*
Age of household head (years)	0.032	0.002	−0.031	0.003	0.037**	0.004
	(0.03)	*(0.04)*	*(0.04)*	*(0.00)*	*(0.02)*	*(0.01)*
Age squared	0.000	0.000	0.000	0.000	−0.000**	0.000
	(0.00)	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*
Constant	−0.096	−2.147**	−4.413***	0.100	−2.331***	−4.591***
	(1.63)	*(0.90)*	*(0.94)*	*(0.30)*	*(0.90)*	*(0.94)*
Prob > chi^2	0.000	0.000	0.000	0.000	0.000	0.000
Rho	0.068	0.205	0.099	0.608	0.205	0.099
Observations	1527	1527	1527	1527	1527	1527

Significance levels: *10%, **5%, ***1% and we report robust standard errors in the parenthesis. The italics identifies the residual from fertilizer use and farm size equations.

Table A2
Full results of Table 4 for use and use intensity of organic manure.

Variable	Use of organic manure		Log manure (kg/ha)	
	CRE probit	CMP	CRE tobit	CMP
Longest early dry spell (1-year lag), days	0.032*	0.024	0.104***	0.177
	(0.02)	*(0.02)*	*(0.02)*	*(0.11)*
Longest early dry spell (2-year lag), days	−0.024	−0.020	−0.020	−0.146
	(0.02)	*(0.01)*	*(0.02)*	*(0.09)*
Longest early dry spell (3-year lag), days	0.056	0.041	0.167***	0.792**
	(0.04)	*(0.05)*	*(0.05)*	*(0.31)*
Longest late dry spell (1-year lag), days	0.029***	0.025***	0.050***	0.170***
	(0.01)	*(0.01)*	*(0.01)*	*(0.06)*
Longest late dry spell (2-year lag), days	−0.075***	−0.065***	−0.040	−0.341***
	(0.02)	*(0.02)*	*(0.03)*	*(0.13)*
Longest late dry spell (3-year lag), days	0.007	−0.004	0.138**	0.489
	(0.04)	*(0.05)*	*(0.06)*	*(0.36)*
3 year average rainfall (mm)	−0.175	−0.183*	0.147	−0.338
	(0.12)	*(0.10)*	*(0.13)*	*(0.71)*
December average rainfall (mm)	0.079	0.085*	0.090	0.008
	(0.05)	*(0.05)*	*(0.06)*	*(0.34)*
February average rainfall (mm)	−0.158***	−0.152***	−0.173***	−0.489
	(0.05)	*(0.05)*	*(0.05)*	*(0.33)*
Log-commercial fertilizer (kg/ha)	−0.002	0.003	0.006	0.102
	(0.02)	*(0.02)*	*(0.02)*	*(0.13)*
Fertilizer subsidy, dummy	0.012	0.013	0.149	−0.484
	(0.10)	*(0.09)*	*(0.11)*	*(0.63)*
Log-farm size (ha)	0.132	0.097	0.364*	0.788
	(0.19)	*(0.16)*	*(0.20)*	*(1.05)*
Southern region	0.826***	0.762***	1.292***	2.551
	(0.26)	*(0.24)*	*(0.28)*	*(1.59)*
Log asset value (MK)	−0.004	−0.004	0.015	0.050
	(0.02)	*(0.01)*	*(0.02)*	*(0.09)*
Log TLU	−0.058	−0.042	0.056	−0.189
	(0.08)	*(0.07)*	*(0.09)*	*(0.45)*
Distance to market (km)	−0.045**	−0.042**	0.020	−0.293**
	(0.02)	*(0.02)*	*(0.02)*	*(0.14)*

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Table A2 (*continued*)

Variable	Use of organic manure		Log manure (kg/ha)	
	CRE probit	CMP	CRE tobit	CMP
Fertilizer price (Mk/kg)	0.001*	0.001**	0.000	0.006**
	(0.00)	*0.00*	*(0.00)*	*0.00*
1-year lag maize price (Mk/kg)	0.036***	0.032***	0.004	0.197***
	(0.01)	*(0.01)*	*(0.01)*	*(0.08)*
1-year lag legume price (Mk/kg)	0.002**	0.002**	0.002	0.004
	(0.00)	*(0.00)*	*(0.00)*	*(0.01)*
Log-male labor (adult equivalent/ha)	0.162	0.127	−0.542***	1.577
	(0.17)	*(0.13)*	*(0.18)*	*(1.01)*
Log-female labor (adult equivalent/ha)	−0.094	−0.067	0.232	−1.356
	(0.17)	*(0.14)*	*(0.18)*	*(1.04)*
Log-off farm labor (adult equivalent/ha)	0.450**	0.399**	0.027	2.588**
	(0.21)	*(0.17)*	*(0.22)*	*(1.14)*
Sex of household head (1 = female)	0.025	0.019	0.325***	−0.292
	(0.11)	*(0.09)*	*(0.12)*	*(0.60)*
Education of household head (years)	0.024*	0.020	0.042**	0.098
	(0.01)	*(0.01)*	*(0.02)*	*(0.09)*
Age of household head (years)	0.041***	0.037**	0.000	0.233**
	(0.02)	*(0.01)*	*(0.02)*	*(0.10)*
Age squared	−0.000***	−0.000***	0.000	−0.002***
	0.00	*0.00*	*0.00*	*0.00*
Household size	0.022	0.021	0.022	0.194
	(0.03)	*(0.03)*	*(0.04)*	*(0.22)*
Plot distance (km)	0.000	0.000	0.000	0.000
	0.00	*0.00*	*0.00*	*0.00*
Loam soil (1 = yes)	−0.057	−0.053	−0.065	−0.044
	(0.10)	*(0.08)*	*(0.11)*	*(0.59)*
Clay soil (1 = yes)	0.128	0.154	0.039	1.052
	(0.13)	*(0.11)*	*(0.13)*	*(0.74)*
Moderate slope (1 = yes)	0.094	0.071	0.121	0.771
	(0.08)	*(0.07)*	*(0.09)*	*(0.51)*
Steep slope (1 = yes)	0.122	0.058	0.238	1.102
	(0.18)	*(0.14)*	*(0.19)*	*(0.90)*
Medium soil fertility (1 = yes)	−0.072	−0.047	0.006	−0.305
	(0.11)	*(0.10)*	*(0.12)*	*(0.74)*
Low soil fertility (1 = yes)	−0.046	−0.035	0.008	0.106
	(0.13)	*(0.12)*	*(0.15)*	*(0.84)*
2009 year dummy	−0.157	−0.165	0.723***	−1.852
	(0.25)	*(0.23)*	*(0.26)*	*(1.56)*
2012 year dummy	1.010***	0.884***	1.222***	5.478***
	(0.21)	*(0.19)*	*(0.23)*	*(1.28)*
2015 year dummy	0.675***	0.560***	2.357***	3.519***
	(0.20)	*(0.17)*	*(0.23)*	*(1.17)*
Mean log male labor	−0.461*	−0.351	0.275	−2.094
	(0.26)	*(0.26)*	*(0.28)*	*(1.82)*
Mean log female labor	0.457*	0.354	−0.294	1.771
	(0.26)	*(0.27)*	*(0.27)*	*(1.89)*
Mean log off-farm labor	−0.431	−0.364	−0.087	−2.187
	(0.33)	*(0.29)*	*(0.35)*	*(2.04)*
Mean household head sex	0.097	0.088	−0.133	1.092
	(0.20)	*(0.17)*	*(0.21)*	*(1.16)*
Mean education	−0.001	−0.001	−0.033	−0.005
	(0.02)	*(0.02)*	*(0.02)*	*(0.13)*
Mean age	0.001	0.000	0.006	0.019
	(0.01)	*(0.01)*	*(0.01)*	*(0.04)*
Mean household size	0.009	0.001	0.034	−0.028
	(0.05)	*(0.04)*	*(0.05)*	*(0.28)*
Mean plot distance	0.000	0.000	−0.000**	−0.001
	0.00	*0.00*	*0.00*	*0.00*

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Table A2 (*continued*)

Variable	Use of organic manure		Log manure (kg/ha)	
	CRE probit	CMP	CRE tobit	CMP
Mean log asset value	0.063**	0.051*	−0.030	0.162
	(0.03)	*(0.03)*	*(0.03)*	*(0.19)*
Mean log TLU	0.320***	0.279***	−0.153	1.823***
	(0.12)	*(0.11)*	*(0.12)*	*(0.70)*
Mean fertilizer subsidy	0.502***	0.460***	−0.237	3.689***
	(0.20)	*(0.17)*	*(0.20)*	*(1.15)*
Mean log fertilizer	−0.040	−0.035	0.061	−0.074
	(0.04)	*(0.04)*	*(0.05)*	*(0.28)*
Mean log farm size	−0.224	−0.132	−0.400	−1.421
	(0.32)	*(0.29)*	*(0.34)*	*(1.94)*
Constant	−3.160***	−2.588***	−5.856***	−26.947***
	(0.99)	*(1.00)*	*(1.18)*	*(6.75)*
Prob > chi^2	0.000	0.000	0.000	0.000
Observations	1527	1527	1527	1527

Significance levels: *10%, **5%, ***1% and we report robust standard errors in the parenthesis. The italics identifies the residual from fertilizer use and farm size equations.

Table A3
Full results of Table 5 for use and use intensity of maize-legume intercropping.

Variable	Use of intercropping		Farm size share	
	CRE probit	CMP	CRE fractional probit	CMP
Longest early dry spell (1-year lag), days	0.200*	0.094***	0.020***	0.073***
	(0.11)	*(0.02)*	*(0.00)*	*(0.02)*
Longest early dry spell (2-year lag), days	−0.143	−0.018	−0.004	−0.017*
	(0.09)	*(0.01)*	*(0.00)*	*(0.01)*
Longest early dry spell (3-year lag), days	0.816***	0.155***	0.039***	0.124***
	(0.30)	*(0.05)*	*(0.01)*	*(0.04)*
Longest late dry spell (1-year lag), days	0.173***	0.046***	0.011***	0.038***
	(0.06)	*(0.01)*	*(0.00)*	*(0.01)*
Longest late dry spell (2-year lag), days	−0.360***	−0.037*	−0.009*	−0.055***
	(0.13)	*(0.02)*	*(0.01)*	*(0.02)*
Longest late dry spell (3-year lag), days	0.522	0.128**	0.031***	0.115**
	(0.34)	*(0.06)*	*(0.01)*	*(0.05)*
3 year average rainfall (mm)	−0.065	0.130	0.080***	0.086
	(0.73)	*(0.11)*	*(0.03)*	*(0.10)*
December average rainfall (mm)	−0.029	0.083	0.022**	0.088*
	(0.33)	*(0.05)*	*(0.01)*	*(0.05)*
February average rainfall (mm)	−0.520*	−0.168***	−0.046***	−0.145***
	(0.31)	*(0.05)*	*(0.01)*	*(0.04)*
Log-commercial fertilizer (kg/ha)	0.076	0.006	0.000	−0.001
	(0.13)	*(0.02)*	*(0.01)*	*(0.02)*
Fertilizer subsidy, dummy	−0.444	0.132	0.031	0.094
	(0.61)	*(0.10)*	*(0.02)*	*(0.08)*
Log-farm size (ha)	0.882	0.342*	−0.025	−0.086
	(1.11)	*(0.18)*	*(0.04)*	*(0.15)*
Southern region	2.333	1.231***	0.229***	1.057***
	(1.64)	*(0.25)*	*(0.06)*	*(0.22)*
Log asset value (MK)	0.046	0.014	0.001	0.004
	(0.09)	*(0.01)*	*(0.00)*	*(0.01)*
Log TLU	−0.318	0.048	0.003	0.032
	(0.48)	*(0.08)*	*(0.02)*	*(0.06)*
Distance to market (km)	−0.290**	0.019	0.005	0.014
	(0.12)	*(0.02)*	*(0.00)*	*(0.02)*
Fertilizer price (Mk/kg)	0.005*	0.000	0.000	0.000
	(0.00)	*0.00*	*0.00*	*0.00*

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Table A3 (*continued*)

Variable	Use of intercropping		Farm size share	
	CRE probit	CMP	CRE fractional probit	CMP
1-year lag maize price (Mk/kg)	0.188**	0.004	0.002	0.004
	(0.07)	*(0.01)*	*(0.00)*	*(0.01)*
1-year lag legume price (Mk/kg)	0.004	0.002*	0.000	0.001
	(0.01)	*(0.00)*	*(0.00)*	*(0.00)*
Log-male labor (adult equivalent/ha)	1.653	−0.485***	−0.101***	−0.311**
	(1.04)	*(0.16)*	*(0.04)*	*(0.14)*
Log-female labor (adult equivalent/ha)	−1.470	0.203	0.071*	0.196
	(1.04)	*(0.17)*	*(0.04)*	*(0.14)*
Log-off farm labor (adult equivalent/ha)	2.598**	0.012	−0.002	0.014
	(1.20)	*(0.20)*	*(0.05)*	*(0.15)*
Sex of household head (1 = female)	−0.289	0.299***	0.024	0.100
	(0.62)	*(0.10)*	*(0.02)*	*(0.07)*
Education of household head (years)	0.108	0.037**	0.010***	0.036**
	(0.09)	*(0.02)*	*(0.00)*	*(0.02)*
Age of household head (years)	0.217**	0.001	−0.001	−0.001
	(0.09)	*(0.02)*	*(0.00)*	*(0.01)*
Age squared	−0.002***	0.000	0.000	0.000
	(0.00)	*(0.00)*	*(0.00)*	*(0.00)*
Household size	0.193	0.018	0.007	0.025
	(0.20)	*(0.03)*	*(0.01)*	*(0.03)*
Plot distance (km)	0.000	0.000	0.000	0.000
	(0.00)	*(0.00)*	*(0.00)*	*(0.00)*
Loam soil (1 = yes)	0.113	−0.035	−0.010	−0.015
	(0.60)	*(0.11)*	*(0.02)*	*(0.09)*
Clay soil (1 = yes)	0.989	0.044	0.007	0.008
	(0.76)	*(0.12)*	*(0.03)*	*(0.10)*
Moderate slope (1 = yes)	0.869*	0.124	0.041**	0.144**
	(0.50)	*(0.08)*	*(0.02)*	*(0.06)*
Steep slope (1 = yes)	1.403	0.218	0.037	0.100
	(1.03)	*(0.19)*	*(0.04)*	*(0.13)*
Medium soil fertility (1 = yes)	−0.364	−0.019	0.030	0.109
	(0.67)	*(0.10)*	*(0.03)*	*(0.09)*
Low soil fertility (1 = yes)	0.100	−0.024	0.035	0.119
	(0.81)	*(0.13)*	*(0.03)*	*(0.11)*
2009 year dummy	−1.642	0.667***	−0.044	0.022
	(1.50)	*(0.25)*	*(0.05)*	*(0.21)*
2012 year dummy	5.441***	1.133***	0.159***	0.489***
	(1.24)	*(0.21)*	*(0.05)*	*(0.15)*
2015 year dummy	3.726***	2.157***	0.298***	1.162***
	(1.15)	*(0.19)*	*(0.04)*	*(0.15)*
Mean log male labor	−2.511	0.241	0.062	0.182
	(1.58)	*(0.22)*	*(0.06)*	*(0.18)*
Mean log female labor	2.101	−0.245	−0.084	−0.236
	(1.57)	*(0.22)*	*(0.06)*	*(0.18)*
Mean log off-farm labor	−2.359	−0.102	0.024	0.039
	(2.02)	*(0.31)*	*(0.07)*	*(0.24)*
Mean household head sex	1.180	−0.110	0.012	0.040
	(1.23)	*(0.19)*	*(0.04)*	*(0.15)*
Mean education	−0.006	−0.028	−0.012***	−0.041*
	(0.13)	*(0.02)*	*(0.01)*	*(0.02)*
Mean age	0.023	0.006	0.001	0.004
	(0.04)	*(0.01)*	*(0.00)*	*(0.01)*
Mean household size	0.016	0.034	−0.001	−0.003
	(0.27)	*(0.04)*	*(0.01)*	*(0.03)*
Mean plot distance	−0.001	−0.000**	0.000	0.000
	(0.00)	*(0.00)*	*(0.00)*	*(0.00)*
Mean log asset value	0.201	−0.028	−0.006	−0.017
	(0.19)	*(0.03)*	*(0.01)*	*(0.02)*

(*continued on next page*)

Table A3 (*continued*)

Variable	Use of intercropping		Farm size share	
	CRE probit	CMP	CRE fractional probit	CMP
Mean log TLU	1.914***	−0.129	−0.034	−0.129
	(0.72)	*(0.10)*	*(0.03)*	*(0.08)*
Mean fertilizer subsidy	3.651***	−0.223	0.011	0.042
	(1.19)	*(0.18)*	*(0.04)*	*(0.15)*
Mean log fertilizer	−0.119	0.053	−0.001	−0.016
	(0.27)	*(0.04)*	*(0.01)*	*(0.04)*
Mean log farm size	−1.915	−0.393	−0.130*	−0.488**
	(1.97)	*(0.29)*	*(0.07)*	*(0.23)*
Constant	−27.755***	−5.394***	−0.949***	−3.908***
	(6.62)	*(1.10)*	*(0.22)*	*(0.87)*
Prob > chi^2	0.000	0.000	0.000	0.000
Observations	1527	1527	1527	1527

Significance levels: *10%, **5%, ***1% and we report robust standard errors in the parenthesis. The italics identifies the residual from fertilizer use and farm size equations.

Table A4
CRE models for use and use intensity of organic manure and intercropping with lagged dependent variables (without 2006 data).

Variable	Organic manure		Maize-legume intercropping	
	Use	Log manure (kg/ha)	Use	Farm size share
Longest early dry spell (1-year lag), days	0.046*	0.170	0.200***	0.028***
	(0.03)	*(0.13)*	*(0.03)*	*(0.01)*
Longest early dry spell (2-year lag), days	−0.028	−0.109	−0.021	−0.003
	(0.02)	*(0.10)*	*(0.02)*	*(0.00)*
Longest early dry spell (3-year lag), days	0.083	0.411	0.083	0.039**
	(0.10)	*(0.52)*	*(0.15)*	*(0.02)*
Longest late dry spell (1-year lag), days	0.020	0.126**	0.049***	0.008***
	(0.01)	*(0.06)*	*(0.01)*	*(0.00)*
Longest late dry spell (2-year lag), days	−0.011	−0.188	0.186***	0.020**
	(0.05)	*(0.24)*	*(0.06)*	*(0.01)*
Longest late dry spell (3-year lag), days	0.091	0.434	−0.220	0.009
	(0.13)	*(0.66)*	*(0.20)*	*(0.03)*
Perceived drought (1 = yes, 1-year lag)	−0.021	−0.048	−0.258*	−0.042*
	(0.13)	*(0.63)*	*(0.15)*	*(0.03)*
Perceived drought (1 = yes, 2-year lag)	−0.224	−1.465	−0.128	−0.029
	(0.20)	*(0.97)*	*(0.20)*	*(0.04)*
Perceived drought (1 = yes, 3-year lag)	−0.094	−0.035	−0.291	−0.056*
	(0.17)	*(0.85)*	*(0.19)*	*(0.03)*
3 year average rainfall (mm)	−0.589*	−2.422	0.451	0.087
	(0.36)	*(1.76)*	*(0.40)*	*(0.07)*
December average rainfall (mm)	−0.226	−1.230	0.976***	0.094*
	(0.26)	*(1.28)*	*(0.34)*	*(0.05)*
February average rainfall (mm)	−0.333	−1.506	0.132	0.003
	(0.20)	*(1.00)*	*(0.23)*	*(0.04)*
Number of extension visits	0.119***	0.319***	0.003	0.001
	(0.02)	*(0.05)*	*(0.01)*	*(0.00)*
Input credit access (1 = yes)	−0.079	0.319	0.009	−0.015
	(0.19)	*(0.91)*	*(0.20)*	*(0.04)*
Farm organization (=yes)	0.286**	1.069*	0.072	−0.003
	(0.14)	*(0.64)*	*(0.15)*	*(0.03)*
Log-commercial fertilizer (kg/ha)	0.014	0.092	0.030	0.006
	(0.03)	*(0.14)*	*(0.03)*	*(0.01)*
Fertilizer subsidy, dummy	0.070	0.284	0.032	−0.003
	(0.13)	*(0.65)*	*(0.15)*	*(0.03)*
Log-farm size (ha)	0.482*	2.497*	0.011	−0.126**
	(0.27)	*(1.34)*	*(0.29)*	*(0.05)*

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Table A4 (*continued*)

Variable	Organic manure		Maize-legume intercropping	
	Use	Log manure (kg/ha)	Use	Farm size share
Southern region dummy	3.025	13.662	−3.467	−0.289
	(2.07)	*(10.14)*	*(2.31)*	*(0.40)*
Log asset value (MK)	−0.027	−0.150	−0.015	−0.004
	(0.02)	*(0.11)*	*(0.02)*	*(0.00)*
Log TLU	−0.012	−0.142	0.081	0.009
	(0.11)	*(0.52)*	*(0.12)*	*(0.02)*
Distance to market (km)	−0.063**	−0.363***	0.035	0.008
	(0.03)	*(0.13)*	*(0.03)*	*(0.01)*
Fertilizer price (Mk/kg)	0.001	0.003	0.000	0.000
	(0.00)	*(0.00)*	*(0.00)*	*(0.00)*
1-year lag maize price (Mk/kg)	0.018	0.170	−0.127***	−0.015***
	(0.03)	*(0.14)*	*(0.03)*	*(0.01)*
1-year lag legume price (Mk/kg)	0.001	0.003	−0.001	0.000
	(0.00)	*(0.01)*	*(0.00)*	*(0.00)*
Log-male labor (adult equivalent/ha)	0.456	2.967*	−0.506	0.006
	(0.35)	*(1.75)*	*(0.38)*	*(0.06)*
Log-female labor (adult equivalent/ha)	−0.409	−2.469	−0.021	−0.066
	(0.36)	*(1.76)*	*(0.38)*	*(0.07)*
Log-off farm labor (adult equivalent/ha)	0.344	1.816	−0.048	−0.010
	(0.25)	*(1.23)*	*(0.28)*	*(0.05)*
Sex of household head (1 = female)	−0.121	−0.659	0.225	−0.006
	(0.12)	*(0.60)*	*(0.14)*	*(0.02)*
Education of household head (years)	0.011	0.039	0.020	0.007*
	(0.02)	*(0.10)*	*(0.02)*	*(0.00)*
Age of household head (years)	0.019	0.111	−0.003	−0.001
	(0.02)	*(0.11)*	*(0.02)*	*(0.00)*
Age squared	0.000	−0.001	0.000	0.000
	(0.00)	*(0.00)*	*(0.00)*	*(0.00)*
Household size	−0.013	−0.014	0.054	0.013
	(0.04)	*(0.21)*	*(0.05)*	*(0.01)*
Plot distance (km)	0.000	0.000	0.000	0.000
	(0.00)	*(0.00)*	*(0.00)*	*(0.00)*
2012 year dummy	0.816	6.955*	−2.781***	−0.261*
	(0.76)	*(3.70)*	*(0.90)*	*(0.15)*
2015 year dummy	0.699*	5.533***	0.430	0.132*
	(0.40)	*(1.94)*	*(0.46)*	*(0.08)*
Lag manure use	0.099	0.011	−0.028	−0.028
	(0.14)	*(0.71)*	*(0.12)*	*(0.02)*
Lag intercropping use	−0.145	−0.380	−0.003	0.008
	(0.11)	*(0.56)*	*(0.16)*	*(0.02)*
Constant	0.956	−3.375	−3.813	−0.757
	(3.24)	*(16.21)*	*(3.71)*	*(0.63)*
Prob > chi^2	0.000	0.000	0.000	0.000
Observations	1036	1036	1036	1036

Significance levels: *10%, **5%, ***1% and we report robust standard errors in the parenthesis. The italics identifies the residual from fertilizer use and farm size equations.

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References

Alabi, R.A., Adams, O.O., Abu, G., 2016. Does an inorganic fertilizer subsidy promote the use of organic fertilizers in Nigeria? In: AGRODEP Working Paper 0036.
Andersson, J.A., D'Souza, S., 2014. From adoption claims to understanding farmers and contexts: a literature review of Conservation Agriculture (CA) adoption among smallholder farmers in southern Africa. Agric. Ecosyst. Environ. 187, 116–132.
Arslan, A., McCarthy, N., Lipper, L., Asfaw, S., Cattaneo, A., 2014. Adoption and intensity of adoption of conservation farming practices in Zambia. Agric. Ecosyst. Environ. 187, 72–86.
Arslan, A., Belotti, F., Lipper, L., 2017. Smallholder productivity and weather shocks: adoption and impact of widely promoted agricultural practices in Tanzania. Food

Policy 69, 68–81.
Asfaw, S., McCarthy, N., Lipper, L., Arslan, A., Cattaneo, A., Kachulu, M., 2014. Climate variability, adaptation strategies and food security in Malawi. In: ESA Working Paper, No. 14-08, . www.fao.org/economic/esa. www.fao.org/economic/esa.
Benson, C., Clay, E., 1998. Drought and sub-Saharan African economies. In: Africa Region Findings & Good Practice Infobriefs. World Bank, Washington, DC No. 118. ©World Bank. https://openknowledge.worldbank.org/handle/10986/9884.
Bunda College, 2008. Situation analysis of agricultural research and training in the SADC Region (Malawi). In: Implementation and Coordination of Agricultural Research and Training (ICART) in the SADC Region. FANR Directorate SADC Secretariat, Gaborone, Botswana.
Carletto, C., Gourlay, S., Winters, P., 2015. From guesstimates to GPStimates: land area measurement and implications for agricultural analysis. J. Afr. Econ. 24 (5), 593–628.
Chabvungma, S., Mawenda, J., Kambauwa, G., 2015. Drought conditions and management strategies in Malawi. In: Tsegai, D., Ardakanian, R. (Eds.), Proceedings (Series No.14) of the Regional Workshops on Capacity Development to Support National Drought Management Policies for Eastern and Southern Africa and the Near East and North Africa Regions. UN-Water Decade Programe on Capacity Development (UNW-DPC), Bonn, Germany, pp. 78–83.
Chabvunguma, S., Munthali, G., 2008. Determination of maize planting dates using some meteorological factors-Case Study Chitipa. In: Paper presented at the Proceedings of the 8th National Research Council of Malawi Conference.
Chamberlain, G., 1984. Panel data. Handb. Econ. 2, 1247–1318.
Chatsika, L., 2016. Adoption of Soil and Water Conservation Technologies Among Smallholder Farmers in the Face of Climate Risks (unpublished MSc. Thesis). Norwegian University of Life Sciences, Ås.
Chibwana, C., Fisher, M., Shively, G., 2012. Cropland allocation effects of agricultural input subsidies in Malawi. World Dev. 40 (1), 124–133.
Chilimba, A., Shano, B., Chigowo, M., Komwa, M., 2005. Quality Assessment of Compost Manure Produced By Smallholder Farmers in Malawi. Lilongwe, Malawi.
Chinsinga, B., Poulton, C., 2014. Beyond technocratic debates: the significance and transience of political incentives in the Malawi farm input subsidy programme (FISP). Dev. Policy Rev. 32 (s2).
CIMMYT, 2013. The Drought Tolerant Maize for Africa Project. Retrieved 29 March 2018, from DTMA Brief. http://dtma.cimmyt.org/index.php/about/background.
Corbeels, M., De Graaff, J., Ndah, T.H., Penot, E., Baudron, F., Naudin, K., ... Nyagumbo, I., 2014. Understanding the impact and adoption of conservation agriculture in Africa: a multi-scale analysis. Agric. Ecosyst. Environ. 187, 155–170.
DCCMS, D. o. C. C. a. M. S, 2006. Towards Reliable, Responsive and High Quality Weather and Climate Services in Malawi. Blantyre, Malawi, Ministry of Natural Resources, Energy and Environment.
Denning, G., Kabambe, P., Sanchez, P., Malik, A., Flor, R., Harawa, R., ... Magombo, C., 2009. Input subsidies to improve smallholder maize productivity in Malawi: toward an African Green Revolution. PLoS Biol. 7 (1), 0002–0010.
Ding, Y., Schoengold, K., Tadesse, T., 2009. The impact of weather extremes on agricultural production methods: does drought increase adoption of conservation tillage practices? J. Agric. Resour. Econ. 43 (3), 395–411.
Duinen, R.v., Filatova, T., Geurts, P., Veen, A.v.d., 2015. Empirical analysis of farmers' drought risk perception: objective factors, personal circumstances, and social influence. Risk Anal. 35 (4), 741–755.
EM-DAT, 2018. The Emergency Events Database. Université catholique de Louvain (UCL) - CRED - D. Guha-Sapir, Brussels, Belgium. www.emdat.be.
FAO, 2012. Plan of Action for Malawi 2012–2016. Emergency Operations and Rehabilitation Division. Food and Agriculture Organization of the United Nations. http://www.fao.org/fileadmin/user_upload/emergencies/docs/PoA_Malawi.pdf.
FEWS NET, 2015. Malawi Food Security Outlook July to December 2015. Famine Early Warning Systems Network, Malawi. http://fews.net/sites/default/files/documents/reports/Malawi_FSO_2015_07_1.pdf.
Fitzgerald, J., Gottschalk, P., Moffitt, R.A., 1998. An Analysis of Sample Attrition in Panel Data: The Michigan Panel Study of Income Dynamics. National Bureau of Economic Research Cambridge, Mass., USA.
Gebreeyesus, M., 2015. Firm adoption of international standards: evidence from the Ethiopian floriculture sector. Agric. Econ. 46 (S1), 139–155.
Government of Malawi, 2009. Annual Economic Report 2009. Ministry of Finance, Economic Planning and Development. Department of Economic Planning and Development, Lilongwe, Malawi.
Government of Malawi, 2011a. Malawi Agricultural Sector Wide Approach (ASWAp) 2011–2015. Ministry of Agriculture and Food Security, Lilongwe, Malawi.
Government of Malawi, 2011b. The Second National Communication of the Republic of Malawi to the Conference of the Parties of the United Nations Framework Convention on Climate Change. Ministry of Natural Resources, Energy, and Environment, Lilongwe, Malawi Retrieved from. http://unfccc.int/resource/docs/natc/mwinc2.pdf.
Government of Malawi, 2012. Approaches to the Implementation of Conservation Agriculture Among Promoters in Malawi. Ministry of Agriculture, Irrigation and Water Development, Lilongwe, Malawi.
Government of Malawi, 2015. Intended Nationally Determined Contribution (INDC). Lilongwe, Malawi.
Harrigan, J., 2008. Food insecurity, poverty and the Malawian Starter Pack: fresh start or false start? Food Policy 33 (3), 237–249.
Hausman, J., 1978. Specification tests in econometrics. Econometrica 46, 1251–1271.
Heerink, N., 2005. Soil fertility decline and economic policy reform in Sub-Saharan Africa. Land Use Policy 22 (1), 67–74.
Heisey, P.W., Smale, M., 1995. Maize Technology in Malawi: A Green Revolution in the Making? (Vol. Research Report No. 4). CIMMYT, Mexico.
Holden, S.T., Fisher, M., 2013. Can area measurement error explain the inverse farm size productivity relationship? In: CLTS WP No.12/13. Centre for Land Tenure Studies, Norwegian University of Life Sciences, Norway.
Holden, S., Lunduka, R., 2012. Do fertilizer subsidies crowd out organic manures? The case of Malawi. Agric. Econ. 43 (3), 303–314.
Holden, S.T., Quiggin, J., 2017. Climate risk and state-contingent technology adoption: shocks, drought tolerance and preferences. Eur. Rev. Agric. Econ. 44 (2), 285–308.
Inocencio, A.B., 2007. Costs and Performance of Irrigation Projects: A Comparison of Sub-Saharan Africa and Other Developing Regions. 109 IWMI.
Kabuli, A., Phiri, M., 2006. Farmer Perceptions, Choice and Adoption of Soil Management Technologies in Maize-based Farming Systems of Malawi, KARI.
Kamanga, B., Waddington, S., Robertson, M., Giller, K., 2010. Risk analysis of maize-legume crop combinations with smallholder farmers varying in resource endowment in central Malawi. Exp. Agric. 46 (01), 1–21.
Kassie, M., Jaleta, M., Shiferaw, B., Mmbando, F., Mekuria, M., 2013. Adoption of interrelated sustainable agricultural practices in smallholder systems: evidence from rural Tanzania. Technol. Forecast. Soc. Chang. 80 (3), 525–540.
Kassie, M., Teklewold, H., Jaleta, M., Marenya, P., Erenstein, O., 2015. Understanding the adoption of a portfolio of sustainable intensification practices in eastern and southern Africa. Land Use Policy 42, 400–411.
Kerr, R.B., Snapp, S., Chirwa, M., Shumba, L., Msachi, R., 2007. Participatory research on legume diversification with Malawian smallholder farmers for improved human nutrition and soil fertility. Exp. Agric. 43 (04), 437–453.
Kilcher, L., 2007. How organic agriculture contributes to sustainable development. J. Agric. Res. Trop. Subtrop. 89 (Supplement), 31–49.
Koundouri, P., Nauges, C., Tzouvelekas, V., 2006. Technology adoption under production uncertainty: theory and application to irrigation technology. Am. J. Agric. Econ. 88 (3), 657–670.
Kydd, J., Christiansen, R., 1982. Structural change in Malawi since independence: consequences of a development strategy based on large-scale agriculture. World Dev. 10 (5), 355–375.
Lunduka, R.W., 2009. Land Rental Markets, Investment and Productivity Under Customary Land Tenure Systems in Malawi (unpublished PhD Thesis). Norwegian University of Life Sciences, Ås, Norway.
Lunduka, R., Ricker-Gilbert, J., Fisher, M., 2013. What are the farm-level impacts of Malawi's farm input subsidy program? A critical review. Agric. Econ. 44 (6), 563–579.
Mafongoya, P., Bationo, A., Kihara, J., Waswa, B.S., 2006. Appropriate technologies to replenish soil fertility in southern Africa. Nutr. Cycl. Agroecosyst. 76 (2–3), 137–151.
Makate, C., Makate, M., Mango, N., 2017a. Smallholder farmers' perceptions on climate change and the use of sustainable agricultural practices in the Chinyanja Triangle, Southern Africa. Soc. Sci. 6 (1), 30.
Makate, C., Wang, R., Makate, M., Mango, N., 2017b. Impact of drought tolerant maize adoption on maize productivity, sales and consumption in rural Zimbabwe. Agrekon 1–15.
Mango, N., Siziba, S., Makate, C., 2017. The impact of adoption of conservation agriculture on smallholder farmers' food security in semi-arid zones of southern Africa. Agric. Food Secur. 6 (1), 32.
Matchaya, G.C., 2007. Does size of operated area matter? Evidence from Malawi's agricultural production. Int. J. Agric. Rural Dev. (IJARD) 10 (2), 114–125.
Msowoya, K., Madani, K., Davtalab, R., Mirchi, A., Lund, J.R., 2016. Climate change impacts on maize production in the warm heart of Africa. Water Resour. Manag. 30 (14), 5299–5312.
Mundlak, Y., 1978. On the pooling of time series and cross section data. Econometrica J. Econ. Soc. 46 (1), 69–85.
Mustafa-Msukwa, A.K., Mutimba, J.K., Masangano, C., Edriss, A.K., 2011. An assessment of the adoption of compost manure by smallholder farmers in Balaka District, Malawi. S. Afr. J. Agric. Ext. 39 (1), 17–25.
Muzari, W., Gatsi, W., Muvhunzi, S., 2012. The impacts of technology adoption on smallholder agricultural productivity in Sub-Saharan Africa: a review. J. Sustain. Dev. 5 (8), 69.
Nangoma, E., 2007. National adaptation strategy to climate change impacts: a case study of Malawi. In: Human Development Report, 2007/2008, 2008. United Nations Development Program.
Nyasimi, M., Kimeli, P., Sayula, G., Radeny, M., Kinyangi, J., Mungai, C., 2017. Adoption and dissemination pathways for climate-smart agriculture technologies and practices for climate-resilient livelihoods in Lushoto, Northeast Tanzania. Climate 5 (3), 63. https://doi.org/10.3390/cli5030063.
Ortega, D.L., Waldman, K.B., Richardson, R.B., Clay, D.C., Snapp, S., 2016. Sustainable intensification and farmer preferences for crop system attributes: evidence from Malawi's central and southern regions. World Dev. 87, 139–151.
Papke, L.E., Wooldridge, J.M., 2008. Panel data methods for fractional response variables with an application to test pass rates. J. Econ. 145 (1), 121–133.
Petrin, A., Train, K., 2010. A control function approach to endogeneity in consumer choice models. J. Mark. Res. 47 (1), 3–13.
Roodman, D., 2011. Fitting fully observed recursive mixed-process models with cmp. Stata J. 11 (2), 159–206.
Shiferaw, B., Kassie, M., Jaleta, M., Yirga, C., 2014. Adoption of improved wheat varieties and impacts on household food security in Ethiopia. Food Policy 44, 272–284.
Silberg, T.R., Richardson, R.B., Hockett, M., Snapp, S.S., 2017. Maize-legume intercropping in central Malawi: determinants of practice. Int. J. Agric. Sustain. 15 (6), 662–680.
Smale, M., 1995. "Maize is life": Malawi's delayed green revolution. World Dev. 23 (5), 819–831.
Snapp, S., Mafongoya, P., Waddington, S., 1998. Organic matter technologies for integrated nutrient management in smallholder cropping systems of southern Africa.

Agric. Ecosyst. Environ. 71 (1), 185–200.
Snapp, S., Rohrbach, D., Simtowe, F., Freeman, H., 2002. Sustainable soil management options for Malawi: can smallholder farmers grow more legumes? Agric. Ecosyst. Environ. 91 (1), 159–174.
Snapp, S., Jayne, T.S., Mhango, W., Benson, T., Ricker-Gilbert, J., 2014. Maize yield response to nitrogen in Malawi's smallholder production systems. In: Malawi Strategy Support Program, Working Paper 9. International Food Policy Institute.
Tchale, H., 2009. The efficiency of smallholder agriculture in Malawi. Afr. J. Agric. Resour. Econ. 3 (2), 101–121.
Thierfelder, C., Matemba-Mutasa, R., Rusinamhodzi, L., 2015a. Yield response of maize (*Zea mays* L.) to conservation agriculture cropping system in Southern Africa. Soil Tillage Res. 146, 230–242.
Thierfelder, C., Rusinamhodzi, L., Ngwira, A.R., Mupangwa, W., Nyagumbo, I., Kassie, G.T., Cairns, J.E., 2015b. Conservation agriculture in Southern Africa: advances in knowledge. Renew. Agric. Food Syst. 30 (4), 328–348.
Tobin, J., 1958. Estimation of relationships for limited dependent variables. Econometrica J. Econ. Soc. 24–36.
Valbuena, D., Erenstein, O., Tui, S.H.-K., Abdoulaye, T., Claessens, L., Duncan, A.J., ... van Rooyen, A., 2012. Conservation Agriculture in mixed crop–livestock systems: scoping crop residue trade-offs in Sub-Saharan Africa and South Asia. Field Crop Res. 132, 175–184.
Van Den Berg, M., Fort, R., Burger, K., 2009. Natural hazards and risk aversion: Experimental evidence from Latin America. In: Paper Presented at the International Association of Agricultural Economists Conference, Beijing, China.
Vanlauwe, B., Descheemaeker, K., Giller, K., Huising, J., Merckx, R., Nziguheba, G., ... Zingore, S., 2015. Integrated soil fertility management in sub-Saharan Africa: unravelling local adaptation. Soil 1 (1), 491–508.
Waddington, S.R., 1990. Research Methods for Cereal/Legume Intercropping: Proceedings of a Workshop on Research Methods for Cereal/Legume Intercropping in Eastern and Southern Africa Held at Lilongwe, Malawi, 23–27 January 1989. CIMMYT.
Waddington, S., Mekuria, M., Siziba, S., Karigwindi, J., 2007. Long-term yield sustainability and financial returns from grain legume–maize intercrops on a sandy soil in subhumid north central Zimbabwe. Exp. Agric. 43 (4), 489–503.
Waldman, K.B., Ortega, D.L., Richardson, R.B., Snapp, S.S., 2017. Estimating demand for perennial pigeon pea in Malawi using choice experiments. Ecol. Econ. 131, 222–230.
Weber, V.S., Melchinger, A.E., Magorokosho, C., Makumbi, D., Bänziger, M., Atlin, G.N., 2012. Efficiency of managed-stress screening of elite maize hybrids under drought and low nitrogen for yield under rainfed conditions in Southern Africa. Crop Sci. 52 (3), 1011–1020.
Weidmann, G., Kilcher, L., 2011. African Organic Agriculture Training Manual. Research Institute of Organic Agriculture (FiBL).
Woodhouse, P., Veldwisch, G.J., Venot, J.-P., Brockington, D., Komakech, H., Manjichi, Â., 2017. African farmer-led irrigation development: re-framing agricultural policy and investment? J. Peasant Stud. 44 (1), 213–233.
Wooldridge, J.M., 2009. New Developments in Econometrics, Lecture 6: Non-linear Panel Data Models. Cemmap Lectures. University College London Retrieved from. http://www.cemmap.ac.uk/resources/imbenswooldridge/slides6.pdf.
Wooldridge, J.M., 2010a. Correlated Random Effects Models With Unbalanced Panels. Michigan State University, Department of Economics.
Wooldridge, J.M., 2010b. Econometric Analysis of Cross Section and Panel Data. MIT Press, Cambridge, Massachusetts. London, England.
Wooldridge, J.M., 2011. Fractional response models with endogeneous explanatory variables and heterogeneity. In: Paper Presented at the CHI11 Stata Conference.
Woomer, P., Lan'gat, M., Tungani, J., 2004. Innovative maize-legume intercropping results in above-and below-ground competitive advantages for understorey legumes. West Afr J. App. Ecol. 6 (1).
World Bank, 2010. Malawi: Economic Vulnerability and Disaster Risk Assessment. United States of America, Washington D.C.
Zellner, A., 1962. An efficient method of estimating seemingly unrelated regressions and tests for aggregation bias. J. Am. Stat. Assoc. 57 (298), 348–368.