Title: Assessing smallholder preferences for incentivised climate-smart agriculture using a discrete choice experiment

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Highlights

- Options for climate smart agriculture in Malawi get mixed responses from farmers
- A discrete choice experiment reveals that farmers prefer crops for local use
- Conditional payments as adoption incentives may exclude certain farmers
- Options vary in poverty reduction, drought adaptation and commercialisation
- Different options can contribute to different sustainable development goals

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Abstract

The promotion of climate smart agriculture (CSA) techniques to increase farmer resilience against climate change and their livelihoods is high on the international development agenda and aims to help achieve Sustainable Development Goals of food security (SDG 2), climate resilience and mitigation (SDG 13). We present the results of a discrete choice experiment (DCE) conducted in face-to-face interviews. In a study in Malawi, farmers responded to a series of questions about different cropping techniques and tree planting options to improve soil fertility and climate change resilience. A combination of financial and non-financial incentives was proposed to increase adoption and success rates. The results show that for different policy objectives, different climate smart packages are suitable. Our results demonstrate that farmers prefer options that secure the production of maize and include crops with both domestic use and local markets. The drought-resistant crop sorghum was unpopular among respondents; achieving SDG 13 through this CSA approach would therefore require high incentive payments. If CSA is to help achieve multiple goals e.g. poverty and inequality reduction (SDGs 1 and 10) as well as SDGs 2 and 13, a range of CSA packages, with different types of crops, rotation versus intercropping techniques and incentive levels, should be offered to smallholders.

1. Introduction - Climate smart agriculture and adoption

Globally, there are an estimated 500 million smallholder farms, who produce 75% of all food (Lowder et al. 2016), yet many smallholders live below the international income poverty line. Widespread calls for radical changes in the current food and agriculture system (e.g. TEEB 2018) towards sustainable agricultural intensification (Rockström et al. 2017) have been motivated by damage to biodiversity and ecosystems – with estimated costs of up to 18% of global economic output by 2050, up from around 3.1% (US$2 trillion) in 2008 (UNPRI 2017). The food and agriculture system is therefore considered as one of the four biggest opportunities for SDG investment for business and governments (ibid.).

Several international development organisations, including the World Bank and the FAO, have adopted Climate Smart Agriculture (CSA), as the main strategy for sustainable agriculture driven development to support food security under climate change (Lipper et al. 2014). These organisations, who have set up networks with large private sector agents but also work with local stakeholders, try to promote CSA practices and its recognition in policy. CSA aims to improve farmer incomes and livelihoods, increase farmer resilience to climate change, and where possible reduce greenhouse gas emissions from farming. The set of CSA techniques include off- and on-farm techniques, covering multiple steps in the agricultural commodity chain.

There is an intense debate across stakeholder groups about the advantages and disadvantages of sustainable intensification and CSA. Proponents argue that poor and non-farming households benefit from agricultural development through higher food availability, lower prices and labour opportunities (Gómez et al. 2011). Arguably, CSA and intensification practices provide win-wins (Waldron et al. 2017) and help to reduce emissions globally by reducing forest and woodland conversion (Burney et al. 2010). The introduction of new crops and tree planting may help to increase farm revenue, climate resilience, soil fertility (Akinnifesi et al. 2011) and reduce deforestation (Kaczan et al. 2013).

Critics question the socio-political dimension of CSA, the emphasis on technology rather than political reform, and on win-wins rather than trade-offs in complex systems (Taylor 2018, Whitfield et al. 2018). Civil society organisations have published their concerns about CSA leading up to the COP21 and reject the Global Alliance for Climate-Smart Agriculture (GACSA). They argue that CSA is a re-branding of industrial practices, some of which may help to adapt to climate change, but which increase dependencies on corporations without

respecting ecological boundaries and local culture, knowledge and skills. They claim that private sector projects often fail to engage the poorest farmers or take their land (Rosset 2011).

Others warn against win-win thinking. Evaluations of existing projects have found that projects fail to deliver on social and ecological goals simultaneously (Zeng et al. 2014, Rasmussen et al. 2018). Successful implementation require agricultural extension services and appropriate institutions (Coulibaly et al. 2015). Rosenstock et al. (2015) find that win-wins (synergies) between resilience and yield improvements are found in just over half the CSA studies.

Moreover, sustainable agricultural practices, including agroforestry and conservation agriculture (Pittelkow et al. 2015), have seen little to no sustained adoption among smallholder farmers (Nebraska Declaration 2013[1], Corbeels et al. 2014) and have very mixed effects on the wellbeing of farmers (Pannell et al. 2014, Rasmussen et al. 2018). Preliminary results of a meta-analysis on CSA adoption did not reveal any systematic impacts of factors on adoption (Rosenstock et al. 2015). This finding holds for gender, credit and market access, information and extension, assets, social networks, and off-farm income – these factors were statistically insignificant in 70% or more of the studies. The low adoption rates have also been attributed to insecure tenure rights, limited information and high upfront investment costs; factors which have hindered agricultural development in general for decades (Williams et al. 2015). In some cases, farmers with larger farm sizes and higher education were more likely to adopt conservation agriculture (Knowler and Bradshaw 2007), while lack of access to farm inputs reduces adoption rates (Giller et al. 2011). However, land (tenure) and income constraints are most likely to reduce the accessibility of CSA techniques to the poorest and most vulnerable segments of society. Project designs to increase adoption rates have had little effect. Projects that have used so-called 'lead-farmers', i.e. farmers who are most likely to adopt first get investment support and are stimulated to demonstrate their success and spread adoption through their social networks, have had limited success (Steenwerth et al. 2014). This is despite ethnographic findings that peer-effects play a role in uptake decisions (Bell et al. 2018). Other projects have provided inputs such as chemical fertiliser for free to increase initial adoption. However, if such inputs are no longer supplied after the projects end, dis-adoption of the promoted agricultural techniques has often followed (Andersson and D'Souza

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[1] Available from: https://ispc.cgiar.org/publication/nebraska-declaration-conservation-agriculture

2014). The reason of dis-adoption may be that farmers cannot consistently realise high yields from conservation agriculture, and the application of additional chemical fertiliser is often necessary to generate acceptable yield levels (Corbeels et al. 2014; Vanlauwe et al. (2013). Without free inputs, farmers cannot bear the additional costs of conservation agriculture.

The question is to what extent a CSA strategy can contribute directly to the Sustainable Development Goals 1 (no poverty) and 10 (reduced inequalities) (Karlsson et al. 2018). In light of these pressing goals but the mixed evidence, a clear demand for enhancing the evidence base for strategic choices towards successful CSA implementation has been expressed (Williams et al. 2015). As public investment in agriculture is showing a steady decline (-40% between 2000 and 2015)[2], evidence from context-sensitive studies (Giller et al. 2015) should ensure that development resources are invested in agricultural development projects that can deliver on their promise of improving the livelihoods of smallholder farmers.

The aim of this study was to understand whether preference for on-farm climate-smart agricultural projects would vary with individual wealth and wellbeing levels. In a discrete choice experiment, we elicited farmers' preferences for a program combining on-farm tree planting and crop diversification, supported by a conditional payment to overcome the initial investment cost as a risk-sharing mechanism (Mapfumo et al. 2015). More specifically, we asked farmers to make choices about the adoption of extra trees on their farms with different tree products, different cropping techniques, the level of credit they would want, and different maize yield increases following tree planting and intercropping or crop rotation after a certain period of time. We test whether the conditional preference parameters of the DCE attributes are associated with indicators for different types of capital (physical, human, financial, social and natural), using a seemingly unrelated regression model.

2. Existing climate smart agriculture initiatives in Malawi

We conducted our empirical research in the Zomba district in Southern Malawi. Poverty levels in Malawi are high: the country ranks 170 on the Human Development Index 2016, with 56% of the total population qualified as multidimensionally poor and 71% living below

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[2] Available at: http://www.fao.org/sustainable-development-goals/indicators/2a1/en/

the $1.90/day poverty line (HDR 2016). The Southern Region has the highest poverty rate (63%) and ultra-poverty rate (34%) (NSO 2012).

The economy of Malawi is largely dependent on agriculture, in terms of GDP and even more so in terms of employment and informal economy. Agriculture is the main source of rural livelihoods and half of the rural households are pure subsistence farmers. The average cultivated area per household is about 0.6 ha (NSO 2017a). Besides agriculture, local poor households depend on multiple forest resources for their livelihoods (Kamanga et al. 2010). Stakeholders at national level, especially in urban areas, want to maintain forests for water provision and hydropower, but their demand for timber and fuelwood also leads to continuous forest degradation. The level of deforestation varies within the Zomba district, with denser forest patches remaining in the North, the Zomba-Malosa forest, and high levels of deforestation near Zomba, caused mainly by charcoal production for urban dwellers (Smith et al. 2015).

National self-sufficiency in maize is a priority of the Government of Malawi. The Government interferes in the maize market through input subsidies, price fixing, domestic trade limitations and import and export bans. Ellis and Manda (2012) argue that these interventions may have increased price spikes on the black maize market that have caused hunger among a large proportion of people. Despite subsidies, fertilisers are still expensive, farmers do not have access to loans and other financial services (Lea and Hanmer 2009), and market infrastructure is underdeveloped (Dorward et al. 2009, Tchale and Keyser 2010). The farmer input subsidies have been criticised for failing to increase maize yields and to alleviate poverty as they were not distributed at the right time and to the right people (Lunduka et al. 2013, Pauw et al. 2016); and for causing fraud, corruption and distortion of the market for agricultural inputs (World Bank 2013). The fertiliser coupons are insufficient and fail to reach the poorest (Denning et al. 2009, Lunduka et al. 2013). The emphasis on maize and subsidies has taken up so much of the government budget for agriculture that it causes underinvestment in agricultural diversification and technological development (Dorward et al. 2009; Chinsinga and Cabral 2010; Chinsinga 2014). Moreover, maize promotion may have negatively affected public perception of alternative cereals such as millet and sorghum which are seen as inferior, crops for the desperate (Chinsinga et al. 2011). In addition, besides soil loss, climate change is putting increasing pressure on farmers in Malawi. Both droughts and floods have had devastating impacts on food security in the country (Stevens and Madani

2016). Climate change may increase maize production in some areas in the short-term, but this will increase the rate of soil loss (ibid.).

In response, several organisations in Malawi have trialled climate-smart, agroforestry and conservation agriculture practices (Gilbert 2012, Carsan et al. 2014), but with mixed levels of success. Agroforestry studies in Malawi have reported increased yields compared to unfertilised mono-cropping (Ajayi et al. 2011), and higher farm revenues through tree product sales (Akinnifesi et al. 2008), improved resilience to climate change (Verchot et al. 2007) and food security (Snapp et al. 2010). However, lack of land and knowledge about agroforestry practices mean that farmers do not prioritise agroforestry (Cromwell et al. 2001). Poverty can also limit the adoption of trees on farmland, when farmers are not willing to invest scarce resources in trees which have delayed benefits and involve risks of food insecurity and technological failure (Walker 2004; Kamanga et al. 2010; Jerneck and Olsson 2014; Meijer et al. 2015). Land scarcity, lack of tree seeds and seedlings, tree theft and low tree survival rates were reported in focus groups discussing agroforestry (Meijer et al. 2015). Support to invest in agroforestry through microfinance has therefore been put forward as a possible way to increase adoption and success rates (ibid.).

Short-term benefits are hence important for adoption of on-farm trees and other sustainable farming options, especially in the context of Malawi with high subsistence farming rates. Farmers are most likely to adopt legume intercropping systems with crops that fulfil immediate food needs or have easy market access, such as pigeon peas (Sirrine et al. 2010, Waldman et al. 2017), and more likely to adopt improved grains than non-grain legumes (Pircher et al. 2013). Intercropping maize with legumes may be more beneficial and less risky than rotation of these crops (Kamanga et al. 2010).

If sustainable techniques do not generate short-term net-benefits, external incentives may be necessary for adoption. In dry low-elevation areas, yields under conservation agriculture have been found to increase compared to high-elevation areas and control settings, suggesting that farmers in high-elevation areas may need considerably higher incentives for some of the conservation agriculture techniques (Ngwira et al. 2013). Agroforestry may also need short-term subsidies, because the number of trees necessary to improve maize yields takes up land while the improvement of soil properties takes multiple years, which therefore may mean that farmers have to forego yields in the initial years (Sirrine et al. 2010). Other labour and capital costs of agroforestry also tend to be higher in the short-term: maize agroforestry is more

labour-intensive than conventional maize cropping during the first two years, when the management of the saplings and tree growth requires considerable attention (Garrity et al. 2010). However, there are few studies that have investigated whether and what level of subsidies farmers perceive to be necessary to offset their opportunity costs.

3. Methods

3.1 Discrete choice experiments

This study uses a discrete choice experiment (DCE) to elicited farmers' preferences for a climate-smart agricultural program to understand whether preference for on-farm agricultural projects would vary with individual wealth and wellbeing levels. DCEs are useful for eliciting values when no functioning markets exist in which farmers reveal their preferences for CSA. Instead, DCE rely on hypothetical markets to analyse the welfare effects of policies. This can inform decisions on investment in CSA, especially if the flow of benefits of different CSA options can be compared against their costs (Thornton et al. 2018).

In the standard economic model of rational choice in decision making, individuals are assumed to maximise their utility by determining what options are available and then choosing the most preferred one. The DCE is a method in which respondents are asked to indicate their preference among two or more multi-attribute alternatives; the value of these alternatives can be associated with changes beyond existing markets or conditions (Johnston et al. 2017). In a DCE, respondents are usually asked to complete a sequence of choice sets, which each consists of two or more options, together with an opt-out option.

The DCE data can be used to estimate discrete choice models. In the random utility framework which underlies the DCE technique, utility is comprised of a systematic component V_{int} and an error term ε_{int}, formalized in the following basic relationship:

$$U_{int} = V_{int} + \varepsilon_{int}$$

V_{int} is the deterministic component of the utility and can be specified as linear function of parameters where a respondent n chooses option i out of a set of options J in choice situation t so that the utility function U for respondent n is defined as:

$$U_{int} = \theta_n X_{int} + \varepsilon_{int}$$

$$= \sum_{i=1,2} (\alpha_i + \sigma_{in}^\alpha) A_{int} + \sum_{k=1}^{k} \left(\beta_k + \sigma_{kn}^\beta\right) x_{knt} + \sum_{k=k+1}^{K} (\gamma_k x_{knt}) + \varepsilon_{int}$$

θ is the vector of parameters to estimate and the matrix X summarizes observable variables. A_i is a dummy variable that takes the value 1 for the two alternative policies, and 0 for the opt-out, and α is the mean parameter of these alternative specific constants. The attributes x_{knt} of matrix X are portioned in k random coefficients β across respondents (n) and in the remaining fixed γ coefficients. Both alternative specific constants and random parameters are normally distributed with standard deviation parameters $\sigma^{\alpha,\beta}$. The component of respondent n's utility that cannot be observed is denoted by ε_{int} and distributed as extreme value type I. The parameter α, and its normal random distribution, characterise an error-component model that can accommodate correlation among alternatives to reflect that less familiar hypothetical alternatives are compared with the current situation (Brownstone and Train 1998; Scarpa et al. 2005). The random component model is defined by the parameters β and σ^β and allows for heterogeneous preferences within the sampled population, unrestricted substitution patterns and correlation between the different aspects of utility (Train 2009).

Choices are a function of the probability that the utility of option i is higher than for the other alternatives. In the mixed logit model, the choice probability function is described as the integral of the conditional individual probabilities over all possible choice variables and their marginal effects, where $f(\theta |\Phi)$ is the density function of θ with distribution Φ:

$$P_{int} = \int \left(\frac{e^{\theta' x_{int}}}{\sum_j e^{\theta' x_{jn_t}}}\right) f(\theta|\Phi)) d\theta \text{ for all } i{\neq}j.$$

Because the unconditional probability of the sequence of observed choices (i.e. t = 1; 2; … 6) has no closed form, the probability needs to be approximated through simulation by factoring out the random and error component coefficients over the standard normal distributions. This model specification can also account for the panel structure of the data.

The estimates of the coefficient vector indicate the average utility weights of the attributes included in the choice tasks. The willingness to pay value or the implicit price for each non-price attribute z can be calculated as WTP $= - \beta_z / \beta_p$ where β_z and β_p represent the (mean of the distribution of the) coefficients of the z-th attribute and of the price attribute respectively.

With the estimates of the coefficient vector it is also possible to derive individual-specific (conditional) WTP measures (Train 2009). These post-estimation measures provide a marginal WTP (i.e. compared to a baseline) for the adoption of the z attributes considered in the DCE for each individual. Individual characteristic and socio-economic conditions can play a role in explaining these WTP measures and alternative approaches are available to disentangle heterogeneity in preferences (e.g. Ward et al. 2016). Seemingly unrelated regression (SUR) models the n individual WTP by considering a set of $z=(1,..Z)$ marginal WTP equations that are explained by the matrix of characteristics (Y_{nz}) and their error terms are correlated:

$$MWTP_{nz} = f(Y_{nz}, \vartheta_z) + \epsilon_{nz}$$

$$E[\epsilon_{nz}|Y_{nz}] = 0$$

$$E[\epsilon_{nz}\epsilon_{nz}|Y_{nz}] \neq 0$$

Different individual and social characteristics can influence the matrix Y_{nz}. The SUR model efficiently accommodates the correlation across equations but not across individuals (Cameron and Trivedi 2005). The SUR model provides a broad understanding of factors influencing the adoption of CSA techniques and results can support decision makers in tailoring interventions to different subpopulations.

DCEs have not been applied extensively to understand agricultural choices in Malawi. Waldman et al. (2017) assess the choices farmers make between annual and perennial maize-pigeon pea intercropping systems, and how farmer characteristics affect opt-out choices. Ward et al. (2016) investigate the impact of subsidies on adoption of conservation agriculture and reveal preference heterogeneity among farmers in Malawi by assessing individual WTP estimates for different attributes. Marenya et al. (2014) used framed choice experiments to investigate whether farmers were interested in crop insurance to cope with drought risks, and risk aversion affected insurance uptake. Our study provides further insight into the preferred CSA techniques of different subgroups among rural farmers to provide recommendations for CSA package design.

3.2 Discrete Choice Experiment design

For the DCE we defined two attributes reflecting on-farm CSA techniques, two attributes that explained the additional yields of these techniques, an attribute indicating the temporal distribution of these additional yields, and one attribute reflecting a conditional payment to cover the adoption costs (see Table 1). Farmers were assumed to be able to assess and trade-off the costs and benefits of these techniques over time, and thereby indicate the minimum compensation level they would require.

Table 1. DCE attributes and levels

Attribute	Levels			
Cropping technique	Soy - maize rotation	Groundnut - maize intercropping	Pigeon pea - maize intercropping	Sorghum - maize intercropping
Number of extra trees	3	5	10	20
Time until improvement	1 year	2 years	5 years	10 years
Increase in maize yield	0 bags of 50kg	1 bag of 50kg	2 bags of 50kg	4 bags of 50kg
Tree product	fuelwood	fruits	poles	
Credit (MKW/year)	5000	15000	25000	40000

The first attribute was the crop diversification attribute, with four levels: soy-maize rotation, pigeon pea-maize intercropping, groundnut-maize intercropping and sorghum-maize intercropping. Soy is mostly a cash crop (Tinsley 2009), pigeon pea and groundnuts are food crops traded in local markets, and sorghum is a climate resistant wheat crop (Cooper et al. 2008). The second attribute was the additional number of trees planted on the "mundas" (main type of plot, not riverine), varying from three to twenty trees in total. The levels of this attribute were based on the required 25-30 trees per hectare for achieving improved maize yields, and the relatively small land parcels in the area (NSO 2017a). The third attribute was the number of years that it would take to improve maize yields and harvest tree products, varying from one to ten years as reported in Garrity et al. (2010). The fourth was the

increase in maize yields, varying from zero to three bags of 50kg per year, based on studies such as Kamanga et al. (2010) and Kaczan et al. (2013). The tree products included fruits, poles and firewood, as represented by the fifth attribute.

The sixth attribute was the financial incentive, which was presented as a conditional annual credit that farmers would receive for five years, and that they would not have to pay back if the trees were still present on their land after five years. However, should they fail to manage the trees then the payments would be turned into a loan. The amounts, varying from five to forty thousand Malawian Kwacha (MKW) per year (EUR 7-40), were based on a calculation of the costs of additional labour required for the systems, and the loss of maize in initial years. The choice for a WTA question was not only motivated by the fact that implementation of the programs would impose costs on farmers in the first few years, but also that part of the benefits of such projects would accrue to the more distant communities that could potentially benefit from regulation of water flow, carbon sequestration and lower pressure on forests. A subsidy is coherent with the current fertiliser subsidy programme even if the subsidy is provided in the form of coupons. Moreover, in low-income countries, household budget constraints can prohibit WTP questions (Rai and Scarborough 2015).

In the hypothetical scenario, the options would be supported by additional extension services to train farmers in the methods and tree caring, and seedlings as well as seeds for the new crop would be provided in year 1. The program would be implemented by an NGO in collaboration with the village development committee. The NGO would monitor and check the presence of the trees; the village development committee would manage the conditional credit scheme.

Figure 1 presents an example of a choice card. The design for the DCE was generated using SAS software following procedures for a D-efficient design with non-informative priors as outlined in Kuhfeld (2010). The design consisted of 36 choice cards split into six versions (blocks). The experimental design was optimised for main effects but does not allow for the analysis of interaction effects (synergies) between the attributes.

	A	B	C
Mbeu zosiyanasiyana mkalimidwe	Kusinthasintha chimanga ndi soya	Kupachiza chimanga ndi mtedza	Kungodalira ulimi wanu (mwanthawi zonse)
Nambala ya mitengo yowonjezera m'munda	Mitengo 3 younjedzera	Mitengo 10 younjedzera	Osawoyenjedzera mitengo
Zaka zomwe zingadutse kuti muthu ayambe kukolola kuchokera ku mitengo ndiponso chimanga	Chaka chimodzi 1	Chaka makumi 10	0
Zokolola zowonjezera pachaka	4 nthumba la 50kg	4 nthumba la 50kg	Popanda mtengo woonjezera (nthaka osasitha)
Zokolola ku mitengo	Zipatso	Mapolo	-
Khubili kwa dzaka zitsano	MK 25000	MK 15000	MK 0
	□ A	□ B	□ C

Figure 1. Example choice card.

3.3 Pre-tests and data collection

The methods were pre-tested in comparable villages during April 2015 with the help of experienced Malawian enumerators. Low levels of literacy necessitated the use of figures and pictograms to explain the attributes, levels, and hypothetical market. The main change made during the pre-tests was an increase in the level of credit, as pre-test respondents deemed the initial levels too low to overcome the adoption costs.

Data were collected from mid-June until mid-August 2015. Four trained Malawi interviewers conducted the interviews. The household questionnaire consisted of seven parts, including questions on (a) current agricultural yields, (b) forest use and revenues, (c) the choice experiment, (d) perceptions on the barriers, financial credit, and institutions involved in the hypothetical market, (e) perception on benefits of tree planting, crop diversification and forest conservation, (f) household characteristics, and (g) an interview assessment completed by the interviewer.

Respondents were selected after a household mapping exercise in the villages. Four group-villages were selected, with ten sub-villages in total. One group-village is located in Zomba District, the other three in Machinga District. The locations were chosen based on the distance to the town of Zomba and to the most intact part of the Zomba-Malosa forest. One of the group-villages was involved in the community-based forest management of this forest. In each group-village, fifty individual choice experiments were conducted. Participants had to be aged between 18 and 65 years and were selected to achieve proportional representation of gender and age groups, representative of the village population.

4. Results

4.1 Descriptive statistics

In total, 198 respondents participated in the DCE, and 196 observations remained for analysis after data cleaning; descriptive statistics are presented in Table 2. The number of female respondents was higher than male respondents. Education levels were low, with only 34% of the sample having completed primary schooling or above. The mean household size was 4.5. The average land holdings were just under 1 hectare per household and 35% of the respondents had only one plot.

Households produced on average 681 kg of maize, but the skewed maize yield distribution implies that for a considerable proportion of the sample the farm does not produce sufficient food to last the whole year – on average, respondents reported that their farm produced enough food for 9 months of the year. Other important crops are groundnuts (with a yield of 237 kg/ha), pigeon peas (32 kg/ha) and cotton (57 kg/ha); sorghum and soy production were low.

Almost all respondents (96%) use chemical fertiliser, but the amount of fertiliser that households can get or afford is low (median = 87kg/ha) in comparison to industrialised countries (e.g. 200 kg/ha for maize in Germany) (Roser and Ritchie 2017). The mean number of fertiliser coupons that households get is 0.95; village politics dictate that coupons are shared among families and friends irrespective of need.

As most of the farm produce is used for domestic consumption, cash revenues from respondents' farms are relatively low. Few households own a private woodlot, and mean woodlot revenues are negligible, but public or communal forest revenues (mainly from selling charcoal, bamboo, firewood and grasses) are relevant. More than half of the households (58%) own livestock. Within the 'other income' pool, the largest source is formal employment, with smaller contributions from charcoal trade, non-agricultural activities, remittances, social cash transfers and agricultural wage labour. Compared to the sample statistics for household cash revenues, the chosen credit levels in the DCE appear to be of the right order of magnitude, especially if one considers that the options would imply a considerable change in people's main source of food production.

Previous research has found that the number of relatives on which one can rely in times of need can have significant impact on the probability that households adopt new farming techniques (Kassie et al. 2015). On average, households reported that they have 2.5 potentially supporting relatives. More than half of the sample did not trust the traders to whom they sold their maize and main crops. Two-fifth of the sample expected that the Government would help in case of harvest failure. Relevant to our DCE is also that 20% of the respondents had previously been involved in intercropping or crop rotation projects, and more than half had been exposed to tree planting projects.

Table 2. Sample statistics (n=196)

Variable	Mean (s.d.) [median]	Proportion (s.d.)
Respondent gender (proportion male)		0.45 (0.50)
Respondent age (in years)	42 (16) [38.5]	
Respondent education primary school or above		0.34 (0.48)
Respondent head of household		0.66 (0.48)
Household size	4.5 (2.0) [4]	
Only 1 plot owned		0.35 (0.48)
Number of plots	1.9 (0.88)	
Total land size (in hectares)	0.92 (0.79) [0.77]	
Maize produced (in kg)	681 (673) [500]	
No. of months that food was sufficient for family	9.2 (3.4)	
Fertiliser use (in kg)	80 (57) [50]	
Number of fertiliser coupons used	0.95 (0.60) [1]	
Total number of trees on farm	18 (51) [4]	
Woodlot owned		0.12 (0.32)
Number of livestock owned	4.2 (6.6) [2]	
Farm revenues (in MKW)	16,278 (46,828) [1,600]	
Woodland revenues (in MKW)	208 (2274) [0]	
Forest revenues (in MKW)	10,443 (54,854) [0]	
Livestock revenues (in MKW)	6,404 (26,541) [0]	
Other income (in MKW)	98,713 (220,736) [32,000]	
Number of relatives in village for support	2.5 (3.0) [1.5]	
Expecting government assistance		0.43 (0.50)
Trust in traders		0.55 (0.50)
Involved in intercropping/rotation projects		0.21 (0.41)
Involved in tree planting projects		0.55 (0.50)

Notes: based on data collected in 2015 in Malawi.

4.2 Choice model results

The opt-out rate was very low, with only 7% of choices for the current situation. The main motivations for choosing the opt-out were that respondents thought the options would not be more beneficial than their current farming practices, they would not be able to afford the additional labour required for the new practices, or number of trees in the options was too high for the size of plots owned.

Table 3 presents the results of the mixed logit models estimated in preference-space for the choice data from our DCE, using R software (version 3.1.1). Because of the categorical attributes (cropping techniques, tree products), the baseline is a choice for an alternative with groundnuts and fuelwood. The alternative specific constant captures this baseline, plus a general propensity to choose an alternative different from the status quo. Random parameters with normal distributions were estimated for all attributes, and an error-component was included for the two options versus the opt-out. For five of the attributes, preference heterogeneity in our sample is significant. We opted for a parsimonious model and in the final model only those variables with significant heterogeneity are included as random parameters; otherwise they are kept fixed.

The model results show that, as theoretically expected, the probability of choosing one of the CSA packages increases with higher credit levels, lower number of trees, and higher number of maize bags. The respondents differ significantly in their preferences for these attributes, as can be seen from the significant distributions of the random parameters. Moreover, the standard deviations are larger than the means of the random parameters: for all parameters there is a sign-switch within the sample.

The posterior estimates suggest that the mean estimate for around 65% is positive as expected, but about 35% of the sample is estimated to prefer smaller amounts of credit (column 4 of Table 3). While this would be perceived as problematic (theoretically invalid) in WTP studies, it is reasonable in this case where the risk of not meeting the credit requirements (successful tree management) led to a preference for lower amounts among some respondents. The posterior estimates furthermore suggest that approximately 18% of the sample would prefer a higher number of trees rather than a lower number, and 7% would prefer a lower number of bags.

The ranking of the crops shows that groundnuts and pigeon peas are ranked highest, with lower preferences for sorghum and lowest for soy. The parameter estimate for pigeon peas is insignificant, meaning that this crop is not ranked differently from the baseline crop groundnuts. No significant heterogeneity was found in preferences for sorghum or pigeon peas when we included these variables as random parameters with normal distributions. However, the distribution of the random parameter of soy is significant. The posterior analysis of the conditional mean estimates shows that around 7% of respondents would have a positive preference for soy compared to groundnuts.

The alternative specific constant has a large effect size and is significant. We expect that this effect, which is the opposite of a status quo bias, largely reflects the dissatisfaction with the current situation among smallholders in our study area and indicates a general interest in change. The alternative specific constant value also reflects the baseline levels of the dummies, i.e. groundnut intercropping and fuelwood benefits.

Contrary to other studies, we find no significant effect for the time it takes until the yield increases and tree products can be harvested. Fruit trees are valued higher than trees with poles or firewood, but this effect is only weakly significant. Although the mean of the poles parameter is insignificant, the significant standard deviation of the random parameter suggests that respondents' preferences for poles is heterogeneous. Together these results suggest that the tree products are not a dominant factor in the utility of the proposed CSA techniques.

The final column of Table 3 presents the WTA estimates and their 95% confidence intervals, estimated by $-(\beta_z/\beta_{price})$. Hence, positive estimates for attributes imply that respondents would require an incentive to adopt a package containing those attributes, such as for soy rotation and sorghum intercropping. The wide confidence intervals of the random parameters also demonstrate the preference heterogeneity present in the sample. We explore this in the next section.

Table 3. Choice model results

Random parameters	Mean (s.d.)	Standard deviation (s.d.)	% β > 0	WTA[1] (95% C.I.)
Extra bags of maize	0.382*** (0.065)	0.446*** (0.086)	93	-7.16 (-14.44; -4.29)
Extra trees	-0.091*** (0.018)	-0.146*** (0.022)	18	1.70 (0.77; 3.38)
Soy rotation (mean)	-1.223*** (0.220)	-1.375*** (0.294)	7	23.17 (10.44; 46.46)
Poles (mean)	0.216 (0.186)	1.113*** (0.311)	n.s.	-4.29 (-14.12; 2.95)
Credit level (in MKW 1000)	0.064*** (0.018)	-0.114*** (0.033)	65	
Fixed parameters				
Alternative specific constant	4.915*** (0.681)			-93.54 (-193.39; -45.73)
Sorghum intercrop	-0.741*** (-3.503)			14.34 (4.90; 30.67)
Pigeon pea intercrop (mean)	0.080 (0.189)			2.07 (-5.12; 10.70)
Time (in years)	-0.023 (0.018)			0.42 (-0.26; 1.25)
Fruits (mean)	0.402* (0.158)			-7.23 (-16.23; -1.47)
Error component		-2.696*** (0.502)		
Loglikelihood	-886.6			
No. Obs.	1176			

Notes: *** p<0.01, ** p<0.05, *p<0.10. N.s.=not significant. [1] Note that WTA is calculated as: $-(\beta_z/\beta_{price})$, so that positive WTA estimates imply that farmers require compensation, while negative WTA estimates imply that farmers would be willing to pay to achieve increases in the attribute.

4.3 Observed preference heterogeneity

The results of the mixed logit model show considerable heterogeneity, with some respondents assigning positive utility changes to some of the attributes, while others express negative utility changes. Explaining this heterogeneity would help to understand which segments of the population are likely to adopt certain CSA packages. Therefore, we estimate how the heterogeneity in the conditional means of the random parameters of the DCE attributes are associated with indicators for different types of capitals (human, financial, natural, social and physical). We estimated a SUR model using STATA software and procedures and present the results in Table 4.

The resulting pattern is diverse, with effects related to different capitals: physical (land ownership), social (assistance from government and relatives), financial (revenues), human (education, knowledge of intercropping), and natural (trees owned). Preferences for soy are lower among men than women; the latter may prefer the nutritional value, especially for their children. Owners of only one plot have a lower preference for soy than owners of multiple plots, which can be explained by the aversion towards soy rotation which does not provide maize for domestic consumption in years of soy production. Owners of only one plot also have a lower preference for extra number of bags; possibly, owners of multiple plots expected to realise the yield increase more easily. While having more supporting relatives was related to a lower preference for maize yield increases, higher education was associated with higher preferences for more maize.

The extra number of trees, which farmers would need to maintain to avoid paying back the credit, shows that respondents with more plots are estimated to have a weaker negative preference for higher numbers of trees than farmers with fewer plots. Higher revenues (from livestock, agriculture, woodlands and forests) were also associated with higher preferences for extra trees. Respondents expecting governments to assist in times of need and those who had previously been involved in intercropping projects were also estimated to have more positive preferences towards extra trees. Preferences for poles was positively associated with the number of trees that respondents already owned on their plots, which may reflect a knowledge effect.

Finally, the preferred credit amount was negatively associated with having more supporting relatives and with living in village 1. There are differences between the four villages in various characteristics, but none of these had a direct effect on the conditional parameter of

the credit amount. Several variables found to be significant in previous studies (e.g. Giller et al 2011; Kassie et al. 2015), such as the access to fertiliser inputs, to financial and agricultural markets, were not significant in our dataset.

Table 4. Results of seemingly unrelated regression model

Conditional mean	R^2 (χ^2)	Explanatory variable	Coefficient	Standard error
Soy rotation	0.03** (7.50)	Gender respondent (1=male)	-0.229**	0.115
		Only 1 plot owned	-0.251**	0.121
		Constant	-1.062***	0.090
Number of extra maize bags	0.08*** (18.13)	Number of relatives in village for support	-0.014**	0.006
		Education level of 5 years or more	0.099**	0.038
		Only 1 plot owned	-0.084**	0.039
		Constant	0.414***	0.030
Number of extra trees	0.15*** (33.65)	Expecting government assistance	0.025*	0.014
		Involved in intercropping projects	0.035**	0.017
		Revenues (log)	0.004***	0.002
		Number of plots	0.024***	0.008
		Constant	-0.182***	0.018
Poles	0.04*** (3.94)	Total number of trees on farm (log)	0.072***	0.027
		Constant	0.101***	0.062
Credit	0.07*** (15.35)	Living in village 1	-0.006**	0.002
		Number of relatives in village for support	-0.001***	0.001
		Constant	0.011***	0.002
Number of observations			*186*	
Breusch-Pagan test of independence ($\chi^2(10)$)			*25.15; P=0.0051*	

Notes: *** $p<0.01$, ** $p<0.05$, *$p<0.10$. The χ^2 tests of the individual regressions demonstrate that the models are significantly better than their constant-only counterparts; the Breusch-Pagan test of independence is a Lagrange multiple statistic, of which the results here show that the errors of the five equations are significantly correlated. For 10 respondents, data on the relevant characteristics were missing, so they were excluded from this analysis.

4.4. Implications for CSA policies: estimating conditional adoption rates of CSA packages

To demonstrate the implications of our findings on the incentive payments required for different packages, Table 5 provides estimates of WTA and proportion of market shares for four different potential packages, informed by existing research on CSA in East and Southern Africa (Snapp et al. 2002, Kamanga et al. 2010, Sani et al. 2011, Sirrine et al. 2010, Kazcan et al. 2013, Carsan et al. 2014, Smith et al. 2016, Franke et al. 2018, Snapp et al. 2018). Package 1 is a soy rotation package, that is expected to provide fuelwood from the 5 trees, and improve soil fertility and therefore maize production by about 4 bags a year after 5 years. Package 2 is a pigeon pea package intercropped with maize, where 5 additional trees provide fruits and maize yields increase by 2 bags a year due to the soil improvements of nitrogen fixation of the pigeon peas after 5 years. Package 3 is the drought-resistant sorghum package, where 10 extra trees for poles are planted, and one extra maize is earned from 3 years onwards. Package 4 is a basic package, which provides fuelwood from three extra trees and 1 extra bags of maize after 5 years thanks to trees improving soils.

Firstly, the WTA estimates show that Package 2 has a negative WTA estimate (-8.86 thousand MKW), which suggests that respondents would not require a financial incentive to adopt this package. We exclude the alternative specific constant from the WTA estimation. If Package 2 was the only option on offer, the WTA results suggest that 71% of smallholders in our sample would not experience a utility loss and hence not require a financial incentive. The WTA estimates are higher for the other packages, ranging from approximately zero MKW for Package 4, to 21 thousand MKW for the unpopular Package 3. If the policy objective is to increase soy production (Package 1), 49% of the farmers in our sample would require no financial incentive. However, if the policy objective is to increase farmers' resilience to droughts, then either a different crop than sorghum should be offered, or 80% of farmers would require a financial incentive to adopt sorghum (Package 3).

Second, if multiple packages were offered to farmers at the same time, the estimates show that Package 2 is ranked highest of the four packages by 61% of the respondents of our sample. Although intercropping pigeon peas is not valued higher than intercropping groundnuts, the higher number of additional bags of maize (as a result of higher expected soil improvements when intercropping with pigeon peas) lead to a higher ranking of Package 2 than the other packages.

Noticeable from the percentage of respondents that ranked Package 1 highest is the effect of heterogeneity towards soy rotation package. Package 1 has a higher mean WTA than Package 4, i.e. its adoption requires a higher financial incentive, yet more respondents rank it highest (26% compared to 11%).

A further exploration of these results, informed by the SUR analysis in Section 4.3, shows that Package 1 is ranked highest by 31% of respondents with multiple plots, compared to only 15% of respondents with a single plot. Respondents who own one plot rank Package 4 first almost as often as Package 1. Hence, if the policy objective is to include farmers with small land holdings, then Package 4 is important to include in a portfolio of CSA programmes.

Finally, if the policy is to achieve a yield target for individual crops when multiple packages are on offer, the results show that Package 4 would have to be accompanied by an incentive payment of MKW 40 thousand for this Package to be ranked highest by a majority of respondents (more often than package 2). This shows not only that Package 2 is most popular on average, but also that the heterogeneity towards the incentive payment creates a need for a higher compensation than would be expected from the difference in mean WTA estimates alone.

Table 5. Willingness to Accept and ranking estimates for four CSA policy packages

	Package 1	Package 2	Package 3	Package 4
Cropping technique	Soy - maize rotation	Pigeon pea - maize intercrop	Sorghum - maize intercrop	Groundnut - maize intercrop
Number of extra trees	5	5	10	3
Tree product	fuelwood	fruits	poles	fuelwood
Increase in maize yield	4 bags of 50kg	2 bags of 50kg	1 bag of 50kg	1 bag of 50kg
Time until improvement	5 years	5 years	3 years	5 years
WTA (no ASC) (95% CI)	5.15 (-7.91; 18.11)	-8.86 (-25.77; 3.00)	21.18 (6.12; 46.24)	-0.04 (-5.27; 4.80)
Proportion of sample with positive WTA	49%	71%	20%	63%
Proportion of 1st ranks	26%	61%	3%	11%
owner >1 plot	31%	59%	2%	8%
owner 1 plot	15%	66%	3%	16%
Incentive needed for highest majority rank	52	0	135	40

Notes: Based on Krinsky and Robb Monte Carlo simulation procedures with 2000 draws. WTA values and incentives are expressed in Malawi Kwacha (2015) * 1000, per farmer per year for a period of 5 years.

4.5. Limitations

There are some limitations to our study that affect the use of the results for further policy appraisal and implications for poverty and inequality reduction. Firstly, the sample size of our study (n=196) is too small to aggregate the findings across the wider population of the two sampled districts of our study (over 1 million people), as the socioeconomic and

agroecological conditions of two districts are more diverse than reflected in our sample. We therefore do not provide population level estimates of WTA. Our scenario analysis aimed to provide insight into the profiles of farmers that would be likely to adopt different packages, but not to estimate aggregate welfare estimates or adoption rates. We argue that such profiles provide valuable information to development practitioners who tend to operate in selected communities and would be able to target farmers depending on their profiles with the appropriate packages.

Secondly, we expect that the high effect size of the alternative specific constant should not be used to assess potential adoption rates of the climate smart agriculture packages evaluated in this study. We expect that these estimates are subject to hypothetical bias and suggest a propensity to change that is much higher than observed in ex-post evaluation studies on the adoption of conservation agriculture and agroforestry programmes (Andersson and D'Souza 2014, Chinseu et al. 2019).

Thirdly, the effect of land ownership on preferences for the proposed CSA options was important. Our study sample included farmers with at least one plot and excluded landless people who would not be able to adopt the practices. CSA projects focused on-farm practices (rather than off-farm activities further down the value chain) may fail to reach landless people, who represent an estimated 16.7% of Malawi's rural households (NSO 2017b). It was beyond the scope of our study to assess preferences of landless people, or for off-farm CSA activities. Also excluded from our sampling frame were households where the head of the household was younger than 18 years, such as orphaned children living alone, and respondents older than 65 years. These groups may be more vulnerable or poor, and whether CSA projects will be able to provide benefits to these groups remains an open question.

5. Conclusions

Different agricultural projects have been implemented in Sub-Saharan Africa with the aim to increase food production as well as smallholder wellbeing and resilience, including climate smart agriculture, sustainable intensification and conservation agriculture. Our ex-ante evaluation of different climate smart agriculture packages, using a discrete choice experiment among smallholders in Malawi, shows that the 'best' strategy depends on the objectives of governments and development organisations promoting CSA. Our study provides relevant

recommendations towards adoption of climate smart agriculture and demonstrates that land ownership plays a key role in the preferences of smallholders, which may also apply to other agricultural development programs.

If the aim for CSA is to increase overall yields in line with SDG 2, organisations may mainly be interested in reaching out to as many smallholders as possible by offering the most attractive package. In our study, this was a package offering pigeon pea-maize intercropping with considerable maize yield gains. However, if the aim is to increase soy production, then our results suggest that farmers will require significant incentive payments to overcome the perceived utility losses. In the case of soy, the need for self-sufficiency in maize combined with the lack of market access, considerably reduced the attractiveness of soy-maize rotation techniques.

However, to achieve poverty and inequality reduction in line with SDG 1 and 10, strategies that target relatively poorer smallholders (i.e. those with a single plot) may require different agricultural techniques. Farmers with multiple plots were more likely to prefer soy-maize rotation schemes, whilst single-plot owners preferred groundnut-maize intercropping more often. Groundnuts have a local market and are used for self-consumption. Tree adoption, often promoted to improve or maintain soil quality, is also restricted by land ownership. Our study hence shows that for CSA to be pro-poor, options are necessary that do not lead to reduced staple food yields in the short-term, irrespective of (financial) compensation or long-term benefits. A wider CSA strategy focused on SDG 1 and 10 should also consider off-farm activities to involve landless community members.

If the aim is to increase climate resilience of farmers (SDG 13) through increasing the adoption of crops that are more resistant to droughts, offering sorghum-maize intercropping packages does not appear to be an effective strategy. Low marketability, limited use in current diets or perhaps the stigma of a 'poor man's crop' may explain this. Governments and development organisations may want to consider other drought resilient crops. Further research would have to assess farmers' preferences towards other crops or drought tolerant maize varieties.

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